Bootstrap methods for multi-task dependency parsing in low-resource conditions

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by

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Abstract

Dependency parsing is an essential component of several NLP applications owing its ability to capture complex relational information in a sentence. Due to the wider availability of dependency treebanks, most dependency parsing systems are built using supervised learning techniques. These systems require a significant amount of annotated data and are thus targeted toward specific languages for which this type of data are available. Unfortunately, producing sufficient annotated data for low-resource languages is time- and resource-consuming. To address the aforementioned issue, the present study investigates three bootstrapping methods, namely, (1) multilingual transfer learning, (2) deep contextualized embedding, and (3) co-training. Multilingual transfer learning is a typical supervised learning approach that can transfer dependency knowledge using multilingual training data based on multilingual lexical representations. Deep contextualized embedding maximizes the use of lexical features during supervised learning based on enhanced sub-word representations and language model (LM). Lastly, co-training is a semi-supervised learning method that leverages parsing accuracies using unlabeled data. Our approaches have the advantage of requiring only a small bilingual dictionary or easily obtainable unlabeled resources (e.g., Wikipedia) to improve parsing accuracy in low-resource conditions. We evaluated our parser on 57 official CoNLL shared task languages as well as on Komi, which is a language we developed as a training and evaluation corpora for low-resource scenarios. The evaluation results demonstrated outstanding performances of our approaches in both low- and high-resource dependency parsing in the 2017 and 2018 CoNLL shared tasks. A survey of both model transfer learning and semi-supervised methods for low-resource dependency parsing was conducted, where the effect of each method under different conditions was extensively investigated.

Méthodes d'amorçage pour l'analyse en dépendances de langues peu dotées

par

KyungTae Lim

Résumé

Note : Le résumé étendu en français se trouve en annexe, à la section (B.1)

L'analyse en dépendances est une composante essentielle de nombreuses applications de TAL (Traitement Automatique des Langues), dans la mesure où il s'agit de fournir une analyse des relations entre les principaux éléments de la phrase. La plupart des systèmes d'analyse en dépendances sont issus de techniques d'apprentissage supervisées, à partir de grands corpus annotés. Ce type d'analyse est dès lors limité à quelques langues seulement, qui disposent des ressources adéquates. Pour les langues peu dotées, la production de données annotées est une tâche impossible le plus souvent, faute de moyens et d'annotateurs disponibles. Afin de résoudre ce problème, la thèse examine trois méthodes d'amorçage, à savoir (1) l'apprentissage par transfert multilingue, (2) les plongements vectoriels contextualisés profonds et (3) le co-entrainement. La première idée, l'apprentissage par transfert multilingue, permet de transférer des connaissances d'une langue pour laquelle on dispose de nombreuses ressources, et donc de traitements efficaces, vers une langue peu dotée. Les plongements vectoriels contextualisés profonds, quant à eux, permettent une représentation optimale du sens des mots en contexte, grâce à la notion de modèle de langage. Enfin, le co-entrainement est une méthode d'apprentissage semi-supervisée, qui permet d'améliorer les performances des systèmes en utilisant les grandes quantités de données non annotées souvent disponibles pour les différentes langues visées. Nos approches ne nécessitent qu'un petit dictionnaire bilingue ou des ressources non étiquetées faciles à obtenir (à partir de Wikipedia par exemple) pour améliorer la précision de l'analyse pour des langues où les ressources disponibles sont insuffisantes. Nous avons évalué notre analyseur syntaxique sur 57 langues à travers la participation aux campagnes d'évaluation proposées dans le cadre de la conférence CoNLL. Nous avons également mené des expériences sur d'autres langues, comme le komi, une langue finno-ougrienne parlée en Russie : le komi offre un scénario réaliste pour tester les idées mises en avant dans la thèse. Notre système a obtenu des résultats très compétitifs lors de campagnes d'évaluation officielles, notamment lors des campagnes CoNLL 2017 et 2018. Cette thèse offre donc des perspectives intéressantes pour le traitement automatique des langues peu dotées, un enjeu majeur pour le TAL dans les années à venir.

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Chapter 1

Introduction

Thus far, natural language processing (NLP) has mainly focused on a small number of languages for which different kinds of resources are available. The gradual development of the Web, as well as of social media, has revealed the need to deal with more languages which, in turn, present new challenges. For example, it is clear that languages exhibit a large diversity of features, particularly concerning morphological and syntactic complexity, and NLP tools (e.g., part-of-speech taggers and dependency parsers) which must tackle this diversity to yield acceptable performance. In this context, developing systems for low-resource languages is a crucial issue for NLP.

Parsing is the process of analyzing the syntactic structure of sentences. The structure of a sentence corresponds to the arrangement of the words within the sentence. This can be expressed as a set of dependencies: each word in the sentence (except the main verb) depends on another one (the subject of a sentence depends on the verb, the determiner in a noun phrase depends on the noun, and so on). All these relations can be formalized as relations between couple of words, a head (i.e. the verb) and a dependent (i.e. the noun that is the subject of the verb). The main element of the sentence (generally, the verb) has no head and is called the root of the sentence.

Syntax encodes the relations between the words in the sentence, and therefore, it is the first step towards semantics. Parsing, the automatic analysis of the syntactic structure of the sentence, is thus important for downstream NLP tasks, such as named entity recognition (Kazama and Torisawa, 2008), discourse understanding (Sagae,

2009), or information extraction (Fares et al., 2018b). The traditional approach to parsing was to manually develop rules encoding the grammar of the language, but in practice, this leads to rather poor results. A large set of rules is hard to produce and to maintain, generally provides a limited coverage, and more importantly, often leads to inconsistencies because different phenomena may appear and interact in a same sentence.

In this context, machine learning and the availability of annotated corpora provided a relevant alternative approach to parsing. More than 20 years ago, most NLP systems were built using supervised learning techniques (Weiss et al., 2015b; Straka et al., 2016; Ballesteros et al., 2016a). These systems observe large annotated corpora to identify regularities and acquire (''learn'') a model that can reproduce the observed annotation as accurately as possible. This model can then be applied to unseen data and provide syntactic annotations (the task known as parsing) over unseen data.

However, this strategy implies that large amounts of annotated data are available: the approach is thus well suited for languages for which this type of data exists. Unfortunately, producing enough annotated data for accurate parsing is known to be time- and resource-consuming. A known problem is the lack of resources (particularly annotated corpora) for most languages. As a recent example, the 2018 CoNLL Shared Task considered around 57 languages; these included approximately all the languages for which sufficient syntactically annotated data are available in the Universal Dependency format. This was probably the most ambitious parsing challenge ever undertaken with regard to language diversity. However, the figure of 57 languages should be viewed in the context of 6,000 languages in the world: even if we consider only the languages for which written data are available, the 57 languages targeted at CoNLL 2018 represent a fraction of all languages in the world.

Therefore, there is no accurate parser for several languages for which this kind of technology would be useful, and the lack of resources constitutes a bottleneck that is hard to overcome.

1.1 Research Questions

As we have just seen, for dependency parsing, **(A) the monolingual** and **(B) supervised** approach based on syntactically annotated corpora has long been the most popular one. However, because of recent developments involving **(A) multilingual** feature representations and **(B) semi-supervised** methods, which allow NLP systems to learn from unlabeled data, more accurate NLP models, even for low resource languages, can now be developed. This leads to two main research questions:

- **(A)** What are the benefits of multilingual models for parsing, especially in low resource scenarios?
- **(B)** Can we make use of unlabeled data for parsing, especially in low resource scenarios?

Although one can sometimes find limited data (such as a list of words or a small dictionary) for low-resource languages, more substantial unlabeled data (e.g., from Wikipedia) can often be obtained, as well as annotated data from other languages that are typologically or geographically related[1]. We detail these questions in the remainder of this section.

Question **A: What are the benefits of multilingual models for parsing, particularly in low resource scenarios?** We know that multilingual approaches to parsing have yielded encouraging results for both low- (Ammar et al., 2016b) and high-resource scenarios (Guo et al., 2015b). Generally, the multilingual approach can be implemented in two ways. The first approach involves projecting annotations available for a high-resource language onto a low-resource language using a parallel corpus, while the second aims at producing a cross-lingual transfer model that can work for several languages using transfer learning. (Guo et al., 2016) and (Ammar et al., 2016b) have conducted multilingual parsing studies on Indo-European languages using this second approach. They demonstrated that a multilingual model

[1]Geography also plays a role. This is known as contact linguistics: two languages that are in close contact, through a community of bilingual speakers (or not bilingual), will often share a common vocabulary, at least some borrowings, and often even syntactic structures.

can yield better results than several monolingual models (one per language) for different European languages. Specifically, (Ammar et al., 2016b) made an artificial low-resource scenario that uses only 50 training sentences to investigate the performance of their multilingual approach. However, their approach relied on the existence of a massive parallel corpus, as their experiment was based on Europarl[2]. Thus, the problem of low-resource languages that do not have a massive parallel corpus remains unaddressed. This raises two sub-questions which are as follows:

- **(A-1)** Is parallel data a requirement for multilingual parsing? (Section 4.2)
- **(A-2)** How can we bootstrap a system when no parallel corpus is available? (Section 4.2 and 4.3)

In order to investigate and answer these questions, we propose a simple but powerful method for creating a dependency parsing model when no annotated corpus or parallel corpus is available for training. Our approach requires only a small bilingual dictionary and a manual annotation of a handful of sentences. It is assumed that the performance we obtain with this approach depends largely on the set of languages used to train the model. Therefore, we developed several models using genetically related and non-related languages, so as to gain a better understanding of the limitations or possibilities of model transfer across different language families.

Question **B: Can we make use of unlabeled data for parsing, especially in low resource scenarios?** This question is related to semi-supervised learning, i.e., the ability to learn from annotated and also from non-annotated data conjointly. Two major semi-supervised approaches have been proposed for parsing: self-training (McClosky et al., 2006; Sagae, 2010) and co-training (Sarkar, 2001; Sagae, 2009; Zhang et al., 2012; Yu, 2018). The goal of co-training is to train multiple learners (parsers in our case) based on different ‘‘views” that can subsequently be applied on unlabeled data. A view in NLP typically corresponds to a specific level of analysis (such as character-based and token-based). The successful use of co-training depends on the

[2]www.statmt.org/europarl

learners being as different as possible. Therefore, previous work on parsing with co-training has mainly focused on using learners that are carefully designed to be distinct. However, this approach yielded marginal improvements for parsing (Zhang et al., 2012; Weiss et al., 2015a). We hypothesize that this is because traditional co-training focuses on local decisions, which leads to errors that could be avoided with a more global decision context. Our hypothesis results in three sub-questions:

- **(B-1)** Can traditional co-training approaches further improve dependency parsing in low-resource scenarios? (Section 6.1)
- **(B-2)** Can co-training models that consider different views globally (i.e. at the sentence level) learn from from one another on unlabeled data? Does this improve the performance for low-resource languages? (Section 6.4)
- **(B-3)** How many labeled and unlabeled sentences are needed for co-training to be beneficial? (Section 6.4)

By maximizing agreement between the predictions provided by learners using unlabeled data, we propose a co-training parsing model that takes decisions based on a non-local context. Specifically, we study whether improving each multi-view model by promoting the consensus in a Semi-Supervised Learning (SSL) manner can lead to learning better parsing models in the context of joint tagging and dependency parsing. Once co-training is applied, we obtain several parsing models trained by each view. Then, with regard to our SSL approach (co-training), the main challenge is to decide which view teaches the others. We suggest three different methods that allow the learners to learn from each other: Entropy, Voting, and the Ensemble-based approach. We employ our SSL methods on top of the graph-based parser with a bi-affine classifier proposed by Dozat et al. (2017b), and we investigate the effectiveness of our co-training approach.

Finally, while investigating (A) and (B), we attempt to answer the following research question:

- **(C)** What are the benefits of simultaneously applying the two proposed approaches, (A) multilingual and (B) SSL, as multilingual SSL models? (Section 7.2)

1.2 Contributions

Considering the aforementioned challenges, the contributions of this thesis are (1) the development and analysis of a new multi-source trainable dependency parser, (2) the investigation of SSL methods using unlabeled data, and (3) the creation of new resources for low-resource languages.

- **Proposal for a new multi-source trainable parser.** The major contribution of this study is the description of a new multilingual dependency parser that integrates multilingual word embeddings. Concerning word embeddings, we show that the bilingual word mapping approach (Artetxe et al., 2016a) can be extended to cope with multilingual data. With this parsing model, we participated in the official CoNLL 2017 and 2018 shared tasks that required to parse 57 languages, including low-resource ones (Zeman et al., 2018b). Our parser regularly ranked among the 5 best systems for parsing, and also achieved the best performance in the so called ‘‘extrinsic evaluation" (especially for information extraction) (Fares et al., 2018a). The parser[3] and POS-tagger[4] are publicly available.

- **Investigation of SSL for parsing.** The study investigates whether co-training is beneficial in both low- and high-resource conditions. As SSL methods use unlabeled (uncertain) data, their performance must be investigated based on the resource used. We experimented with diverse conditions by changing the amount and domains of unlabeled data and the effect of all these variables on the proposed model. Our experiments on joint parsing with SSL methods resulted in three sub-contributions: (1) the proposal of a new formulation for

[3]https://github.com/jujbob/multilingual-bist-parser
[4]https://github.com/jujbob/Utagger

co-training that leverages consensus promotion in addition to multi-views. (2) the analysis of the relative performance of each multi-view model. (3) the exploration of different semi-supervised scenarios, where the amount and domains of unlabeled data vary.

- **Creation of language resources.** New resources were developed over the course of the thesis. With Niko Partanen, we created a new corpus for Komi with syntactic information encoded in the Universal Dependencies format[5], as well as bilingual dictionaries, multilingual word embeddings for Komi and Sami, and a parser for the language, based on the multilingual approach described above. All these resources are available for free in public repositories[6]. These languages are interesting for at least three reasons: (1) they are typical of a large number of languages for which very few resources exist, specifically no annotated corpus but raw corpora in large enough quantities; (2) they are morphologically-rich languages, which makes them hard to process; and (3) they are supported by an active community of users that is very positive towards language technology development. We had the chance to work with Niko Partanen, a specialist of Finno-Ugric languages, especially Komi and Sami, during the course of the thesis.

1.3 Thesis Structure

Each of the chapters 3-6 present a new parsing model that is an increment over the previous one. Chapter 3 presents our baseline model based on monolingual lexical representations. Chapter 4 extends the baseline model to a multilingual one. Chapter 5 describes a more complex version of this model, adding character-level and deep contextualized representations, that improve out-of-vocabulary (i.e., unknown words that appear in the testing data) processing. Finally, Chapter 6 integrates the co-training strategy intended to utilize unlabeled data. Each chapter presents the main idea

[5]github.com/langdoc/UD_Komi-Zyrian

[6]See github.com/jujbob/multilingual-bist-parser, and github.com/jujbob/multilingual-models.

of the chapter, technical developments, experimental results, and a brief discussion of these results. The structure of the thesis, including Background and Conclusion, is as follows:

- **In Chapter 2**, we first describe in detail the background information from previous works. This chapter introduces the idea of dependency parsing along with the two main algorithms: graph- and transition-based parsing. Then, we discuss the more recent deep neural network techniques for developing parsers with an example of the Bi-directional Long Short Term Memory (BIST) parser, which considers contextualized information. We then introduce an overview of the corpora and evaluation metrics used for dependency parsing. In Section 2.2 and 2.3, we present the transfer learning and co-training approaches, which are fundamental for our parser.

- **In Chapters 3 and 4**, we introduce our multilingual parsing approach. We first present an overview of our approach in Chapter 3 with a baseline model, before detailing the multilingual resource representation used, in Chapter 4. In section 4.3, we present our multilingual approach to Komi. As we have seen before (Section 1.2), Komi offers a realistic and relevant use case as a low resource language with no annotated corpora available for training. We also detail the annotated corpora that were developed to test the method in Section 4.3.1. Moreover, we present the details of our participation in the CoNLL 2017 shared task with our parser. In Section 3.2 and 4.4, we compare the performance of our parser with other parsers that applied mono- and multilingual approaches.

- **In chapter 5**, we introduce deep contextualized representations. We begin by discussing the most recent sub-word representations in Section 5.1, as well as a deep contextual representation method, Embeddings from Language Models (ELMo), which is an approach aiming at learning contextualized word vectors (Section 5.2). Then, we detail our implementation of these representations. Specifically, we describe the feature extraction and representation methods for our POS tagger (Section 5.3) and parser, based on multi-task joint learning (Sec-

tion 5.4). Finally we provide an analysis of the experimental results obtained on the CoNLL 2018 shared task data (Section 5.4.2).

- **In chapter 6**, we introduce our experiments with a semi-supervised approach. We first discuss the effect of multi-view learning in Section 6.1. Then, we introduce co-training, along with the multi-view structure in Section 6.2, Then, we describe our experiments performed on unlabeled data from different domains and sizes in Section 6.4.

- **In chapter 7**, we describe a parser that can simultaneously apply the proposed multilingual and semi-supervised approaches. In Section 7.1, we propose a projection method that can integrate multilingual and semi-supervised approaches. The experiment is detailed in Section 7.2, and the results are presented in Section 7.3.

- **In chapter 8**, we summarize our thesis along with providing answers to the questions raised in the Introduction.

1.4 Publications Related to the Thesis

There are seven publications based on this thesis, and the code used for all experiments is publicly available on `https://github.com/jujbob`. The work described in Chapter 4 has given birth to four different publications:

- **KyungTae Lim**, Niko Partanen, and Thierry Poibeau. *Analyse syntaxique de langues faiblement dotées à partir de plongements de mots multilingues.* Traitement Automatique des Langues (2018), volume 59, pages 67-91.

- Niko Partanen, **KyungTae Lim**, Michael Rießler, and Thierry Poibeau. *Dependency parsing of code-switching data with cross-lingual feature representations.* In Proceedings of the Fourth International Workshop on Computatinal Linguistics of Uralic Languages. (2018). pages 117.

- **KyungTae Lim**, Niko Partanen, and Thierry Poibeau. 2018. *Multilingual Dependency Parsing for LowResource Languages: Case Studies on North Sami and Komi-Zyrian.* In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018). Miyazaki, Japan.

- **KyungTae Lim**, and Thierry Poibeau *A System for Multilingual Dependency Parsing based on Bidirectional LSTM Feature Representations.* Proceedings of the CoNLL 2017 Shared Task: Multilingual Parsing from Raw Text to Universal Dependencies (2017). pages 63-70.

The work described in Chapter 5 has given birth to two different publications:

- **KyungTae Lim**, Stephen McGregor and Thierry Poibeau. *Joint Deep Character-Level LSTMs for POS Tagging.* Proceedings of the Twentieth International Conference on Computational Linguistics and Intelligent Text Processing (CICLing 2019), (Accepted)

- **KyungTae Lim**, Cheoneum Park, Changki Lee and Thierry Poibeau. *SEx BiST: A Multi-Source Trainable Parser with Deep Contextualized Lexical Representations.* Proceedings of the CoNLL 2018 Shared Task: Multilingual Parsing from Raw Text to Universal Dependencies (2018)

The work described in Chapter 6, dependency parsing with a semi-supervised learning (co-training), has given birth to a publication:

- **KyungTae Lim** Jay-Yoon Lee, Jaime Carbonell, and Thierry Poibeau. *Semi–Supervised Learning on Meta Structure: Multi-Task Tagging and Parsing in Low-Resource Scenarios.* Proceedings of the Thirty-Fourth AAAI Conference on Artificial Intelligence (AAAI 2020), (Accepted)

Chapter 2

Background

In this chapter, we introduce the notion of dependency parsing. We describe the main algorithms, datasets and evaluation metrics used in the field.

2.1 Syntactic Representation

Syntax refers to the set of rules that govern the relations between words within a sentence (and therefore the structure of this sentence), in a given language. This domain is of crucial importance for natural language processing, since it is mandatory to first establish the relations between words in order to then capture the meaning of a sequence of words. Any advanced natural language application (e.g., information extraction, question-answering, etc.) requires some kind of syntactic analysis to produce accurate outputs.

A sentence can be hierarchically decomposed into logical groups of words, like a noun phrase (a group of words around a noun) and a verb phrase (idem, around a verb), until individual words are reached. This process is called ''constituent analysis" (or ''phrase analysis'') (Chomsky and Lightfoot, 2002)[1]. An alternative is a dependency analysis (or ''dependency representation''), where each word in the sentence is directly linked to another one, called the head (the word than depends on the head is called a dependent) (Tesnière, 1959; De Marneffe et al., 2006; de Marneffe and

[1]http://en.wikipedia.org/wiki/Phrase_structure_grammar

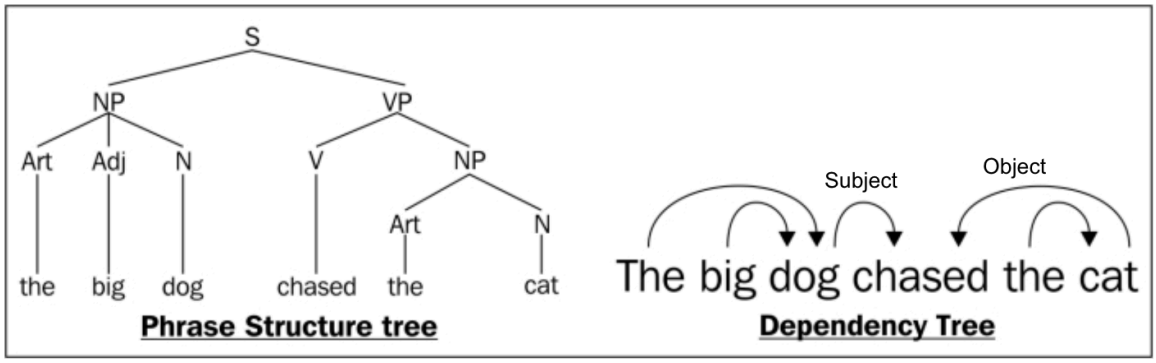


Figure 2-1: Syntactic representation of the sentence ‘‘The big dog chased the cat’’. On the left a constituent analysis, on the right the dependency analysis.

Manning, 2008; Nivre et al., 2016a)[2]. Generally the verb is the main element in the sentence (it is the only element that does not have a head in the sentence). With a dependency analysis, the main constituents of the sentence are not directly visible (as opposed to a constituent-base analysis), but the relations between the main lexical elements in the sentence (i.e., the arguments of the verb) are more directly accessible.

Let's take a simple example, with the sentence ‘‘The big dog chased the cat’’. A phrase-based representation of this sentence is shown on the left of Figure 2-1. In this figure, the terminal and non-terminal nodes are categorized with tags such as: NP (Noun phrase), VP (Verb phrase), Art (article), Adj (adjective), N (noun), and V (verb). The constituent structure and the labels can also be represented in a labeled bracketed structure, as follows:

- Input : The big dog chased the cat
- Representation: [NP The big dog NP] [VP chased [NP the cat NP] VP][3]

A dependency representation of ‘‘The big dog chased the cat” would the one in the right of Figure 2-1. In this example, we can see that both the subject (*dog*) and the object (*cat*) are directly linked to the verb (*chased*) This structure has only terminal nodes, which means there is no distinction between terminal and non-terminal

[2]http://en.wikipedia.org/wiki/Dependency_grammar, Lucien Tesnière, Professor for Comparative Linguistics at the University of Montpellier from 1937 to his death in 1954, is the undoubted father of dependency

[3]This example is taken from: http://www.ilc.cnr.it/EAGLES96/segsasg1/node44.html

categories.

The result of a dependency analysis is generally a tree (called ‘‘dependency tree’’, or ‘‘parse tree’’). In the tree, arrows ‘depart’ from dependents and point to their *Head*. Thus, in this example, ‘‘The” and ‘‘big” are dependents of ‘‘dog” and ‘‘dog” is the *Head* of ‘‘The” and ‘‘big’’. Also, ‘‘dog” is dependent on ‘‘chased” with a ‘‘Subject” relation. We will call this type of dependency label *Dep*. As a consequence, each word in a sentence has a pair of dependency information *(Head, Dep)*. The dependency structure and the labels can also be represented in a tabular format where each line is a word with related information: more specifically, each word is associated with and index and a series of features. The head of a word is represented by the index of the word that is its head. Our example sentence can thus be represented as:

- Input: The big dog chased the cat
- Representation:

1	The	3	Determiner
2	big	3	Adjectival modifier
3	dog	4	Subject
4	chased	0	Root
5	the	6	Determiner
6	cat	4	Object

The verb ‘‘chased” is the fourth word of the sentence and it has no head (hence the 0 in the third column). The noun ‘‘dog” is the subject and its head is the verb (hence the 4 in the third column), etc.

In general, a dependency-based representation of a sentence is simpler than a phrase-based representation because it contains fewer nodes. Phrase-based representations are supposed to be useful and convenient for languages with a rather fixed word order patterns and clear constituent structures (e.g., Finnish and the Slavonic languages). At the opposite, dependency representations are more suitable for languages with a greater freedom of word order (e.g., Italian and Spanish)[4].

[4]According to http://www.ilc.cnr.it/EAGLES96/segsasg1/node44.html

The task consisting in automatically (i.e., by means of a computer) analyzing the structure of sentences in a given language is called parsing. The main idea is to automatically produce, from a sentence taken in input, a tree structure encoding the relations among words in the sentence. Different parsers have been developed to produce a constituent-based analysis, as well as a dependency analysis. A parser that follows phrase structure principles is thus called a phrase structure parser (constituency parser). At the opposite, a parser that follows dependency principles is called a dependency parser.

Initially, the parsing community primarily focused on constituency parsing systems; as a result, a number of high accuracy constituency parsers have been introduced, such as the Collins Parser (Collins, 2003), the Stanford PCFG Parser (Klein and Manning, 2003), and the Berkeley Parser (Petrov and Klein, 2007). In the past decade, dependency-based systems have gained more attention (McDonald and Pereira, 2006; Nivre, 2004; Bohnet, 2010; Martins et al., 2013), as they have better multilingual capacity and are supposed to be more efficient. All the experiments described in this thesis have been done within the dependency framework.

In the following section, we will concentrate on the recent developments in the field, especially the Universal dependencies initiative, and then recent dependency parsing algorithms (Section 2.2).

Universal Dependency Representation

Several syntactic dependency representations have been proposed during the last decade. As said on the Universal Dependencies (UD) website, UD ‘‘is a project that is developing cross-linguistically consistent treebank annotation for many languages, with the goal of facilitating multilingual parser development, cross-lingual learning, and parsing research from a language typology perspective. The annotation scheme is based on an evolution of (universal) Stanford dependencies (De Marneffe et al., 2006; de Marneffe and Manning, 2008; De Marneffe et al., 2014), Google universal part-of-speech tags (Petrov and McDonald, 2012), and the Interset interlingua for

morphosyntactic tagsets (Zeman, 2008)"[5].

The Stanford Dependencies framework was originally invented in 2005 as a practical way to encode English syntax and help natural language understanding (NLU) applications. The annotation scheme was then extended as the main annotation scheme for the dependency analysis of English (De Marneffe et al., 2006). This schema has then been adapted to several other languages such as Chinese (Chang et al., 2009), Italian (Bosco et al., 2013), or Finnish (Haverinen et al., 2014).

Meanwhile, the 2006 CoNLL shared task dealt with multilingual dependency parsing McDonald and Nivre (2007a). The goal of this shared task was to evaluate dependency parsing for 13 languages. The annotations used for each language was different, hence the need to define a common format so as to make the comparison of the results possible. Google decided to develop its own tag set in 2006 for the evaluation done in the framework of the 2006 CoNLL shared task (Buchholz and Marsi, 2006). The Google universal tag set also served to convert other tag sets developed in different places, in multilingual contexts.

At some point, each treebank was annotated using some specific tools, with different tagsets, even for the same task. This led researchers to propose a conversion method, for different tagsets, with the aim of making these tagsets reusable. (Zeman, 2008) proposed a universal approach *"Interset"* that converts different tagsets from a source language to a target language. This universal tagset later served as a basis for the Universal Dependency standard, especially for language-specific morphological features and part of speech tags.

There was thus a need for a common annotation format across languages. This is not trivial because every language has its own grammar and its own tradition, hence different ways of encoding linguistic phenomena. The first attempt to combine Stanford dependencies and Google universal tags into a universal annotation scheme was the Universal Dependency Treebank (UDT) project (McDonald et al., 2013). This project was aiming at converting different treebanks into a common annotation scheme. Finally, this initiative became the Universal Dependency (UD) project.

[5]https://universaldependencies.org/

In this study, we use Universal Dependencies (UD), which is a framework providing a consistent syntactic annotation scheme (including parts of speech, morphological features, and syntactic dependencies) across different human languages. UD is an open community effort with over 200 contributors who have so far produced more than 100 treebanks in over 70 languages.

The CoNLL-U format is a standard format for the practical encoding of Universal Dependencies treebanks. In this format, each word stands on a line along with different associated features (word form, lemma, POS tag, etc.) in tab-separated columns. A sentence consists of one or more lines, and each line contains the following fields[6]:

1. ID: Word index, integer starting at 1 for each new sentence.
2. FORM: Word form or punctuation symbol.
3. LEMMA: Lemma or stem of the word form.
4. UPOS: Universal part-of-speech tag. The part-of-speech indicates how the word functions grammatically in the sentence.
5. XPOS: Language-specific part-of-speech tag; underscore if not available.
6. FEATS: List of morphological features from the universal feature inventory or from a defined language-specific extension; underscore if not available.
7. HEAD: Head of the current word, which is either a value of ID or zero (0).
8. DEPREL: Universal dependency relation to the HEAD (root if HEAD = 0) or a defined language-specific subtype of one.
9. DEPS: Enhanced dependency graph in the form of a list of head-deprel pairs.
10. MISC: Any other annotation.

For instance, Figure 2-2 encodes the English sentence, ‘‘I have no clue’’. In this sentence , ‘‘I” is a dependent of the verb ‘‘have’’; thus, ‘‘have” is the syntactic

[6]The description that follows are based on the official website:
https://universaldependencies.org/format.html

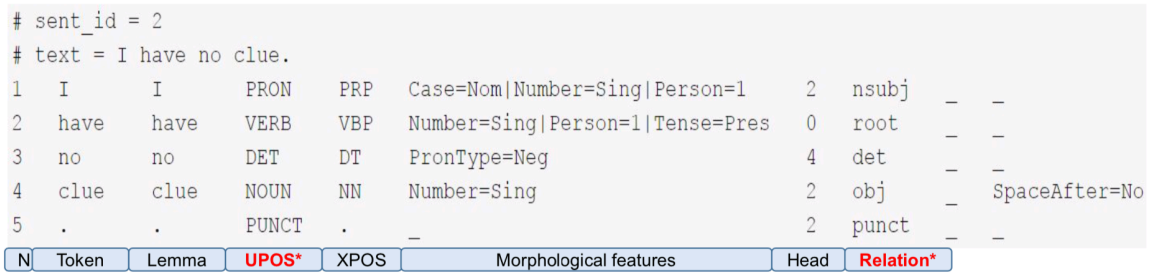


Figure 2-2: An example of English Universal Dependency corpus

head (*Head*) of "I", with a "Subject" relation (*Dep*). Additionally, "I" is a pronoun (PRON in UPOS), but was also considered as a proper noun (PRP) in XPOS. "I" has additional morphological features: the word s considered nominative (Case=Nom), singular (Number=Sing), first person (Person=1). UD has 37 unified (standard) different possible relations (described as *Dep* in Section 2.1), as well as 17 Universal Part-Of-Speech (UPOS) tags, regardless of languages. The definition of tagsets for UPOS and *Dep*, the differences between UPOS and XPOS, the definition of Words, Tokens, and Empty Nodes with syntactic annotation examples are given in Appendix A.

2.2 Dependency Parsing

Dependency parsing consists in automatically analyzing the grammatical structure of a sentence following the dependency framework. The system thus has to establish, for each word in a sentence, whats its head can be.

The task is an essential component of many NLP applications because of its ability to capture complex relational information within the sentence. Figure 2-3 shows a dependency analysis of the sentence, "I prefer the morning flight through Denver". Basically, a dependency structure consists of dependency arcs. Each arc is a relation between a $Head$, w_h, and one or more dependent words, w_m; each arc is labeled *Dep* to define the relation between w_m and w_h.

For instance, in Figure 2-3, an arc is directed from "prefer" to "I", "prefer" is the $Head$ and "I" is the $Modifier$ with the relation "nsubj" (subject). Because the

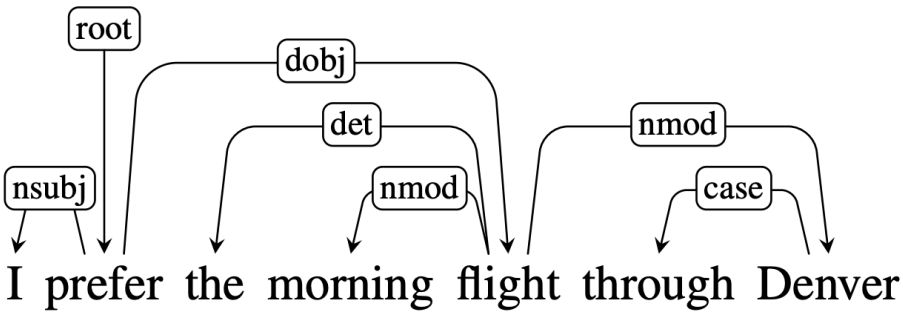


Figure 2-3: Representation of the structure of the sentence "I prefer the morning flight through Denver" using a dependency representation. The goal of a parser is to produce this kind of representation for unseen sentences, i.e., find relations among words and represent these relations with directed labeled arcs. We call this a typed dependency structure because the labels are drawn from a fixed inventory of grammatical relations. (taken from Stanford Lecture: `https://web.stanford.edu/~jurafsky/slp3/15.pdf`)

dependency structure represents the overall syntactic structure for a sentence, it is widely used for tasks ranging from named entity recognition (Kazama and Torisawa, 2008), to discourse understanding (Sagae, 2009), and information extraction (Fares et al., 2018b).

Several approaches have been proposed for dependency parsing, but all of them can be said to be graph-based or transition-based (McDonald and Nivre, 2007b, 2011). Transition-based parsing considers parsing as a classification task, aiming at predicting the next transition given the current configuration, in one left-to-right sweep over the input. Parsing is thus made through a series of local decisions performed thanks to greed search algorithms applied over the whole parsed tree.

At the opposite, graph-based parsing tries to find maximum spanning trees (MST) based on global optimization to find the best possible tree. A MST is an edge-weighted undirected graph that "connects all the vertices together, without any cycles and with the maximum possible total edge weight"[7]. In the following sub-sections, we detail the notions of Transition-based parsing (Section 2.2.1) and Graph-based parsing (Section 2.2.2).

Recently, neural networks and continuous representation models have played a

[7]https://en.wikipedia.org/wiki/Minimum_spanning_tree

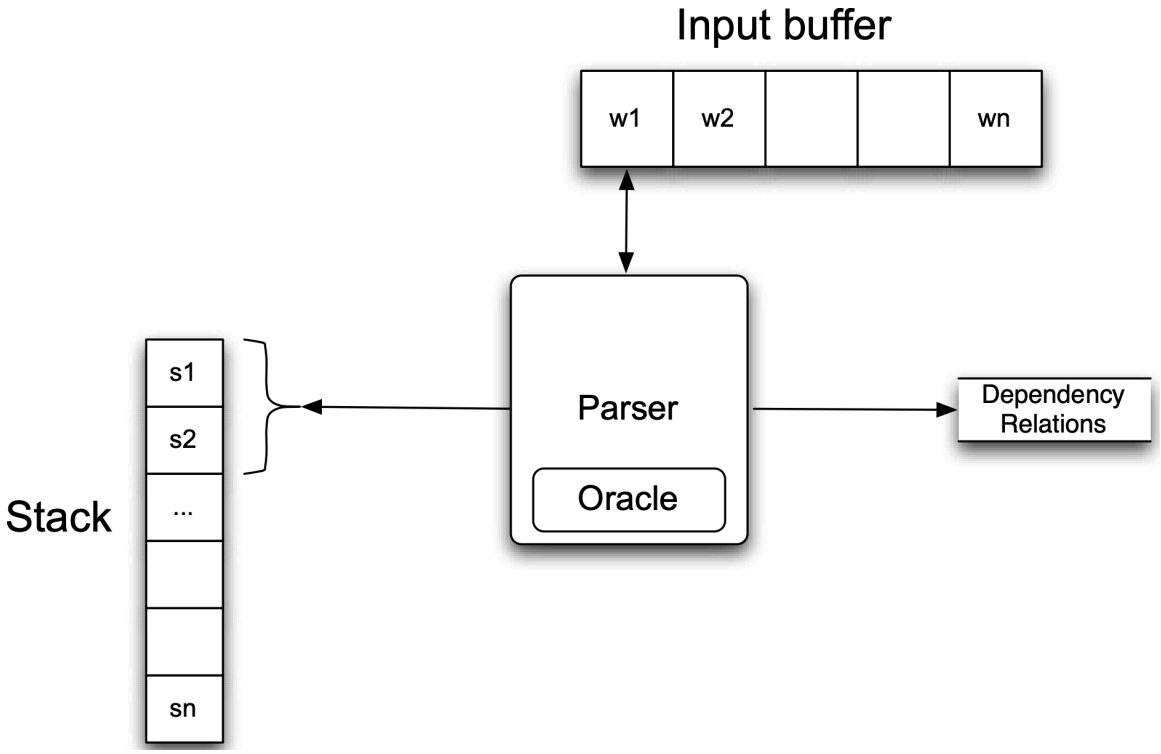


Figure 2-4: Basic transition-based parser. (taken from Stanford Lecture: `https://web.stanford.edu/~jurafsky/slp3/15.pdf`)

major role in most NLP areas, leading to significant improvements for many NLP tasks. Parsing has seen the same evolution, and all state of the art systems nowadays are based on a neural network approach, aka deep learning. This approach has been introduced for both transition-based and graph-based parsers. Since we will mainly focus on neural network based parsing in the rest of this thesis, I will briefly summarize modern neural network structures that have been used in parsing in Section 2.2.3. I will also describe a neural dependency parser called BI-directional Long Short Term Memory (BIST) parser, as it is a very popular, state of the art system for parsing (Kiperwasser and Goldberg, 2016a) in Section 2.2.4.

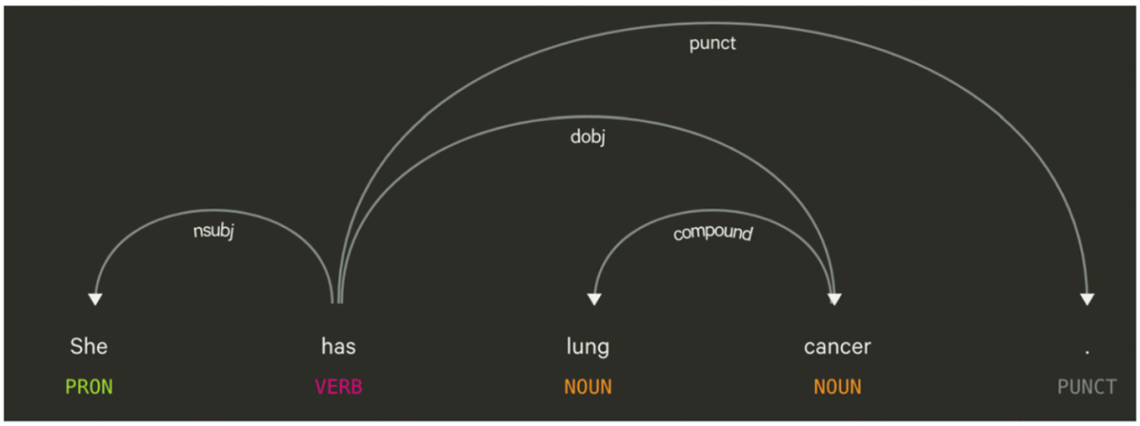
2.2.1 Transition-based Parsing

As already said, transition-based parsing considers parsing as a classification task, aiming at predicting the next transition given the current configuration, in one left–to-right sweep over the input. At each step, the algorthm has to choose between one

of several possible transitions (actions). The idea is to reduce parsing to a classification problem: the algorithm has to predict the next parsing action, i.e., produce one arc at a time.

Transition-based dependency parsing is a popular approach to the problem (Nivre, 2003; Yamada and Matsumoto, 2003). It is generally based on a shift-reduce parsing strategy (Veenstra and Daelemans, 2000; Black et al., 1993), which parses the input text in one forward pass over the text (generally a left-to-right pass over the text). In fact, the process of the transition action is almost identical to a greedy search problem. Typically, transition actions can be configured to use different transition systems and the algorithm performs one transition at a time in a deterministic fashion until the system reaches the final configuration. We thus can say that the goal of transition-based parsing is to search for the optimal sequence of actions, thanks to a classifier trained to take into account local configurations. Parser configurations generally represent the current state of the parser, as presented in Figure 2-4. A parsing configuration for a sentence $w = (w_1 ... w_n)$ consists of three components: (1) a buffer containing the words of w, (2) a stack containing the words of w, (3) a set of dependency relations. The transition action is decided by taking into account these three features.

Different transition configurations have been proposed, but in this study, we mainly use the Arc-Standard system which is the most popular and has been applied to many neural-based parsers. Figure 2-5 shows the structure and an example of transition-based parsing with the Arc-standard algorithm. This approach employs a context-free grammar, a stack, and a buffer that contains the tokens to be parsed. In the initial stage, all the words are in the buffer, the stack is empty, and the dependency relation is empty. In Figure 2-5-(B), the pre-defined transitions consist of three discrete actions (LEFT-ARC, RIGHT-ARC, and SHIFT, see below for explanations). ‘‘In the standard approach to transition-based parsing, the operators used to produce new configurations are surprisingly simple and correspond to the intuitive actions one might take in creating a dependency tree by examining the words in a single pass



(a)

Transition	Stack	Buffer	A
	[ROOT]	[She has lung cancer .]	∅
SHIFT	[ROOT She]	[has lung cancer .]	
SHIFT	[ROOT She has]	[lung cancer .]	
LEFT-ARC(nsubj)	[ROOT has]	[lung cancer .]	AUnsubj(has, She)
SHIFT	[ROOT has lung]	[cancer .]	
SHIFT	[ROOT has lung cancer]	[.]	
LEFT-ARC(amod)	[ROOT has cancer]	[.]	AUamod(cancer,lung)
	…	…	…
RIGHT-ARC(root)	[ROOT]	[]	AUroot(ROOT,has)

(b)

Figure 2-5: An example of a dependency tree and the transitions-based parsing process (taken from (Zhang et al., 2019))

over the input from left to right"[8]. Possible actions include:

- Assign the current word as the head of some previously seen word
- Assign some previously seen word as the head of the current word
- Or postpone doing anything with the current word, adding it to a store for later processing.

To make these actions more precise, let's imagine we have three transition operators that will operate on the top two elements of the stack:

[8]This paragraph and the following six items are taken from the Stanford lecture, https://web.stanford.edu/ jurafsky/slp3/14.pdf

- LEFTARC: Assert a head-dependent relation between the word at the top of the stack and the word directly beneath it; remove the lower word from the stack (e.g., the fourth line of Figure 2-5-(B))

- RIGHTARC: Assert a head-dependent relation between the second word on the stack and the word at the top; remove the word at the top of the stack (e.g. the last line of Figure 2-5-(B)).

- SHIFT: Remove the word from the front of the input buffer and push it onto the stack (e.g., the second line of Figure 2-5-(B)).

To classify the transition at each step, the parser should be able to see the surrounding context of the target word that is at the top of the stack. This context information can be created as templates, by taking into account N-gram based linguistic features from the training data. Generally, a set of extracted features from the training data is called the feature template. An example of a bigram feature template, (''she-has'', LEFT-ARC) can be made by the given example of Figure 2-5-(A) if it is found in a training sentence. Based on this template, when the top two elements of the stack are ''She" and ''has" and if there is a template of the same pair, the system returns 1, otherwise 0 as a binary representation of a configuration (e.g., a one-hot vector [0, 1, 0, 0, 0]). Several templates from training data can be applied, such as trigrams, and the system also considers other combinations of Stack-Buffer pair. For example, when the top of the Stack-Buffer pair is "has" and "lung" and there is a template corresponding to the same pair, the system returns 1, otherwise 0 (e.g., a one-hot vector [0, 0, 0, 1, 0]). This binary representation is widely used as a feature representation method because lexical features can be easily represented as a single vector (e.g., a one-hot vector [0, 1, 0, 1, 0]) using several templates. The system then needs to compute a learnable parameter (a weight vector learned from the training data) w such as a linear model (e.g., $w[0,1,0,1,0] + b$) to classify the transition actions. In the domain, Support Vector Machine classifiers (SVMs) have been applied before the neural approach became more popular. A SVM is a classifier that maximizes the margin between the target transition and the other transitions. Specif-

ically, SVM classifiers are trained for predicting the next transition based on given parser configurations using binary feature representations (Yamada and Matsumoto, 2003).

Parsers trained with the transition-based approach are very efficient in terms of time complexity (basically linear time) and can benefit from rich non-local features defined over parser configurations (Kulmizev et al., 2019).

2.2.2 Graph-based Parsing

The graph-based approach to dependency parsing has been proposed by McDonald et al. (2005a,d); Eisner (1996). The main idea is to score dependency trees with a linear combination of scored local sub-graphs (sub-parts of dependency trees) by searching for the maximum spanning trees (MST). For example, a score is first assigned to all the directed edges between the different tokens of a sentence. The system then searches a valid dependency tree with the highest score.

More formally, given an input sentence $X = (x_1,\ x_2\ ...x_n)$, let Y be the dependency tree of X. Let the directed edge between x_{head} and x_{dep} (dependent) and dt(X) represent the set of possible dependency trees (graphs) from the input X. The goal of graph-based parsing is to take into account all the valid directed arcs among all the tokens in X with their scores and find the tree with the highest score. The parse tree is scored y_k by summing up the scores s(x_{head},x_{dep}) of all the edges. The score s(x_{head},x_{dep}) is computed according to a high-dimensional binary feature representation f and a weight vector w learned from the training data T. Specifically, the score of a parse tree y_k of an input sentence X is calculated as follows (Yu, 2018):

$$score(X, Y) = \sum_{(head,dep \in Y)} score(head, dep) = \sum_{(head,dep \in Y)} w * f(head, dep)$$

where f consists in a set of binary feature representations associated with a number of feature templates. For example, an edge (*she, has*) with a bigram feature template ($Head$, $Modifier$) will get a score of 1 when the pair, (*she, has*), exists in the tem-

plate, otherwise 0. After scoring the possible parse trees dt(X), the parser outputs the dependency tree y_{best} with the highest-score. Figure 2-6 shows an example of a sentence parsed with a basic graph-based parser. During training, the parser uses an online algorithm to learn the weight vector w from the input T. At each training step, only one training instance is considered, and w is updated after each step (Yu, 2018).

The MST parser (McDonald and Pereira, 2006) was one of the most popular graph-based parsers before the advent of neural networks. It has been later improved by (McDonald and Pereira, 2006; Koo and Collins, 2010) to include more lexical features. The Turbo (Martins et al., 2013) and Mate (Bohnet, 2010) graph-based parsers also showed relatively accurate performance before the new era of Neural-based parsing.

2.2.3 Neural Network based Parsers

Neural network based dependency parsing has been proposed by (Titov and Henderson, 2010; Attardi et al., 2009). Parsers following this approach have continuously achieved the best performance over the last five years. While this new generation of parsers have dramatically changed (1) feature representation methods and (2) contextualization methods, parsing algorithms themselves are still either transition-based (Chen and Manning, 2014a; Dyer et al., 2015; Weiss et al., 2015b; Andor et al., 2016; Kiperwasser and Goldberg, 2016a) or graph-based (Kiperwasser and Goldberg, 2016a; Dozat and Manning, 2016).

Feature Representations of Neural Net based Systems

The biggest difference between traditional parsing systems and neural network based systems is thus the feature representation method. Traditionally, conventional systems have adopted binary feature representations: the value of each feature is thus either 0 or 1 (e.g., a one-hot vector [0, 1, 0, 0, 0]) as shown in Figure 2-7. The representation of word vectors based on binary feature representations is orthogonal[9];

[9]For example, a vector v is an orthogonal vector when imposing the constraint $vv^T = 1$

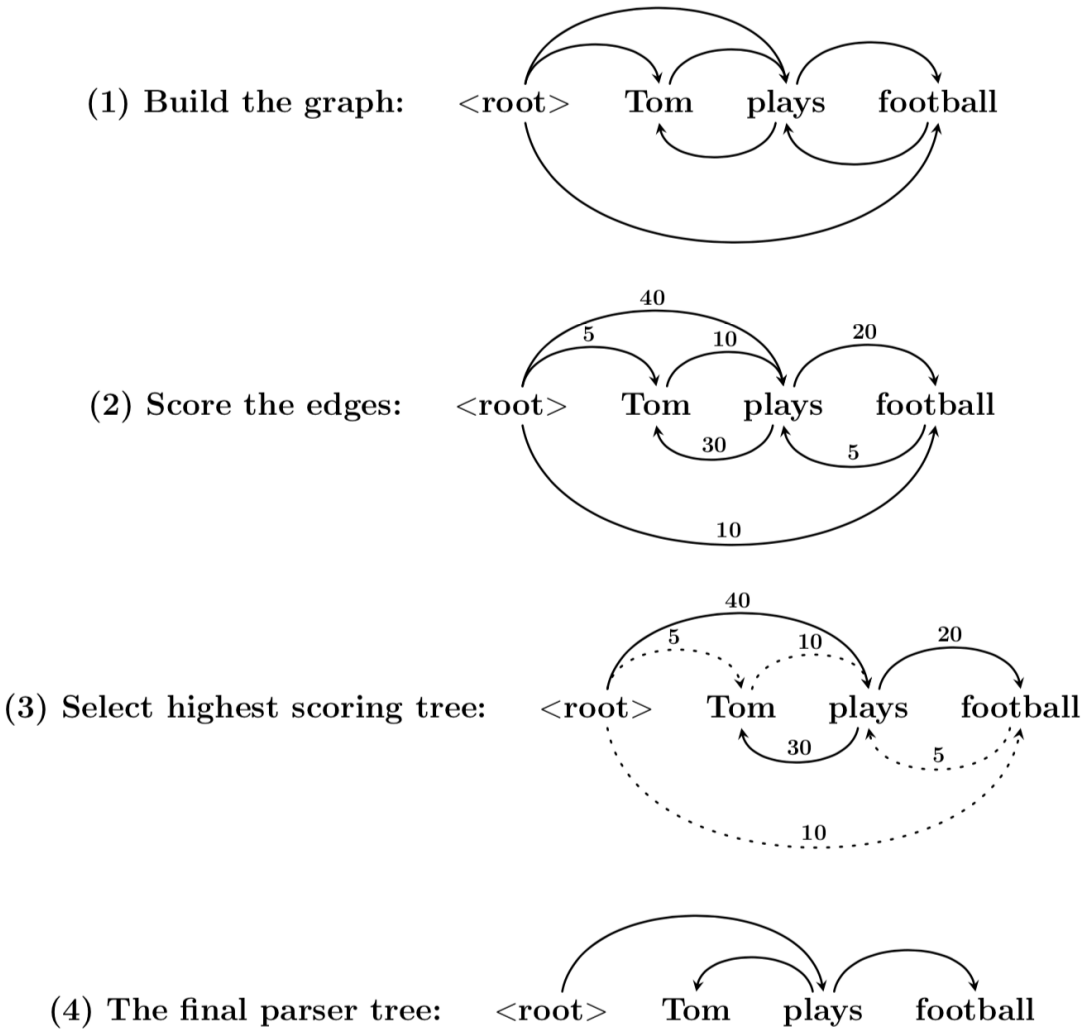


Figure 2-6: An example of a graph-based dependency parsing (taken from (Yu, 2018))

thus, there is no natural notion of similarity in a set of one-hot vectors. For instance, the dot product of two vectors "Queen" and "Woman" is 0 (orthogonal) in Figure 2-7. At the opposite, the neural network based approaches represent features as continuous representations (e.g., [0.99, 0.99, 0.05, 0.7]) as shown in Figure 2-8. Continuous representations are based on the analysis of the distributions of words in very large corpora. In this context words are mapped to fix size vectors of real numbers. Continuous representations entail simpler system architectures, because they eliminate the need for feature templates (e.g., a bigram feature template for *Head-Modifier* mentioned in the previous section) that were previously necessary to calculate the similarity between words.

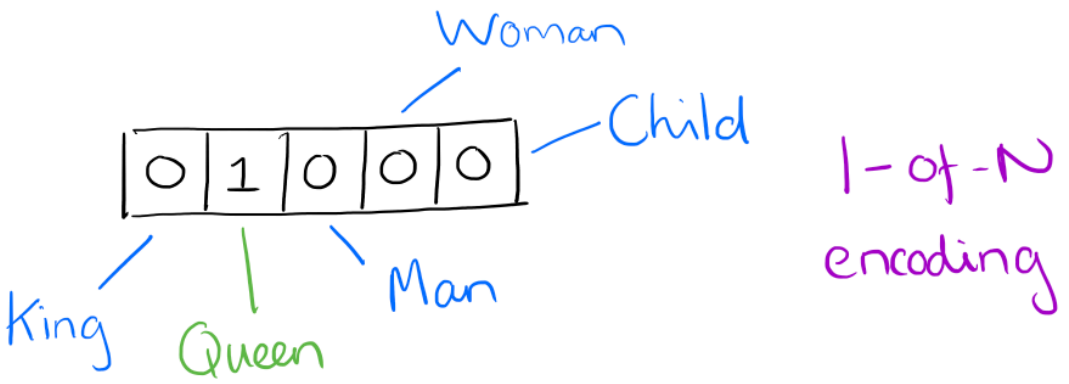


Figure 2-7: An example of binary feature representations (from `https://blog.acolyer.org/2016/04/21/the-amazing-power-of-word-vectors/`)

Figure 2-8: An example of the continuous representations (same source as for the previous figure).

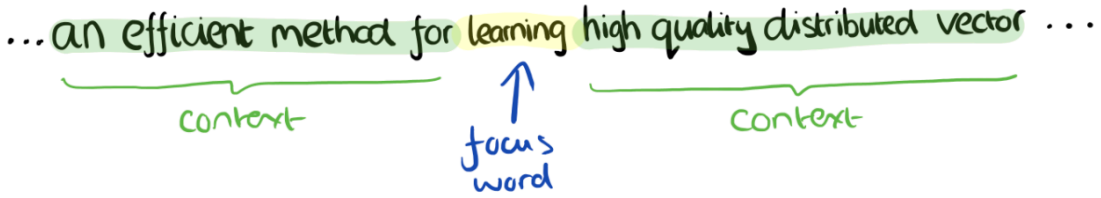


Figure 2-9: An example of the skip-gram model. Here, it predicts the center (focus) word ‘‘learning” based on the context words (same source as for the previous figure).

Word embedding is currently the most popular continuous representation. The main idea is to represent semantic similarities between words based on their distributional properties. Specifically, this approach aims at mapping each word in the training corpus with a vector whose content is filled with information coming from regularities in the context of the word under study (thanks to a supervised-learning process during training). The resulting vector captures both syntactic and semantic information. For example, the system may identify that “man” and “boy” appear in similar contexts, whereas “man” and “cartridge” do not. Therefore “man” and “boy” will get very similar representations (very similar vectors), whereas “man” and “cartridge” will be very different. So “man” and “boy” are very close from a semantic point of view, whereas “man” and “cartridge” are not. Word embeddings are useful in that they reduce the feature sparsity problem by representing all the information in a fixed dimensional space, in opposition to traditional binary representation methods that usually represent different token(s) combination by different independent feature spaces as an additional dimension; thus, are highly sparse.

Another advantage of neural network based parsing is that the system allows the usage of pre-trained word embeddings. Pre-trained word embeddings are embeddings that have been trained on very large unlabeled corpora. The main idea of the pre-trained word embedding is to learn context information by predicting the words that surround it. For instance, Figure 2-9 describes the prediction of the center word “learning”, using context words based on the skip-gram model (Mikolov et al., 2013b). The output of this system is a vector that contains probabilities of the appearance

of other words in the context of the input word. This means that the model learns to predict a word's company, and it carries the statistical strength of the words. Applying the pre-trained word embedding is a huge advantage for the parser when compared to the model that uses word embeddings only. There has been a lot of investigation on the pre-trained word embeddings (Mikolov et al., 2013b; Pennington et al., 2014), and mostly reported large performance gains could be achieved by using it.

Contextualizing Methods

Even though we also use continuous representations for sequences of words, these representations do not directly take into account contextual information because each token is just transferred as a vector. The meaning of a word is however polysemic (context-dependent); their embeddings should also consider various contextual meanings. The main reason for this is that word embeddings, including pre-trained word embeddings, do not consider word order during training. Considering word order into word representations has been an issue ever since word embeddings took off because it is a way to address the polysemy problem. For example, given two sentences (A) "Go to the bank and get some money" and (B) "We could see some fishes from the bank of the river", the word representation for "bank" will always be the same regardless of its meaning. In reality, the vector representing any word should change depending on the words around it.

In order to address this problem, Long-Short Term Memory (LSTM) can deal with sequences of words and can take into account the previous words to produce context-dependent representations. LSTM process entire sequences of data based on time series (e.g., sentences or speech). LSTM has a memory cell and three gates (input, output, and forget gates). Among them, the memory cell remembers parameter values over arbitrary time intervals[10]. The three gates have their own learnable parameters and regulate the flow of information into and out of the memory cell. The memory cell for each sequence can thus control contextual information.

[10]https://en.wikipedia.org/wiki/Long_short-term_memory

Many current parsers have adopted contextualized representation methods that transform simple word embeddings into contextual ones (still encoded as vectors). Bidirectional Long-Short Term Memory (BiLSTM) is a good example of a contextualized representation method. BiLSTM is a neural network structure that "learns bidirectional long-term dependencies between time steps of sequence data"[11]. In NLP, BiLSTM is used to transform a sequence of embeddings as contextualized embeddings. Once the system transforms a word embedding into a contextualized one using a BiLSTM, it is fed into a classifier, as we have seen for graph-based parsing. In the case of transition-based parsing, the classifier predicts a new transition for each token. In the case of graph-based parsing, it looks for the best possible maximum spanning tree. By making information about the sentence-level context available to local-level word representations, BiLSTM is assumed to mitigate error propagation for transition-based parsers and widen the feature scope beyond individual word pairs for graph-based parsers (Kulmizev et al., 2019).

2.2.4 A Typical Neural Dependency Parser: the BIST-Parser

At the beginning of this work in 2017, The BIST parser (Kiperwasser and Goldberg, 2016a) was one of the most popular neural dependency parsers. One of the main features of the BIST parser was to replace the hand-crafted feature functions used to build feature templates by continuous representations, as discussed in the previous section. The BIST parser also used BiLSTM as a contextualized feature function. From this point of view, this parser is typical of what we have just described, and it will serve as a basis for our own work. In what follows, we thus give a shorty description of this parser, following (Kiperwasser and Goldberg, 2016a).

Given an input sentence s with words $s = (w_1, \ldots, w_n)$ together with a set of gold labels $g = (g_1, \ldots, g_n)$, where each g consists of *Head* y and *Dep* ℓ (its dependency relation with *Head*), the parser associates each word w_i with embedding vectors $e(w_i)$,

[11] This expression is taken from
https://www.mathworks.com/help/deeplearning/ug/long-short-term-memory-networks.html

and builds a sequence of input vectors $x_{1:n}$ in which each x_i is an input vector:

$$x_i = e(w_i)$$

In the structure, the word embeddings are at first initialized randomly and are trained together with the model. As discussed in the previous section, this process aims at encoding each word independently from its context. To convert the embeddings into a contextualized one, each input element is fed into a BiLSTM. Finally, the output of the BiLSTM is a contextualized vector, v_i:

$$v_i = \text{BiLSTM}(x_{1:n}, i)$$

The contextualized vectors are then scored based on a Multi-Layer Perceptron (MLP) which contains a linear layer with non-linear function (tanh) as:

$$MLP_\theta(x) = W^2 \cdot \tanh(W^1 \cdot x + b^1) + b^2 \tag{2.1}$$

where $\theta = \{W^1, W^2, b^1, b^2\}$ are learnable parameters.

Besides using the BiLSTM-based feature functions, the parser makes use of both transition and graph-based parsing techniques since the output of a BiLSTM is only a feature vector that is convenient to both parsing algorithms. As presented in Section 2.1.3, the parameters, including word embedding, θ, and BiLSTM's parameter, are trained jointly with the rest of the parsing objective (this will be presented in (Eq 2.2)).

To give an example, consider the concatenation of two BiLSTM vectors ($v_i \circ v_j$) scored using the MLP classifier. The scoring function has access to the words corresponding to v_i and v_j, as well as to the words in an infinite window surrounding them. "As LSTMs are known to memorize length and long-term position information, it is reasonable to think that the scoring function can also be sensitive to the distance between i and j, their ordering, and the sequential material between them" (Kiperwasser and Goldberg, 2016a).

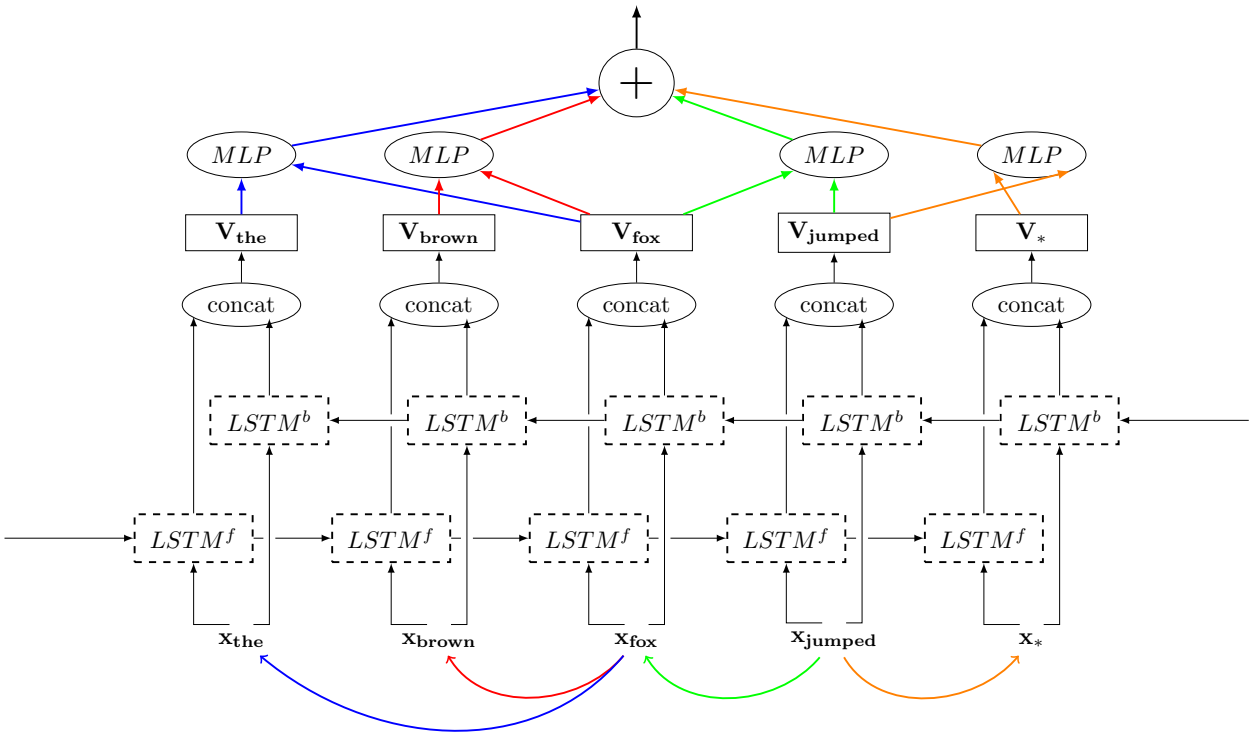


Figure 2-10: Illustration of the neural model scheme of the graph-based parser when calculating the score of a given parse tree (this figure and caption are taken from the original paper (Kiperwasser and Goldberg, 2016a)). The parse tree is depicted below the sentence. Each dependency arc in the sentence is scored using an MLP that is fed by the BiLSTM encoding of the words at the arc's end points (the colors of the arcs correspond to colors of the MLP inputs above), and the individual arc scores are summed to produce the final score. All the MLPs share the same parameters. The figure depicts a single-layer BiLSTM, while in practice they use two layers. When parsing a sentence, they compute scores for all possible n^2 arcs, and find the best scoring tree using a dynamic-programming algorithm.

As discussed in the previous section, there are two major parsing algorithms: the graph and transition-based parsing. Since our parser that will be presented in this thesis is a Graph-based parser, here, we introduce the graph-based BIST parser. Graph-based BIST parser applies the common structured prediction paradigm proposed by (Taskar et al., 2005):

$$predict(s) = \text{argmax}_{y \in \mathcal{Y}(s)}\, score_{global}(s, y)$$
$$score_{global}(s, y) = \sum_{part \in y} score_{local}(s, part)$$

Here s denotes an input sequence and it is transformed the corresponding sequence of vectors $x_{1:n}$. Then, the system needs to search for the highest-scoring parse tree y (as presented in the graph-based parser) in the space $\mathcal{Y}(s)$ of valid dependency trees over s. Following the graph-based parsing algorithm, this parser keeps all local scores for each part of the graph to make the search tractable. This is done by decomposing the score of a tree as the sum of the score based on its head-modifier arcs (h, m):

$$parse(s) = \text{argmax}_{y \in \mathcal{Y}(s)} \sum_{(h,m) \in y} score\big(\phi(s, h, m)\big)$$

where *score* is an MLP classifier presented above, each h and m are the (possible) head-modifier arcs, and $\phi(s, h, m)$ denotes a feature function following:

$$\phi(s, h, m) = \text{BiLSTM}(x_{1:n}, h) \circ \text{BiLSTM}(x_{1:n}, m)$$

The parser uses a simple feature function that the concatenation of two BiLSTM

vectors, v_{head} and $v_{modifier}$. The final model, then:

$$
\begin{aligned}
parse(s) &= \text{argmax}_{y \in \mathcal{Y}(s)}\, score_{global}(s, y) \\
&= \text{argmax}_{y \in \mathcal{Y}(s)} \sum_{(h,m) \in y} score\big(\phi(s, h, m)\big) \\
&= \text{argmax}_{y \in \mathcal{Y}(s)} \sum_{(h,m) \in y} MLP(v_h \circ v_m) \\
v_i &= \text{BiLSTM}(x_{1:n}, i)
\end{aligned}
$$

The overall structure of the parser is presented in Figure 2-10.

As an objective function, this parser uses a margin-based objective, "which means a function intended to give a higher score to the correct tree y compared to all the other competing trees at a given step of the parsing process. This objective function is aiming to maximize the margin between the score of the gold tree y and the highest scoring incorrect tree y'" (Kiperwasser and Goldberg, 2016a). They define a hinge loss with respect to a gold tree y as:

$$
\begin{aligned}
max\Big(0, 1 - \max_{y' \neq y} \quad & \textstyle\sum_{(h,m) \in y'} MLP(v_h \circ v_m) \\
+ \quad & \textstyle\sum_{(h,m) \in y} MLP(v_h \circ v_m)\Big)
\end{aligned}
\tag{2.2}
$$

Note that the objective function only compares between the gold label y and y', and the predicted tree scores are calculated by MLP presented in Eq 2.1. Every predicted label in a graph (sentence) can generate losses by comparing the gold label, and it is computed by the sum of multiple neural networks as $\sum_{(h,m) \in y'} MLP(v_h \circ v_m)$. Based on the hinge loss, the system computes the gradients of the parameters used for the BiLSTM encoder, MLP, and word embeddings, and finally updates the parameters using the gradients.

In order to predict the dependency label ℓ based on the predicted parse tree, the BIST parser first predicts the best-predicted arc (head) following $predict(s)$ and then predicts the labels based on each predicted arc. This is done by another MLP classifier

for predicting dependency labels as:

$$label(h, m) = \text{argmax}_{\ell \in labels}\, MLP_{Label}(v_h \circ v_m)[\ell]$$

In the same way, the margin based hinge loss is applied for the dependency label prediction with another hinge loss. Finally, the BIST parser builds a dependency parsing model using a treebank in a supervised manner.

2.2.5 Evaluation Metrics

Different metrics have been proposed for dependency parsing. Here we propose to keep four metrics that capture different aspects of the problem. None of these metrics is more important than the others. The four main metrics are[12]:

- UAS (unlabeled attachment score) is used to evaluate the structure of a dependency graph. It measures the extent to which the structure of the parsed tree is correct, without taking into account the labels on the different links in the tree.
- LAS (labeled attachment score) is the same as UAS, but takes into account dependency labels.
- MLAS (morphology-aware labeled attachment score) extended LAS with the evaluation of POS tags and morphological features.
- BLEX (bi-lexical dependency score); combines content-word relations with lemmatization (but not with tags and features).

Basically, word segmentation results must be reflected in the evaluation metrics since the systems do not have access to gold-standard segmentation, "and identifying the words is a prerequisite for dependency evaluation"[13]. In this work, however, we use gold segmentation results to focus on the tagging and parsing tasks only.

[12]http://universaldependencies.org/conll18/evaluation.html
[13]http://universaldependencies.org/conll18/evaluation.html

In this study, we mainly report UAS and LAS scores because these are now the most popular metrics. We can thus compare our results with those obtained by many previously proposed parsers. Specifically, Labeled Attachment Score (LAS) is a standard evaluation metric in dependency parsing since it reflects the percentage of words that are assigned both the correct syntactic head and the correct dependency label. Specifically, LAS is composed of two different scores. "Precision (P) is the number of correct relations divided by the number of system-produced nodes; recall (R) is the number of correct relations divided by the number of gold-standard nodes. We then define LAS as the F1 score = 2PR / (P+R)"[14]. Following the 2017 and 2018 shared task guidelines, for scoring purposes, only universal dependency labels will be taken into account in the evaluation. "This means that language-specific subtypes such as acl:relcl (relative clause), a subtype of the universal relation acl (adnominal clause), will be truncated to acl both in the gold standard"[15] and in the parser output during evaluation. Beyond the CoNLL shared task, parsers are however still encouraged to output language-specific relations (e.g., predicting acl:relcl rather than only acl), if they can predict them, as it makes the parsers more useful beyond the shared task.

2.3 Transfer Learning for Dependency Parsing

Building a new annotated corpus is a resource- and time-consuming, as discussed in Chapter 1. However, most NLP systems are now based on supervised learning techniques, which means large training corpora are needed. This is especially the case for Taggers and parsers, but we know that annotated resources are lacking for most languages. Transfer learning has thus been investigated as a way to cope with the problem of the lack of data for training.

Transfer learning aims at improving learning in a target language or domain by

[14]This example is taken from official CoNLL shared task website, http://universaldependencies.org/conll18/evaluation.html

[15]This means both acl and acl:relcl become predictions during evaluation as presented in http://universaldependencies.org/conll18/evaluation.html

leveraging knowledge from a source language or domain. The source can be (A) multiple languages from which one wants to extract information or (B) different types of sub-tasks contributing to a more general goal. For example, knowledge included in a word embedding obtained after training a POS tagger could also be useful to recognize Named Entity (NER). Since the goal of NER is to recognize sequences of words (such as person, organization, and place names, most of them being POS:nouns), storing knowledge gained while solving the POS problem could be helpful for NER.

Using external, pre-trained word embeddings for parsing is one of the most common transfer learning approaches. For instance, pre-trained word embeddings trained by Word2Vec (Mikolov et al., 2013b) leverages dependency parsing performance, as discussed in Section 2.2.3. This type of transfer learning has been recently applied to most NLP tasks because of its ability to handle unseen in the training set (Guo et al., 2015b)[16].

Using a slightly different approach, Figure 2-11 shows that a system trained with English data can help improve a model for French, due to the fact that some kind of knowledge is shared across different languages (transfer of type A). As for dependency parsing, Figure 2-12 describes training a dependency parser for French using both an English and a French treebank, thanks to a shared neural network with the learnable parameter W_d. Due to the fact that this shared parameter is trained by two different languages, it captures syntactic features taking into account both languages. This method can be helpful when one wants to augment the quantity of data available for training in one of the languages considered, and is possible because of the shared POS tagsets coming from UD (Ammar et al., 2016d).

As discussed above, one way to cope with the lack of training data is a multilingual approach, which makes it possible to use different corpora in different languages as training data. In most cases, for instance, in the CoNLL 2017 shared task (Zeman et al., 2017a), the teams that have adopted this approach used a multilingual delexicalized parser (i.e., a multilingual parser trained without taking into account lexical

[16]For example, the pre-trained word embeddings trained from Wikipedia are often useful since they contain large coverage vocabularies for numerous languages.

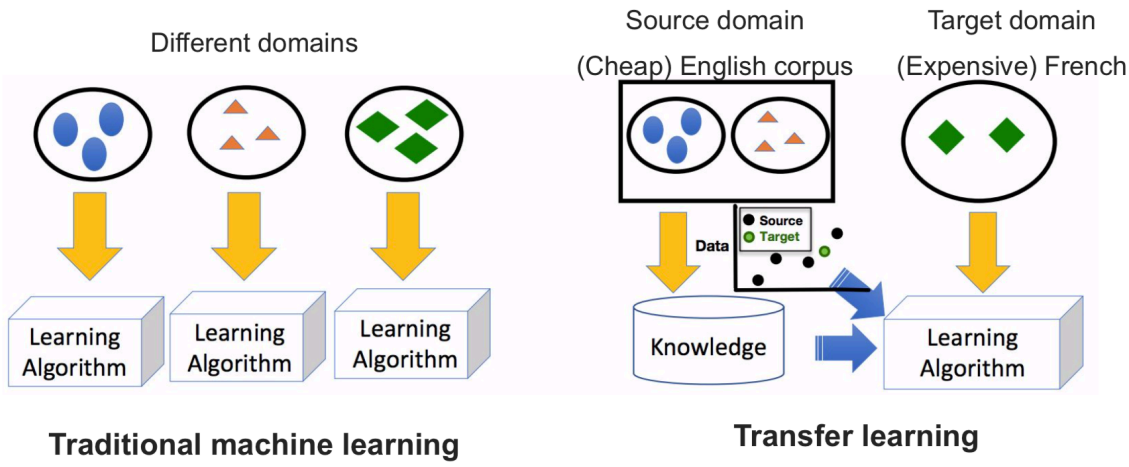


Figure 2-11: Illustration of multilingual transfer learning in NLP (the figure is based from (Jamshidi et al., 2017))

features but POS tags). It is however evident that delexicalized parsing cannot capture contextual features that depend on the meaning of words within the sentence. The delexicalized model can thus not fully take into account (multilingual) lexical information because languages have different word distributions (and then also different word representations). For example, 'en:dog' and 'fr:chien' are represented with different vectors even though the two words have the same meaning (Ammar et al., 2016c). This raises the need for creating multilingual lexical representations.

To address this problem, we will propose in Chapter 4 a dependency parser with a multilingual word representation that implements both (A) a multilingual transfer approach and (B) integrates pre-trained word embeddings. In the following section, we will present the notion of multilingual dependency parsing based on transfer learning.

Multilingual Dependency Parsing

Multilingual dependency parsing consists in defining a parser that can parse several languages using the same model. The idea is that a model trained with different languages will benefit from more data and may recognize similarities across languages, leading to a better coverage of rare phenomena.

Three major approaches have been suggested: 1) projection of cross-lingual annotations, 2) joint modeling, and 3) cross-lingual representation learning (Guo et al.,

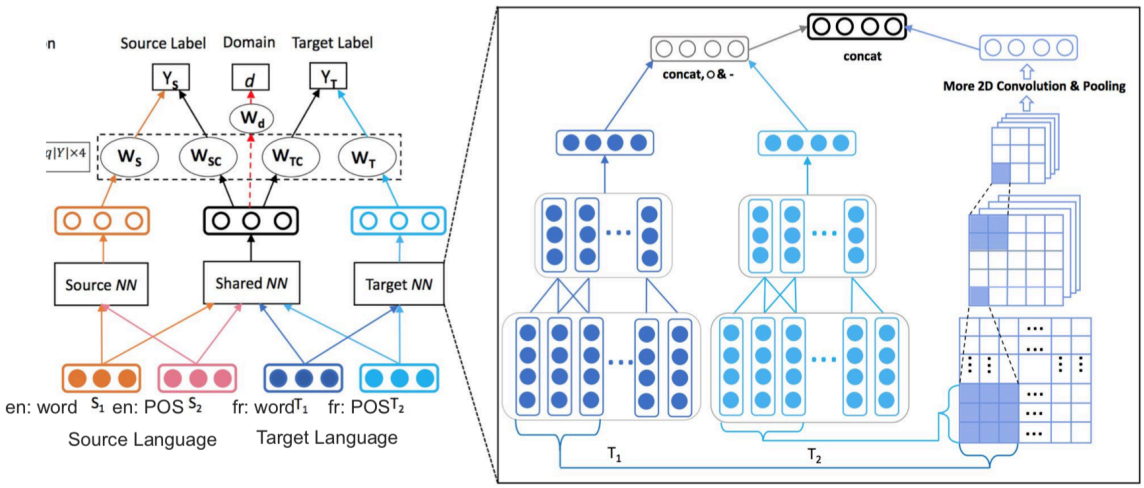


Figure 2-12: ''How the transfer learning transfers knowledge in parsing?''. A parser learns the shared parameters (Wd) based on supervised-learning. Since the learning is a data-driven task with inputs, source language can affect to tune the parameter (Wd) for the target language (the figure is taken from (Yu et al., 2018).

2015b). The main idea of the cross-lingual annotation projection approach is to project syntactic annotations through word alignments from a source language onto a target language (Mann and Yarowsky, 2001; Tiedemann, 2014). For example, let's take a pair of sentences from a parallel corpus between a source language *L1* and a target language *L2*; and let's imagine we have a syntactic analysis of the *L1* sentence. The predicted annotations in *L1* are then mapped onto the sentence in *L2*, based on word alignment. In a similar manner, the joint modeling approach is carried out using projected dependency information for grammar inductions (Liu et al., 2013b) or is based on a previous rule-based system (Naseem et al., 2010, 2012).

The cross-lingual representation learning method is focused on learning cross-lingual features by aligning (or mapping) feature representations (e.g., embedding) between the source and target languages. In general, cross-lingual representation learning can be divided into two approaches depending on whether or not the parser uses lexicalized features (e.g. word embedding). Due to the fact that it is relatively easy to train a parser using supervised learning, many existing cross-lingual representation learning studies have been conducted with the delexicalized approach using POS tag-sets and word sequences (McDonald et al., 2011, 2013; Dozat et al.,

2017b). Such an approach includes training a dependency model with the source language (e.g., English), then process the target language (e.g., French) using the model trained according to the source language. Meanwhile, the lexicalized approach is able to adapt diverse lexical features while in training. The features adapted for dependency parsing include cross-lingual word cluster features (Täckström et al., 2012b), multilingual word embeddings (Guo et al., 2015b, 2016; Ammar et al., 2016c,b) and language identification embeddings (Naseem et al., 2012; Ammar et al., 2016b).

In Section 4.2.1, we will present our method for building multilingual word embedding between two languages and we will discuss the impact of the approach in Section 4.3 and 4.4.

2.4 Semi-Supervised Learning for Dependency Parsing

Semi-supervised learning is a machine learning approach that makes use of both labeled and unlabeled data for training. Over the past few years, unlabeled data has been more and more widely used for parsing tasks, since it is easily obtained.

Two semi-supervised approaches, self-training (McClosky et al., 2006) and co-training (Sarkar, 2001), use auto-parsed data as additional training data (Yu, 2018). Self-training is the oldest semi-supervised learning approach. The idea is first to train a supervised model based on labeled data only, and then analyze unlabeled data to generate more labeled examples as input for the supervised learning algorithm. On the contrary, co-training trains multiple models using different sets of features (e.g., words and characters) and generates labeled examples using unlabeled data. These semi-supervised approaches make it possible for the parser to learn from its own annotation, or from the annotations of other parsers.

Other techniques include word clustering (Koo et al., 2008) and word embedding (Bengio et al., 2003), which are produced using large amounts of unlabeled data, as discussed in the previous section. The output of these training processes can be

used as features or inputs for parsers as a pre-trained embedding[17]. Both groups of techniques have been effective on syntactic parsing tasks (Reichart and Rappoport, 2007; Sagae and Tsujii, 2010; Yu et al., 2011; Weiss et al., 2015a). In this study, we will propose in Chapter 6 to use a co-training approach to bootstrap our dependency parser using unlabeled data.

[17]Pre-trained word embeddings can be classified as a kind of semi-supervised learning approach because it is trained with unlabeled data

Chapter 3

A Baseline Monolingual Parser, Derived from The BIST Parser

In this chapter, we present our baseline parser, derived from the state-of-the-art BIST parser (Kiperwasser and Goldberg, 2016a). The BIST parser is a standard parser trainable on monolingual data, as presented in the previous section. Normally such systems take as input an annotated corpus, along with word embeddings, language specific dictionaries and other knowledge sources. This monolingual parsing approach has yield state-of-the-art performance especially for resource-rich languages, when a huge quantity of annotated corpora is available like for English or French (Chen and Manning, 2014a; Kiperwasser and Goldberg, 2016a). Thus, it is natural to investigate a standard, monolingual approach first, which can then be extended to integrate more complex features.

In order to train a monolingual parsing model, many parsers use Universal Dependency (UD) treebanks (see section 2.2). For many languages, one can find more than one UD treebank, and these treebanks generally differ in several aspects. For example, treebanks available for French include material from different language variants, domains, and genres (one even find treebanks with spoken material). These treebanks are called "heterogeneous treebanks" (Stymne et al., 2018), and the parsers dedicated to these heterogeneous treebanks are called "multi-source" (Lim et al., 2018a; Stymne et al., 2018).

However, many existing parsers, including the BIST parser, are trainable on a single treebank. The easiest way to combine several treebanks for a language is simply to concatenate the training treebanks as a single file. This concatenation method showed better results than the case using a single treebank but did not allow the parser to learn treebank-specific phenomena (Das et al., 2017).

In this chapter, we first describe the development of a traditional monolingual system. This will be our baseline parser that will gradually be extended with additional features so as to deal with various complex linguistic situations. The baseline parser extends the monolingual BIST parser as a multi-source trainable one, able to take into account the specificities of heterogeneous treebanks. We thus add, for each item of the language model, a reference to the treebank it has been trained on, so as to take into account treebank-specific linguistic phenomena. This is done using a one-hot scheme. It allows us to get a better model than the default option consisting in simply learning from concatenated data.

We used this baseline dependency parser for the *CoNLL 2017 UD Shared Task* called "Multilingual Parsing from Raw Text to Universal Dependencies"[1]. We obtained satisfactory results as the system ranked 5^{th} out of 33 teams and achieved 70.93 overall LAS score over the 81 test corpora (measured using macro-averaged LAS F1 score)[2]. It also shows that the system is highly flexible and adaptable since it was possible to get a state-of-the-art parser for all these languages in only a few weeks.

In the following sections we will detail the architecture of our system (section 3.1). We will also provide a description of the CoNLL shared task (section 3.2.1) along with our results for this task (section 3.2.3).

[1] http://universaldependencies.org/conll17/

[2] For the For the evaluation campaign we also used multilingual models that will be presented in the following chapter. This LAS score is 5.3 points lower than the score of the winner.

3.1 A Baseline Parser Derived from the BIST Parser

We want to develop a flexible parser, able to analyze a wide variety of languages. Multi-source trainable parsers (i.e., parsers working with heterogeneous treebanks) are especially flexible, and they are known to perform a lot better than monolingual parsers in high-resource scenarios (Stymne et al., 2018). This is why we chose to develop a multi-source trainable parser, based on the graph-based approach (see Chapter 2, Section 2.2.1): we chose the BIST parser (Kiperwasser and Goldberg, 2016a), a state of the art parser freely available online.

As presented in Section 2.2.4, the BIST parser uses bidirectional Long Short Term Memory (LSTM) feature representations thanks to two neural network layers (Kiperwasser and Goldberg, 2016a). In order to select the best relation and head for each token in a sentence, this parser links the output of the bidirectional LSTM with the Multi-Layer Perceptron (MLP) thanks to one neural layer (please, refer to Section 2.2.4). Here we adapt the same feature representation and MLP but different training features and decision models.

In order to adapt the parser to a multi-source trainable approach, we add new parameters and new features to the training algorithm, notably the possibility to use pre-trained word embeddings and a one-hot encoding to encode domain of treebanks. One-hot encoding is a binary feature representation (e.g. a one-hot vector [0, 1, 0, 0, 0]), as shown in section 2.2.3. The idea is to add a treebank one-hot encoding as an additional feature while training with several treebanks. It allows the model to focus on treebank specificities directly. For instance, there are two different English UD treebanks, English_EWT and English_Partut. English_EWT is made of blog, social, review, and email texts. In contrast, English_Partut based on data originated from Wikipedia. The one-hot encoding scheme can make the training data to which a sentence belongs between English_EWT and English_Partut as a binary feature (e.g. 0 for EWT 1 for Partut). Finally, the parser can be trained on heterogeneous treebanks depending on the parameters chosen for training (e.g. 0 for EWT 1 for Partut). An overview of the overall architecture is given in Figure 3-1. Details on

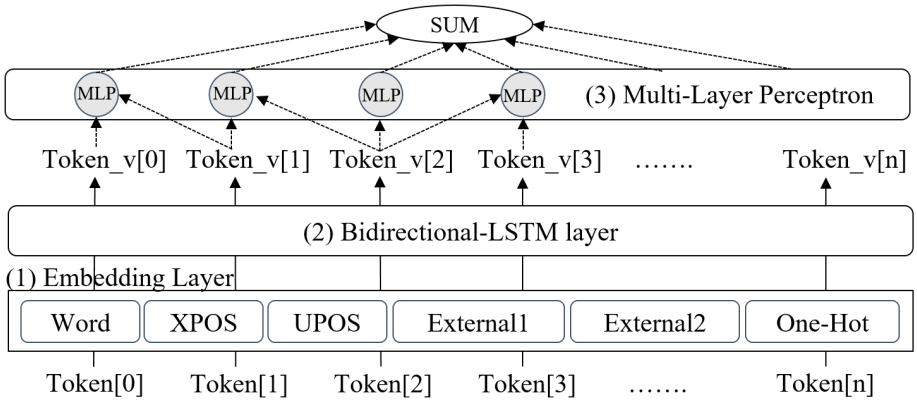


Figure 3-1: Overall system structure for training language models. **(1) Embedding Layer**: vectorized features that are feeding into Bidirectional LSTM. **(2) Bidirectional-LSTM**: train representation of each token as vector values based on bidirectional LSTM neural network. **(3) Multi-Layer Perceptron**: build candidate of parse trees based on trained(changed) features by bidirectional LSTM layer, and then calculate probabilistic scores for each of candidates. Finally, if it has multiple roots, revise it or select the best parse tree.

word embeddings along with the number of dimensions considered are given below.

- ***Word****:* randomly generated word embedding (100)
- **XPOS:** language-specific part-of-speech tags (25)
- **UPOS:** universal part-of-speech tags (25)
- **External embedding1:** pretrained word embedding (100)
- **External embedding2:** pretrained word embedding that is replaced with *Word* (100)
- **one-hot encoding:** one-hot encoding of the treebank ID (65)

Word refers to word embeddings (vectors) learnt using the provided training corpora. Both *XPOS* and *UPOS*[3] are POS embeddings learnt from the training corpora. The content of *Word* and *POS* is set randomly (randomly initialized) when the training phase starts. In addition, two external word embeddings are added to the representations of words, one is concatenated with the *Word* vector additionally, and

[3]Please, refer to Section 2.1.1 or http://universaldependencies.org/format.html

the other is used to replace the *Word* vector. The reason why we adapt two different embeddings is that it shows better results in handling unseen data or those data that do not participate in the training phase. Generally, pre-trained word embeddings trained by different raw texts (contexts) possibly have different sizes of vocabularies. Thus, applying multiple pre-trained embeddings is better to handle unseen data. In contrast, adding pre-trained word embeddings requires more computing resources (e.g. GPU memory) and training time. In addition, we have found that if we use two external word embeddings, replacing one word embedding as the *Word* made better results than concatenating two pre-trained word embeddings based on experiments. For example, let *Word* be generated randomly as a 100-dimensional vector and *External1* and let *External2* be pretrained word embeddings made from different resources with a 100-dimensional vector. If we just add *External1* to an additional word embedding, then final word embedding would be *Word+External1* (200 dimensions) based on concatenation. However, if we add just *External2* as an additional word embedding, *Word* is deleted because it is replaced with *External2* so that final word embedding could be *External2* (100 dimensions). If both are used, final word embedding could be *External1 + External2* (*Word* is deleted because of *External2*).

As mentioned above, training a monolingual model in our system without multi-sources (i.e., without several treebanks from different domains or different languages) is very similar to training a standard BIST-parser model. However, we made one additional modification to the original approach.

Multiple roots: The BIST parser can generate multiple roots for a given sentence. This is not a problem in general but for parsing UD, we need to provide only one single root per sentence. Not detecting the right root for a sentence leads to major errors so the problem had to be addressed carefully.

We chose to develop a simple algorithm: when the parser returns multiple roots, our system revises the overall sentence analysis so as to select one single primary root and other previous roots become links pointing to the new head node. Choosing the primary root is the result of an empirical process depending on the language considered (i.e., taking into account language-specific word order). For example, the

primary root is the first head node in the case of an English sentence and the last one in the case of a Korean sentence because English is SVO whereas Korean is SOV[4]. This very simple trick improved the LAS scores by 0.17 overall F1-measure on the development set of UD2.0 data (Nivre et al., 2017a).

Let's remind the reader that the basic token representation in our parser is as follows. Given a sentence made of tokens $s=(t_1,t_2,..t_n)$, the i^{th} token t_i is represented by a vector v_i, which is the result of the concatenation ($\circ$) of a word embedding w_i, XPOS embedding xp_i, UPOS embedding up_i, External embedding1 $e1_i$, External embedding2 $e2_i$ and one-hot encoding embedding oh_i of t_i (see Section 2.2.4, for a more detailed description of the feature representation used in the BIST parser):

$$
\begin{aligned}
v_i &= w_i \circ xp_i \circ up_i \circ e1_i \circ e2_i \circ oh_i \\
w_i &= WORD(t_i;\theta_w) \\
xp_i &= XPOS(t_i;\theta_{xp}) \\
up_i &= UPOS(t_i;\theta_{up}) \\
e1_i &= EXT1(t_i;\theta_{e1}) \\
e2_i &= EXT2(t_i;\theta_{e2}) \\
oh_i &= HOT(t_i;\theta_{oh})
\end{aligned}
$$

where $\theta = \{w, xp, up, oh\}$ are learnable parameters randomly initialized during training. Additionally, the two pre-trained word embeddings, $\theta = \{e1, e2\}$, are initialized using the external word embeddings provided by Facebook (Bojanowski et al., 2016b) and by the shared task organizer[5], respectively. These two pre-trained embeddings can be formalized through a set of word forms (key) and corresponding vectors (value), as presented in Figure 2-8; thus, we can use this representation as a key-value lookup table during training. Finally, the parser transforms the sequence of shared lexical representation v_i into a context-sensitive vector contextualized by BiLSTM with a

[4]For example, the sentence "I love you" is translated in Korean "나는 너를 사랑한다", where '나는' is Subject, '너를' is Object, and '사랑한다' is Verb

[5]http://universaldependencies.org/conll17/data.html

hidden layer r_0 as:

$$h_i^{(head)} = BiLSTM(r_0^{(head)}, (v_1, .., v_n))_i$$
$$h_i^{(dep)} = BiLSTM(r_0^{(dep)}, (v_1, .., v_n))_i$$

The system uses the vector $h_i^{(head)}$ to predict *Head* thanks to a Multi-layer Perceptron (MLP) classifier, and $h_i^{(dep)}$ for *Dep* thanks to another MLP classifier, as presented in Section 2.2.4. During training, the system adjusts the parameters of the network θ that maximize the probability $P(y_j|x_j, \theta)$ from the training set T based on the conditional negative log-likelihood loss B_loss(θ). Thus,

$$\text{B\_loss} = \sum_{(x_j, y_j) \in T} -\log P(y_j|x_j, \theta) \tag{3.1}$$
$$\hat{y} = \arg\max_y P(y|x_j, \theta)$$

where $(x_j, y_j) \in T$ denotes an element from the training set T, y a set of gold labels (l^{Head}, l^{Dep}), and $\hat{y}$ a set of predicted labels. This model is subsequently used as the BASELINE model.

During the CoNLL shared task, we used the same MLP classifier to score all the possible *Head* and *Modifier* pairs Y = (h,m), following the strategy originally defined for the BIST parser (see Section 2.2.4). We then select the best dependency graph based on Eisner's algorithm (Eisner and Satta, 1999). This algorithm tries to find the maximum spanning tree among all the possible graphs (see Section 2.2.2).

3.2 Experiments during the CoNLL 2017 Shared Task

A shared task is a popular way to evaluate the evolution of performance for a given domain in computer science. A shared task is an evaluation campaign around a predefined task (or set of tasks), for which some material is publicly distributed. All the participants have access to the data following a precise time frame, and should

submit their results before a predefined deadline, so that the results and the different approaches can then be compared. There has been, for example, recently very popular challenges in image and video analysis. More specifically, the ImageNet Large Scale Visual Recognition Challenge (ILSVRC)[6] has been at the origin of huge progress in image recognition. These challenges are especially important to identify relevant approaches, measure relative performance and define new challenges beyond state of the art.

In NLP, several competitions have also been organized since the 1990s, for example in information extraction or machine translation. More recently and since 1999, the annual CoNLL conference (Computational Natural language Learning[7]) has proposed different challenges every year and some of the tasks have been especially popular. The task organizers provide training and test data, which allows participating systems to be evaluated and compared in a systematic way. The 2017 shared task dealt with dependency parsing for 49 languages[8].

We participated in this *CoNLL 2017 UD Shared Task* on "Multilingual Parsing, from Raw Text to Universal Dependencies"[9]. The task offered a very relevant testbed to compare our approach with systems developed by other competing teams. The fact that the CoNLL 2017 Shared Task included different scenarios (low and high resource languages, more than 49 languages covered, etc.) also made this evaluation scheme very relevant for us. For this competition, we developed two different approaches, based on monolingual and multilingual models. Since the approach with multilingual models will be described in the following chapter, we just detail here our results concerning our monolingual approach (we used this strategy for 40 of the 49 languages considered for the 2017 shared task).

[6]http://image-net.org/challenges/LSVRC/2016/index

[7]https://www.conll.org/previous-tasks

[8]Previous shared tasks have been devoted to chunking (1999, 2000), clausing (2001), named entity recognition (2002, 2003), semantic role labeling (2004, 2005), dependency parsing (2006, 2007), joint parsing of syntactic and semantic dependencies (2008, 2009), hedge detection (2010), co-reference resolution (2011, 2012), grammatical error correction (2013, 2014), and shallow discourse parsing (2015, 2016)

[9]http://universaldependencies.org/conll17/

3.2.1 The CoNLL 2017 Shared Task

The goal of the CoNLL 2017 shared task was to evaluate dependency parsers following a real-world setting (starting from raw texts). The task was also intended to evaluate the results for many typologically different languages. The evaluation even included "surprise" languages for which there was no or very little training data. This challenge was possible because of the Universal Dependencies initiative (UD): UD has made available treebanks for many languages using a cross-linguistically consistent annotation scheme (as presented in Section 2.1.2). For the Shared Task, the Universal Dependencies version 2 (UD v2) has been used (Nivre et al., 2017b) which consists of 55 big treebanks, 14 PUD treebanks, 8 small treebanks, 4 surprise language treebanks.

- ***The "big" treebanks (55)****:* Each corpus in this category has more than 2,000 annotated sentences available for training.
- **The "small" treebanks (8):** Each corpus in this category has between 20 and 1,000 annotated sentences available for training. It includes French ParTUT, Galician TreeGal, Irish, Kazakh, Latin, Slovenian SST, Uyghur and Ukrainian.
- **The "surprise" treebanks (4):** Each corpus in this category has less than 20 annotated sentences available for training. Data for four languages were provided (Buryat, Kurmanji Kurdish, North Sami and Upper Sorbian).
- **The "PUD" treebanks (14):** PUD refers to Parallel UD data. The PUD treebank consists of 1,000 sentences in 14 languages (15 K to 27 K words, depending on the language), which were randomly picked from online newswire and Wikipedia.

As is usual in UD, there may be more than one training and development treebank for certain languages. Typically, the different treebanks come from different sources and different domain. Thus, for parsing the new Parallel UD (PUD) treebanks, it is possible to use training data from a different domain. The four "surprise" languages with a reduced amount of training data (20 sentences) were published one week before

Corpus	LAS	UAS	Rank(LAS)	Rank(UAS)	UDpipe(LAS)
Overall (81)	70.93	76.75	5	5	68.35
Big treebanks (55)	75.79	80.55	5	5	73.04
PUD treebanks (14)	70.77	77.64	4	4	68.33
Small treebanks (8)	54.78	64.99	4	5	51.80
Surprise language (4)	36.93	48.66	12	15	37.07
English_PUD	82.38	85.77	2	2	78.95
Russian_PUD	72.03	79.31	2	2	68.31
Spanish	85.22	88.40	2	3	81.47

Table 3.1: Official results with rank. (number): number of corpora

the beginning of the evaluation phase only. The point of having surprise languages was to encourage participants to investigate transfer methods and flexible approaches that can be adapted to a new domain in a few days only (Zeman et al., 2017a). The standard evaluation metric of the competition is the Unlabeled Attachment Score (UAS) and Labeled Attachment Score (LAS) presented in Section 2.2.4.

To ease reproducibility, the CoNLL Shared Task was hosted on the TIRA platform (Potthast et al., 2014)[10]. TIRA implements a proper solution that ensures blind evaluation and an airlock for data. For example, a participant can run his parser on the TIRA platform (server) but cannot see the test data and the result of parsing.

3.2.2 Experimental Setup

The results reported here concerns our baseline parser with monolingual models (Section 3.1). Since the input of the shared task is raw text (plain text), it is thus necessary to first implement or have access to pre-processing tools such as a tokenizer and POS tagger. UDPipe baseline models (Straka et al., 2016) were provided for teams who did not wish to develop their own pre-processing modules. We chose this option and all our preprocessing modules were taken from UDPipe. We used the following modules: word segmentation, tokenization and morphological analysis (lemmas, UPOS, XPOS and FEATS).

[10]http://www.tira.io/

3.2.3 Results

Overall results. Table 3.1 and 3.2 show the official results using the F1-measure computed by the official evaluation metric for the CoNLL 2017 Shared task[11]. Our system achieved 70.93 F1 (LAS) on the overall 81 test sets and ranked 5^{th} out of 33 teams. Our results were generally better than those obtained by UDPipe1.1 (Straka et al., 2016) with a significant margin (on average our system was 2.58 LAS point above UDPipe1.1). When looking at the results on the PUD corpora, our system avoids over-fitting issues because of the different domains used during training. Specifically, performance gaps are narrowed when considering only PUD test sets (for example, our system ranked second best for processing English_PUD and Russian_PUD), which is encouraging for practical applications.

Contributions of the Different System Components to the General results. To analyze the effect of the proposed representation methods on parsing, we evaluated four different models with different components. In our BASELINE model, each token is represented by a vector v_i, which is the concatenation ($\circ$) of a word embedding w_i, XPOS embedding xp_i, UPOS embedding up_i, External embedding1 $e1_i$, External embedding2 $e2_i$, and one-hot encoding embedding oh_i. Where w_i is a randomly initialized word vector, $e1_i$ and $e2_i$ are pre-trained word vectors, and xp_i and up_i are POS vectors predicted by UDpipe1.1 (since we did not implement a specific POS tagger, as said above). In this scenario, we deactivated each of representation in turn during training, so as to investigate the impact of each feature individually. The results are shown in Table 3.4, where *ex* denotes the use of the external word embedding, and *xp* and *up* denote XPOS and UPOS representations, respectively. We observe that each representation improves the overall results. This is especially true regarding LAS when using external embeddings (*ex*), which means this representation has a positive effect on relation labeling. Interestingly, the impact of the two different POS features is almost identical when comparing the model between $-ex, xp$ and $-ex, up$. This is because UPOS for English treebanks is simply based on XPOS; thus,

[11] http://universaldependencies.org/conll17/results.html

Corpus	LATTICE	Baseline
Arabic_PUD	47.13	43.14
Arabic	68.54	65.3
Bulgarian	85.6	83.64
Catalan	86.83	85.39
Czech-CAC	84.77	82.46
Czech_PUD	80.86	79.8
Czech	83.68	82.87
Old_Church_Slavonic	60.81	62.76
Danish	76.47	73.38
Danish_PUD	71.45	66.53
German	75.09	69.11
Greek	81.13	79.26
English-LinES	76.17	72.94
English_PUD	82.38	78.95
English	78.91	75.84
Spanish-AnCora	86.87	83.78
Spanish_PUD	79.87	77.65
Spanish	85.22	81.47
Estonian	62.93	58.79
Basque	72.13	69.15
Persian	82.63	79.24
Finnish-FTB	79.44	74.03
Finnish_PUD	80.82	78.65
Finnish	77.11	73.75
French_PUD	76.55	73.63
French-Sequoia	83.7	79.98
French	82.83	80.75
Irish	64.39	61.52
Galician	80.68	77.31
Gothic	60.55	59.81
Ancient_Greek-PROIEL	60.58	65.22
Ancient_Greek	51.5	56.04
Hebrew	61.24	57.23
Hindi_PUD	50.94	50.85
Hindi	86.99	86.77

Table 3.2: Official results with monolingual models (1).

Corpus	**LATTICE**	**Baseline**
Croatian	80.96	77.18
Hungarian	68.49	64.3
Indonesian	76.6	74.61
Italian_PUD	86.49	83.7
Japanese_PUD	77.41	76.28
Japanese	73.98	72.21
Korean	72.35	59.09
Latin-ITTB	74.33	76.98
Latin-PROIEL	55.04	57.54
Latin	51.95	43.77
Latvian	64.49	59.95
Dutch-LassySmall	75.67	78.15
Dutch	70.6	68.9
Norwegian-Bokmaal	85.55	83.27
Norwegian-Nynorsk	84.57	81.56
Polish	85.94	78.78
Portuguese-BR	88.56	85.36
Portuguese_PUD	76.56	73.96
Romanian	81.93	79.88
Russian_PUD	72.03	68.31
Russian-SynTagRus	87.9	86.76
Russian	78.42	74.03
Slovak	79.23	72.75
Slovenian	84.52	81.15
Swedish-LinES	78.15	74.29
Swedish_PUD	73.4	70.62
Swedish	81.07	76.73
Turkish_PUD	34.82	34.53
Turkish	58.89	53.19
Uyghur	34.94	34.18
Ukrainian	63.63	60.76
Urdu	79.26	76.69
Vietnamese	39.87	37.47
Chinese	61.94	57.4
Average	**73.13**	**70.45**

Table 3.3: Official results with monolingual models (2).

Representation Methods	UAS	LAS
BASELINE	83.17	80.64
$-ex$	82.04	79.77
$-ex$, xp	81.86	79.50
$-ex$, up	81.68	79.52
$-ex$, xp, up	81.09	79.12

Table 3.4: Relative contribution of the different representation methods on the English development set (English_EWT).

Training Corpus	*Method*	UAS	LAS
English_EWT	single-source	83.17	80.64
English_Partut	single-source	76.98	74.81
English_EWT + English_Partut	multi-source	83.89	81.34
English_EWT + English_Partut	concatenation	83.42	80.95

Table 3.5: Contribution of the multi-source trainable methods on the English development set (English_EWT).

two tagsets are very similar, as said in Section 2.2 (Figure 2-2). However, we observe a slight improvement when applying the two POS features at the same time rather than just using one of them (compare for example the two models $-ex, xp$ and $-ex$).

Impact on Multi-Source Training. Another characteristic of our BASELINE parser is the possibility to integrate multi-source treebanks (treebanks from different domains). The one-hot encoding embedding oh_i makes it possible to deal effectively with several treebanks at the same time (the embedding is trained to recognize the domain specificities of each treebank, as presented in Section 3.1). To investigate the impact on the multi-source training method, we have conducted an evaluation using different corpora in English. The results are shown in Table 3.5, where we compare the performance of the parser with one or two different treebanks for the same language (English). The *Method* column corresponds to the strategy used for the model: oh_i corresponds to the concatenation approach, and oh_i to our multi-source proposal. We observe that our multi-source approach works fine for English for example, with a gain of 0.39 LAS score compared to the more traditional approach based on the concatenation method. The impact of multi-source learning will be further investigated in the next chapter, along with our multilingual approach.

3.3 Summary

In this chapter, we have described our BASELINE system for dependency parsing that has been tested over the 81 Universal Dependency corpora provided for the CoNLL 2017 shared task. Our parser mainly extends the monolingual BIST parser as a multi-source trainable parser. We proposed two main extensions to the original BIST parser: (*1*) the use of one-hot encoding to encode the notion of the source (domain and language of the treebank), (*2*) a simple but effective way to solve the multiple roots problem of the original BIST parser. Our system ranked 5^{th} and achieved 70.93 overall F1-measure over the 81 test corpora provided for evaluation during the CoNLL evaluation campaign (CoNLL 2017 shared task on Dependency parsing).

Chapter 4

A Multilingual Parser based on Transfer Learning

Developing systems for low-resource languages is a crucial issue for Natural Language Processing (NLP). Most NLP systems are built using supervised learning techniques (Weiss et al., 2015b; Straka et al., 2016; Ballesteros et al., 2016a). These systems require a large amount of annotated data and are thus targeted toward specific languages for which this kind of data exists. Unfortunately, producing enough annotated data is known to be time- and resource-consuming, which means that annotated data, especially of the type required for parsing, is lacking for most languages. To take a recent example, the 2017 CoNLL shared task presented in the previous section, concerned around 49 languages, roughly all of the languages for which enough syntactically annotated data was available in the Universal Dependency format. This was probably the most ambitious parsing challenge ever undertaken with regard to language diversity, but the figure of 49 languages should be viewed relative to the 7,000 languages in the world. Even if one includes only those languages for which written data is available, the 49 languages targeted at CoNLL 2017 cover only a fraction of all the world's languages.

When it comes to parsing, the supervised, monolingual approach based on syntactically annotated corpora has long been the most common one. As presented in the previous chapter, our BASELINE parser, a multi-source trainable parser, is also mono-

lingual even though it can take heterogeneous (multiple) treebanks for one language as training data. It would be possible to turn our baseline parser into a multilingual one using a delexicalized approach (an approach that does not take into account lexical features), but this strategy does not give as good results as a lexicalized parser. Thanks to recent developments involving cross-lingual feature representation methods and neural network models (as discussed in Section 2.2.3), it is now possible to develop accurate multilingual models even for low resource languages.

Multilingual or cross-lingual parsing models are models able to parse several languages. These models are generally trained using parallel corpora or multilingual treebanks from several, generally closely related languages (e.g. English, German and Swedish). The multilingual approach can be implemented in two ways.

- The first one involves projecting annotations available for a high-resource language onto a low-resource language using a parallel corpus that is aligned at the token level. For example, let's take a pair of sentences between a source language *L1* and a target language *L2*. The system first tries to parse the *L1* sentence. Then, the predicted annotations are mapped from *L1* onto *L2* based on word alignment information (the system tries to identify in *L2* what word corresponds to a given word in *L1*). This method produces a new annotated dependency treebank using parallel corpora.

- The second method aims at producing a cross-lingual parsing model based on the model transfer learning approach using several languages. Model transfer learning is a method that improves learning in the target domain by leveraging knowledge from the source domain. For example, model transfer learning methods improve the parsing performance on a low-resource target language *L1* based on annotated data from other (source) languages *L2*. This method typically utilizes cross-lingual resources such as parallel corpora (see Section 2.3).

Guo et al. (2016) and Ammar et al. (2016b) have conducted multilingual parsing studies for Indo-European languages using the lexicalized transfer approach. They

demonstrate that a lexicalized transfer model yield better results than delexicalized models for different European languages. However, their approach relies on the existence of a massive parallel corpus, as their experiment was based on Europarl.[1] Thus the problem of low-resource languages remains unaddressed, especially in cases when no parallel corpus is available. In this chapter, we propose a simple but efficient method for creating a dependency parsing model when (almost) no annotated corpus or parallel corpus is available for training. Our approach requires only a small bilingual dictionary and the manual annotation of a handful of sentences. We assume that the performance one can obtain with this approach depends largely on the set of languages used to train the model. This is why we have developed several models using genetically related and non-related languages, so as to gain a better understanding of the limitations or possibilities of model transfer across different language families.

In this chapter, we introduce a new parser that extends our BASELINE parser, with an additional multilingual lexical representation that will be presented in Section 4.2. The parser has been used for the CoNLL 2017 shared task on multilingual parsing. Following the previous section where the results obtained by our monolingual parser have been presented, we detail here our results for 13 languages using multilingual models. We are working with languages for which, until very recently, no Universal Dependency corpus was available: North Sami[2] and Komi-Zyrian, henceforth Komi.[3] (in this thesis, we use ISO 639-3 codes to refer to the languages in tables.) This alone does not make them low-resource languages, but they are still poorly equipped with regard to NLP tools. Sami language technology has been in active development for a longer time in the Giellatekno project of the University of Tromsø,[4], but in the case of Komi, resources have just recently begun to emerge. Work has also been done on these languages within the framework of language documentation; however, with the exception of a few individual projects (Blokland et al., 2015; Gerstenberger et al., 2016), this field has generally not paid much attention to the use of NLP tools.

[1] A parallel corpus of Indo-European languages, mainly used for machine translation: www.statmt.org/europarl

[2] glottolog.org/resource/languoid/id/nort2671

[3] glottolog.org/resource/languoid/id/komi1268

[4] giellatekno.uit.no

The same scenario applies to many other low-resource languages. However, despite the lack of resources, we observe that the amount of written data in these languages has grown rapidly in the past years, thanks to the activity of Komi users over the Internet and also thanks to large digitalization projects. This means we can now easily build word embeddings, as the only resource needed for these is a sufficiently large amount of text. An additional contribution of this work is the new resources that have been produced. We have created a new UD-type corpus for Komi[5] (version 0.1 used in this study), as well as bilingual dictionaries, multilingual word embeddings for Komi and Sami, and a multilingual parser, all of which are freely available in public repositories.[6][7]

The structure of this chapter is as follows. We first provide an overview of our approach (Section 4.1) before detailing the multilingual word representation used (Section 4.2.1) and our parsing model (Section 4.3.2). We then describe a series of experiments aiming at validating the approach (Section 4.3) before presenting an analysis of our results in the CoNLL shared task (Section 4.4).

4.1 Our Approach

It is by definition not possible to get large scale training data and resources for a low resource language. Therefore, new techniques adapted to this situation have to be found. In this section, we will first study the multilingual approach to parsing using Sami and Komi languages and then generalize this process with other low-resource languages that were proposed within the CoNLL shared task.

Our aim is to test whether it is possible to use knowledge included in annotated data from resource-rich languages to train an accurate parser for the target language, exploiting structural similarities between source and target languages. The languages used for training must thus be selected with the assumption that language may have highly related languages that will contain such structural similarities and make it

[5]github.com/langdoc/UD_Komi-Zyrian
[6]github.com/jujbob/multilingual-bist-parser
[7]github.com/jujbob/multilingual-models

possible to develop an accurate parser in the target language.

Our work with Northern Sami was initially motivated by it being one of the surprise languages in the CoNLL 2017 Shared Task (presented in Section 3.2.1). After the shared task ended, a larger training corpus became available in the dev-branch of the UD_North_Sami GitHub repository of the Universal Dependencies project[8], which enabled us to carry out the broader evaluation. With Komi-Zyrian, the situation is essentially the same as it was with North Sami before the recent release of the new corpus: we have 85 manually annotated examples that can be used for training and testing. The training and testing set was created manually for Komi for the purpose of this study, but it has been currently expanded. This Komi-Zyrian treebank is included in the Universal Dependencies project since 2018.

Our expectation is that the match rate between Russian and Komi-Zyrian should be exceptionally high, as there has been such a long history of contact between these languages, leading to a variety of morphosyntactic changes in Komi (Leinonen, 2006). North Sami has a complex contact relationship with Finnish, but in addition to this, it is also a closely genetically related language (Aikio, 2012). From this point of view, one could expect Finnish to perform well in parsing both Komi and North Sami, although the similarities between these languages have not been studied in great detail from the perspective of syntax and dependency structures. Other types of experiments have also been conducted using this approach, for example, by using a Komi-Zyrian–Russian multilingual model to parse data that contains both languages in the form of code-switching: in these tests, the parser has been shown to be able to analyze language-specific constructions when they occur within same utterance (Partanen et al., 2018b). This case study and analysis about code-switching is presented in (Lim et al., 2018b).

[8]github.com/UniversalDependencies/UD_North_Sami

4.2 A Multilingual Dependency Parsing Model

We want to extend our BASELINE parser working as a multilingual trainable parser that takes training data from several languages. Let's assume that we need to parse a resource-poor language (Komi) that has no training corpus; our baseline parser can possibly train a multilingual parsing model using other languages' treebanks (English, French). In this case, lexical features, however, are useless for parsing Komi sentences because it did not learn any Komi lexicons from the training data (English, French). This is a typical multi-source cross-lingual delexicalized parsing approach (Rosa, 2015) when parsing Komi. In general, delexicalized cross-lingual parsing approaches have been applied using only POS features for many parsers (Dozat et al., 2017b; Shi et al., 2017a; Das et al., 2017). This approach can also be applied for our BASELINE parser presented in the previous section. For instance, the parser can only take UPOS embeddings as an input representation and then train a parsing model using treebanks from languages that have a similar POS order (e.g. Russian for Komi). However, in terms of availability of language resources, lexical features (e.g. words) deliver both syntactic and semantic information beyond non-lexical features (e.g. POS). Therefore, cross-lingual word representation learning that assimilates word representations based on two different languages is considered the best choice for low-resource languages.

The cross-lingual representation learning method is focused on learning cross-lingual features by aligning (or mapping) feature representations (e.g. embedding) between the source and target languages (see Section 2.3.1). Let's assume that we have cross-lingual word embeddings in which vocabularies with the same meaning are mapped between two languages. For instance, 'Dog' (English) and 'Chien' (French) are mapped with the same word representation (e.g. a vector: [0.17, 0.15]) in the cross-lingual word embeddings. Since words in the mapped embedding are represented by the same vector, the system does not need to worry for its word form. Then we can use English treebanks for training a French parsing model with lexical features. The remaining questions we then need to investigate are (1) how to build cross-

lingual word representations that take into account two different languages in a single representation space (vector space), and (2) how to adapt the cross-lingual word representations in order to build a cross-lingual dependency parsing model on top of our BASELINE parser.

4.2.1 Cross-Lingual Word Representations

Cross-lingual word representations (cross-lingual word embeddings) are one of the most popular approaches for building multilingual lexical representations. Various approaches have been investigated for the training of cross-lingual word embeddings mainly for resource-rich languages. Moreover, most of these approaches relied on the existence of a parallel corpus, especially for languages from the Indo-European family (Ammar et al., 2016b; Guo et al., 2016). As we discussed earlier, however, this study focuses on parsing in low-resource language data. Thus, we are constrained by the fact that there is no parallel corpus and no larger annotated dataset for training a dependency parser for the low-resource languages. However, it must be noted that even for low-resource languages, we need raw texts as the minimum resource to train a word embedding. In this study, we trained a monolingual embedding by using raw text available in the public domain. The Komi texts used have been taken from the National Library of Finland's Fenno-Ugrica collection[9], and proofread versions of those Public Domain texts are available in FU-Lab's portal *Komi Nebögain*[10]. Niko Partanen has created a list of books included both in Fenno-Ugrica and FU-Lab[11], and the currently available data adds up to one million tokens. For the contact language Russian we have used pre-trained Wikipedia word embeddings published by Facebook and described in (Bojanowski et al., 2016c). Since the Komi and Sami Wikipedias are relatively small, we have also trained larger word embeddings using FastText (it is an open-source for training word embedding. (Bojanowski et al., 2016b)).

In a similar manner to the low-resource constraints, Artetxe et al. (2017) sug-

[9]https://fennougrica.kansalliskirjasto.fi
[10]http://komikyv.org
[11]https://github.com/langdoc/kpv-lit

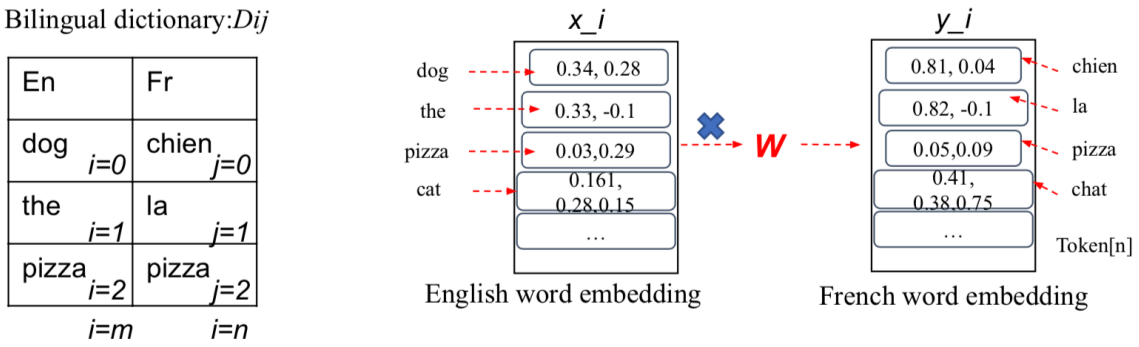


Figure 4-1: An example of the cross-lingual representation learning method between English (Source Language) and French (Target Language)

gested a powerful method for projecting two monolingual embeddings in a single vector space with almost no bilingual data. Traditionally, the projection (or mapping) method for word embeddings requires a large parallel corpus or a bilingual dictionary in order to map two different word embeddings in a distributional space (Artetxe et al., 2016a; Guo et al., 2015b). However, (Artetxe et al., 2017) showed a possible method for mapping two different embeddings based on the linear transformation approach with just 25 pairs of vocabularies but with almost no degradation of performance. The main idea in this method is to project two embeddings trained by different languages based on the linear transformation with bilingual word pairs.

The projection method can be described as follows with an example of Figure 4-1. Let X and Y be the source and target word embedding matrix so that x_i refers to ith word embedding of X and y_j refers to jth word embedding of Y. And let D is a binary matrix, where $D_{ij} = 1$, if x_i and y_j are aligned. Our goal is then to find a transformation matrix W such that Wx approximates y. For instance, the system approximates W that makes the dot product between 'dog' ([0.34,0.28]) and the parameter W have the same vector value as 'chien' ([0.81,0.14]), as shown in Figure 4-1. This is done by minimizing the sum of squared errors following Artetxe et al. (2017).

(1)

$$\arg\min_{W} \sum_{i=1}^{m} \sum_{j=1}^{n} D_{ij} \|x_i W - y_i\|^2$$

Bilingual pairs	Bi-dictionary	Bi-embedding
Finnish--Komi	12,879	2.3GB
Finnish--North Sami	12,398	2.4GB
Komi--English	8,746	7.5GB
North Sami--Finnish	10,541	2.4GB
Russian--Komi	12,354	5.7GB

Table 4.1: Dictionary sizes and size of bilingual word embeddings generated by each dictionary.

We followed Artetxe et al. (2017) mapping idea to train a cross-lingual word embedding based on a bilingual dictionary. To build cross-lingual word embedding, we separately created a mapping system from our parser. This system takes three inputs (two pre-trained embeddings and a bilingual dictionary) and produces a cross-lingual word embedding. Specifically, when our mapping system returns the best-approximated W based on a bilingual dictionary in a supervised manner, it transforms our monolingual embedding to cross-lingual ones using W. The mapping method is relatively simple to apply in our case because once we have a bilingual dictionary available, converting the dictionary as D is not a problem. The size of the dictionary used for training for Komi-Russian is described in Table 4.1. Those dictionaries and projected word embedding are accessible in a public repository.[12] Dictionary is extracted from Jack Rueter's Komi-Zyrian dictionaries that have translations to several languages.[13] In the case of the CoNLL 2017 shared task data, the projected language pairs are shown in Table 4.5 and we will discuss more in Section 4.4.

4.2.2 Cross-Lingual Dependency Parsing Model

As discussed in the previous section, the major idea of the cross-lingual representation learning method is to take aligned features, especially syntactic and lexical features. Since the Universal Dependencies (UD) (Nivre et al., 2017a) model provides cross-linguistically consistent grammatical annotation, we do not need to consider aligning syntactic features among the languages (e.g., POS tags, dependency tags). However,

[12] https://github.com/jujbob/multilingual-models
[13] https://victorio.uit.no/langtech/trunk/words/dicts/kpv2X/src

in terms of the semantic point of view, ignoring lexical features may lead to a lack of semantic information not only in monolingual but also in multilingual dependency parsing.

After the projection between two monolingual word embeddings, all features, including multilingual lexicalized ones, are concatenated as a token representation. Let's remind the reader that the basic token representations for our BASELINE is as follows. Given a sentence of tokens $s=(t_1,t_2,..t_n)$, the i^{th} token t_i can be represented by a vector v_i, which is the result of the concatenation ($\circ$) of a word embedding w_i, XPOS embedding xp_i, UPOS embedding up_i, External embedding1 $e1_i$, External embedding2 $e2_i$ and one-hot encoding embedding oh_i of t_i:

$$v_i = w_i \circ xp_i \circ up_i \circ e1_i \circ e2_i \circ oh_i$$

Once we have a cross-lingual word embedding, the system can easily use the embedding as an external pre-trained word embedding ($e1_i$). However, it should be noted that the system has to keep track of the language of each sentence. It is, therefore, required to add a one-hot encoding (oh_i) as an additional feature. This allows the multilingual model to focus on source (language) specificities directly (see Section 3.1). The parser then transforms the sequence of concatenated lexical representation v_i into a context-sensitive contextualized vector by BiLSTM with a hidden layer r_0 as:

$$h_i^{(head)} = BiLSTM(r_0^{(head)}, (v_1, .., v_n))_i$$
$$h_i^{(dep)} = BiLSTM(r_0^{(dep)}, (v_1, .., v_n))_i$$

By using the contextualized features ($h_i^{(head)}$ and $h_i^{(dep)}$) as input, the system has a graph-based approach, which considers parsing as a search for the best-scored tree graph following our BASELINE model (Section 3.1).

Since we assume that there are no UD corpora for low-resource languages, one common alternative approach is to take a training corpus from another language.

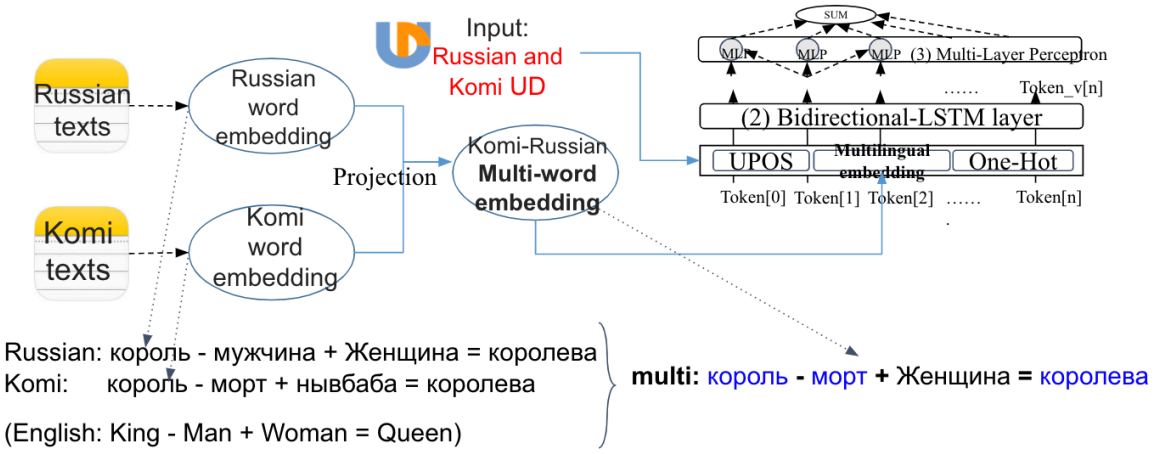


Figure 4-2: An example of our cross-lingual dependency parsing for Russian (Source Language) and Komi (Target Language)

Once we find a grammatically related language, we then simply train a dependency model with the mapped bilingual word embedding and a UD corpus of the related language. Although the training corpus is written in the related language, the system is able to replace tokens with ones from the low-resource language by using bilingual word embeddings, in which vocabulary items with the same meaning are mapped between two languages as described in Figure 4-1. Figure 4-2 presents the structure of our cross-lingual parsing model. For each language, a monolingual word embedding is built from raw texts and then projected into a multilingual embedding. The parser uses both Komi and Russian training corpus as training data to produce the multilingual dependency parsing model.

Overall, we have extended our BASELINE parser using the multilingual word embeddings. The bilingual dictionaries used in the word embedding alignment contained several thousands of word pairs, and the recent study by (Artetxe et al., 2017) shows that the dictionary size we operate with should be large enough to reach a high level of alignment accuracy.

4.3 Experiments on Komi and Sami

We conducted a series of experiments on Sami and Komi. For Sami, we tested different language combinations for the cross-lingual model. All the experiments were carried out using 20 training sentences in Sami, as was the case for the 2017 CoNLL Shared Task, which means these results can be compared to the ones in the official CoNLL evaluation. For Komi, no annotated corpus was available, but we designed ten different experiments, again exploring different language combinations for the cross-lingual model. The experiments for Komi are representative of an extremely low-resource scenario, which is quite common, meaning the approach can be reused for a wide variety of other languages.

4.3.1 Experiment Setup

Training Corpus. We used the corpora available in the Universal Dependency 2.0 format (Nivre et al., 2017a) to train and test all the models except for Komi. Since there was no UD 2.0 Komi corpus, we used 10 sentences for training and 75 sentences for testing (this corpus was designed specifically for this study). Following previous works by (Guo et al., 2015b) and (Zhang and Barzilay, 2015), we used gold POS sets for training and testing for Komi. For Sami, however, the teams in the CoNLL Shared Task used preprocessed POS tags produced by UDpipe. In order to maintain the same conditions as in the Shared Task, we also used the preprocessed POS tagging sets to compare with others in Table 4.3.

Training Conditions. Since we wanted to explore low-resource scenarios (even in the case of Sami, for which larger data now exists), we assumed that there had been no development data for parameter tuning following the CoNLL shared task, and we restricted all training experiments to run just one epoch with the training corpus without early stopping (i.e. the 5_{th}-low of column titled "Case" in Table 4.2 runs only 12,563 iterations). Similar restrictions have also been suggested by (Ammar et al., 2016d), who proposed running one epoch, and by (Guo et al., 2016), who proposed

Case	Training corpus	LAS	UAS
1	sme (20)	32.96	46.85
2	eng (12,217)	32.72	50.44
3	fin (12,543)	40.74	54.24
4	sme (20) + eng (12,217)	46.54	61.61
5	**sme (20) + fin (12,543)**	**51.54**	**63.06**

Table 4.2: Labeled attachment scores (LAS) and unlabeled attachment scores (UAS) for Northern Sami (sme)

restricting iterations to 20,000 for low-resource scenarios. However, when training a model with multilingual training data, the size of training corpora for low-resource languages is comparably smaller than for high-resource languages (e.g. Komi has 10 sentences but Russian has 3,850). Following the previous work of (Guo et al., 2016), we iterated 20 times more for low-resource training data than for high-resource. In Table 4.2 and Table 4.4, the sizes of the training sets used are provided in brackets.

4.3.2 Results

Comparison with the CoNLL Shared Task. We used the same training environments in these experiments as for the CoNLL Shared Task (the same training sets and no development set). Moreover, in order to guarantee similar experimental conditions, we allowed the training models to run just one epoch, following (Guo et al., 2016). Table 4.3 reports the official 2017 CoNLL results. C2L2 (Cornell Univ.) obtained the best performance for Sami with a delexicalized transfer approach (using a Finnish training corpus and a corpus of 20 Sami sentences as a development set for parameter tuning without lexicalized features). IMS (Stuttgart) used a delexicalized transfer approach with a very large training corpus based on 40 different training corpora in UD, obtaining the second-best result. Compared with the result of the Shared Task, it seems that our Finnish–Sami approach (lexicalized cross-lingual transfer parsing with resources from relevant languages) can be effective for parsing low-resource languages. However, additional language features and the application of the ensemble mechanism also seem to be very important. This is due to the fact that the team C2L2 outperform others with more than 6.4 percent of LAS score based

Team	LAS	UAS
C2L2 (Ithaca)	48.96	58.85
IMS (Stuttgart)	40.67	51.56
HIT-SCIR (Harbin)	38.91	52.51
This work	**42.50**	**54.94**

Table 4.3: The highest results of this experiment (FinnishSami model) compared with top 3 results for Sami from the CoNLL 2017 Shared Task.

Case	Training corpus	LAS	UAS
1	kpv (10)	22.33	51.78
2	eng (12,217)	44.47	59.29
3	rus (3,850)	53.85	71.29
4	fin (12,543)	48.22	66.98
5	kpv (10) + eng (12,217)	50.47	66.23
6	kpv (10) + rus (3,850)	53.1	69.98
7	kpv (10) + fin (3,850)	53.66	71.29
8	kpv (10) + fin (12,543)	55.16	**73.73**
9	kpv (10) + eng (12,217) + fin (12,543)	52.5	68.57
10	**kpv (10) + rus (3,850) + fin (12,543)**	**56.66**	71.86

Table 4.4: Labeled attachment scores (LAS) and unlabeled attachment score (UAS) for Komi (kpv). We doesn't conduct training for "kpv + eng + rus" language combination because of unrealistic training scenario (It takes more than 40GB memory for training)

on character-level representations as additional features and an ensemble mechanism composed of three different dependency parsers (these two methods will be presented in the next chapter).

Analysis. All the experiments we conducted using Finnish for training obtained better results than other language combinations (i.e. English for Sami and Russian and English for Komi in Table 4.4). This means that transferring knowledge from genetically related languages is, at least in our case, a very efficient method for parsing. This is true in the case of Sami and Finnish, but also in the case of Finnish and Komi, which is arguably more distantly related to one another than Finnish and Sami. A contact language can also be of significant help in improving the results with a low-resource language, as can be seen in the case of Russian and Komi.

Word order must be one factor that limits the applicability of just the English model, as all other languages analyzed allow rather flexible ordering. Interestingly, the

results obtained using English data show that simply selecting the largest available word embedding can possibly lead to a better result than a monolingual model (e.g, only Komi), but the different multilingual models were also very comparable with that. As the English result improved when the training corpus was smaller, simply adding more data in one language would not alone enable the corpus to outperform smaller or better selected mixed models.

Even in cases where the LAS scores (i.e. labels of the syntactic dependencies) were not significantly different, there was often greater variation in the UAS scores (unlabeled dependencies). This means that although the actual labels may not have been assigned correctly, the basic relations were found and the root was correctly recognized. It is also worth noting that the highest UAS scores were obtained with the Komi–Finnish pair, although the Komi–Russian–Finnish multilingual model gave the best overall result. Our results show that adding even a small number of target-language example sentences (e.g. Komi) into a parser that uses bilingual word embeddings can improve the result significantly. The size of the available training corpus is very important, and the quality of the bilingual dictionaries used to align word embeddings is also crucial.

4.4 Experiments on The CoNLL 2017 data

In the previous section, we showed some results with two languages, North Sami and Komi-Zyrian, for which, until very recently, no Universal Dependency corpus was available. In this section, we present additional results from the CoNLL 2017 shared task using our BASELINE parser. This task offers a very relevant testbed to compare our approach with systems developed by other competing teams. Experiments with 13 languages are presented, especially low-resource languages.

4.4.1 Experiment Setup

Our experiments were conducted using multilingual models integrated to our BASELINE system (Section 3.1) for 13 languages with different conditions, as follows:

Surprise Languages and Kazakh. There were four surprise languages provided for evaluation within the CoNLL 2017 shared task: Buryat, Kurmanji, North Sámi and Upper Sorbian (all in the Universal Dependency format). Less than 30 sentences were provided for training, and Kazakh (although not considered a surprise language) also had 30 sentences for training. We divided the training corpus in half: half of the data were set apart for development and never used for training. We applied our multilingual parsing approach for the languages with two main external resources.

1. (Word embeddings). The first step to build the multilingual model is finding topologically similar languages. Thus, we selected three languages for each surprise language in order to be able to derive the multilingual word embeddings. The choice of languages was based on the *Word Atlas of Language Structures*[14] and on advice from linguists.

2. (Bilingual Dictionary). For some languages, we were able to find bilingual dictionaries from OPUS[15]. When no corpus was available, we used Swadesh lists from Wikipedia. Swadesh lists are composed of 207 bilingual words that are supposed to be *"basic concepts for the purposes of historical-comparative linguistics"*[16].

Finally, we transformed both embeddings in a single vector space using these two lexical resources (the embedding and dictionary). Table 4.5 shows details about the selected pairs of languages and the different sources used for our dictionaries. From these resources, we trained a multilingual model and after testing with the development set apart for each pair of candidate languages, we picked up the best candidate for the different surprise languages and for Kazakh.

[14]The Word Atlas of Language Structures provides information about different languages in the world (family, latitude and longitude, see http://wals.info).
[15]http://opus.lingfil.uu.se/
[16]https://en.wikipedia.org/wiki/Swadesh_list

Corpus	Embedding model	Bilingual Dic	Training corpora
Buryat (bxr)	Buryat-Russian	wiki dump	brx(20), ru
Kurmanji (kmr)	Kurmanji-English	wiki dump	kmr(20), en
North Sámi (sme)	North Sámi-Finnish	wiki dump	sme(20), fi, fi-fbt
Upper Sorbian (hsb)	Upper Sorbian-Polish	OPUS	hsb(20), pl
Kazakh (kk)	Kazakh-Turkish	OPUS	kk(20), tr
Portuguese (pt)	7 languages*	Europarl7,WMT11	en, it, fr, es, pt, de, sv
Italian (it)	7 languages*	Europarl7,WMT11	en, it, fr, es, pt, de, sv
Italian_ParTUT (it_partut)	7 languages*	Europarl7,WMT11	en, en_partut, fr_partut, it, it_partut
English_ParTUT (en_partut)	7 languages*	Europarl7,WMT11	en, en_partut, fr_partut, it_partut
French_ParTUT (fr_partut)	7 languages*	Europarl7,WMT11	en_partut, fr, fr_partut, it_partut
Czech-CLTT (cs_cltt)	Czech	-	cs, cs_cac, cs_cltt
Galician-TreeGal (ga_treegal)	Galician	-	ga, ga_treegal
Slovenian-SST (slovenian_sst)	Slovenian	-	sl, sl_sst

Table 4.5: Languages trained by a multilingual model. **Embedding model:** applied languages that were used for making multilingual word embeddings. **Bilingual Dic:** resources to generate bilingual dictionaries **Training corpora:** Training corpora that were used. **7 languages:** English, Italian, French, Spanish, Portuguese, German, Swedish. **(number):** the number of multiplication to expand the total amount of corpus.

Italian and Portuguese There have been several attempts in the literature aiming at training multilingual models for resource-rich languages (Guo et al., 2016; Ammar et al., 2016b). We have tested our multilingual system in a similar way, as explained in Section 4.2 for resource-rich languages, except that we, of course, changed the resources used depending on the language. We used multilingual word embeddings for the seven languages[17] presented in (Ammar et al., 2016b) trained using word clustering from parallel corpora. We obtained a multilingual model from the training corpora provided for the 7 languages considered. Although the size of our multilingual embedding is almost 10 times smaller than the size of the monolingual embeddings made by Facebook (Bojanowski et al., 2016b), the result (F1-measure) is slightly better than with the monolingual model for Italian and Portuguese, with 0.39 and 0.41 within development sets.

ParTUT corpora Since all ParTUT corpora come from the same source of text regardless of languages, we decided to apply a multilingual approach. We applied the same multilingual approach for Italian Table 4.5 and for the ParTUT corpora, but used different compositions of corpora for training. For example, we used en_partut, fr_partut, it_partut and fr corpora as the training data when parsing French_ParTUT. Finally, the best training compositions are listed in Table 4.5.

Czech-CLTT, Galician-TreeGal, Slovenian-SST These three corpora have a small number of training sentences. We thus train them with heterogeneous treebanks but with different language hot-encoding values, as presented in Section 3.1.

4.4.2 Results

Table 4.6 shows the results obtained when using multilingual models on the small treebank dataset (French_partut, Galician, Galician_treegal, Kazakh, la, Slovenian_sst, Uyghur and Ukrainian). We ranked 4^{th}, with 54.78 LAS score on this group of languages. However, in terms of extremely resource-poor languages (surprise languages),

[17]English, Italian, French, Spanish, Portuguese, German, and Swedish.

Corpus	LAS	UAS	Rank(LAS)	Rank(UAS)	UDpipe(LAS)
Overall (81)	70.93	76.75	5	5	68.35
Small treebanks (8)	54.78	64.99	4	5	51.80
Surprise language (4)	36.93	48.66	12	15	37.07

Table 4.6: Official experiment results with rank. (number): number of corpora

Corpus	LATTICE-Multi	LATTICE-Mono	UDpipe
Buryat	27.08	19.7	31.5
Kurmanji	41.71	37.59	32.35
North Sámi	28.39	25.89	30.6
Upper Sorbian	50.54	41.23	53.83
Kazakh	22.11	19.98	24.51
Italian	87.75	87.98	85.28
Portuguese	84.08	84.08	82.11
English-ParTUT	80.45	77.62	73.64
French-ParTUT	83.26	80.66	77.38
Italian-ParTUT	84.09	80.36	-
Czech-CLTT	75.45	74.85	71.64
Galician-TreeGal	68.01	67.75	65.82
Slovenian-SST	49.94	48.06	46.45

Table 4.7: Official experiment results processed by multilingual models.

we have ranked only 12^{th}, with 36.93 LAS score. This is slightly lower than the UDPipe1.1 baseline model: we assume this is the result of using half of the corpus for training surprise languages (as presented in Section 4.4.1). In contrast, when we used all the training data for training, we obtained a 43.71 LAS score (3rd rank, unofficial result).

Table 4.7 shows a comparison of the performance of the monolingual vs multilingual model of our parser. When we compare monolingual models for surprise languages with multilingual ones, we see an improvement between 2.5 and 9.31 points. The same kind of improvement can be observed for the ParTUT group. In this case, the multilingual approach improves performance by almost 3 points. A further analysis for the impact of the multilingual model will be discussed in Section 5.4.1 and 7.2.

4.5 Summary

In this chapter, we have presented a multilingual approach to parsing that is effective for languages with few resources and no syntactically annotated corpora available for training. We have shown that our multilingual models provide better results than monolingual ones. Adding training material from other languages usually did not decrease the parsing result. It should, however, be noted that the relative size of the different corpora used for training seems to be relevant, since using corpora that are too imbalanced may weaken the result. A more detailed analysis of the results, beyond the LAS and UAS scores, is most likely needed in order to determine the exact influences of different language pairs or combinations. It remains a question for further study whether the improvements observed here are actually attributable to the genetic relationship between the language, or if the same result could be obtained by simply selecting languages that are otherwise typologically similar.

Chapter 5

A Deep Contextualized Tagger and Parser

Natural language processing (NLP) has been long focused on English and a few other languages that were economically (or, more rarely, strategically) profitable. The gradual development of the Web, as well as of social media, has revealed the need to deal with more languages which, in turn, offer new technological challenges. It is, for example, clear that languages exhibit a large diversity of morphological complexity and NLP tools must tackle this diversity in order to obtain acceptable performance beyond English (e.g., on agglutinative or polysynthetic languages). In this context, feature representation methods that capture morphological complexities have been an essential element for neural dependency parsing. As discussed in the previous chapter, methods such as Feed Forward Neural Network (FFN) (Chen and Manning, 2014a) or LSTM-based contextualized representations (Kiperwasser and Goldberg, 2016a; Ballesteros et al., 2016a) have been proposed to provide fine-grained token representations and make it possible to develop accurate parsers. However, word-level representations, focusing only on word forms, have two serious limitations:

- ***A Lack of sub-word information***: Word-level representations cannot capture sub-word information effectively because they focus only on word forms. For example, humans can capture several sub-word information from the word

"delexicalized" such as (1) "de" used to indicate privation, removal, and separation, (2) "ed" represented the tense of the verb. However this is not possible if one does not look for sub-word information.

- ***Out-of-vocabulary words***: Out-of-vocabulary words are unknown words, because they were not present in the training corpus. Word-level representations without external lexical resources (e.g. a pre-trained embedding) are weak to handle these words. For example, if "delexicalized" was not part of the training corpus, the system then cannot figure out its deep context during parsing.

To address the lack of sub-word information, character-level representation methods have become a crucial component offering better feature representations for parsing (Zeman et al., 2017b; Dozat et al., 2017b). Formally, character-level representations (character embeddings) are trained using a sequence of characters, unlike word embedding trained using a sequence of words. This representation is capable of capturing sub-word information in a token or a sentence (this will be presented in the following section). These sub-words can make it easier to represent inflection, common prefixes and suffixes and are thus well-suited for morphologically rich languages[1]. To handle the out-of-vocabulary word issue, we also use a pre-trained word embedding. Generally, such an embedding, trained using massive raw texts (e.g. Wikipedia, OpenCrawl) can deliver more information than a randomly initialized word embedding (see Section 2.2.3 and 3.1). However, even with all these resources, we are still unable to model ambiguity since a word form is associated with one representation, and only one. For example, pre-trained word embeddings do not consider word order[2]. For example, given two sentences (A) "I am walking on the bank of the river" and (B) "I have to put some money in the bank", the representation for "bank" will always be the same though it appears in different contexts. The need for contextualized word representations taking into account context information, pushed the use of Language Model (LM) (i.e., word representation that takes into account word order). An

[1]For example, a word can have multiple forms, making it harder to find and look up in the dictionary since by default a system has no rule to normalize or analyze unknown word forms.

[2]For example, word embedding trained by Wor2Vec can predict neighboring words within a window regardless of their order during training

LM representation (embedding) is a contextualized word representation that learns word representations by trying to predict the next word in a sentence (details will be presented in Section 5.2).

To train contextualized representations, LM representation methods need to keep context information based on word order to predict the next word. Applying LSTM has been one of the popular approaches to build contextualized LM embeddings because of its memory cell (see Section 2.3). In NLP, LMs, which are trained by LSTM that captures both context-sensitive syntactic and semantic information, have been initially called deep contextualized LM (Peters et al., 2017)[3]. Deep contextualized representations generally denote embeddings generated by deep contextualized LMs. Since these LMs are also trained using massive text corpora by taking into account contextual information, they have yield better performance in handling unseen words than pre-trained word embedding (Peters et al., 2017).

Following previous proposals promoting a model transfer approach with lexicalized feature representations (Guo et al., 2016; Ammar et al., 2016b; Lim and Poibeau, 2017b), we propose a deep contextualized tagger and parser, respectively. This system consists of a multi-source trainable system using three different lexical representations as follows:

- ***Multi-attentive character level representations***: A context sensitive character-level representation that takes into account several subword information.

- ***ELMo representation***: A deep contextualized representation integrating abundant contexts gathered from external resources (raw texts) (Peters et al., 2018).

- ***Multilingual word representation***: A multilingual word representation obtained by the projection of several pre-trained monolingual embeddings into a unique semantic space (presented in the previous chapter).

[3]There are, however, several models that are also called deep contextualized LM that apply different neural network techniques.

In general, the impact of each representation depends on the task considered. Previous studies have evaluated the impact of representations over several tasks such as POS tagging, dependency parsing, constituency parsing, named entity recognition, question answering, etc (Peters et al., 2017; Devlin et al., 2018). Here we focus on syntax-related tasks, especially POS tagging and dependency parsing to investigate the effectiveness of the proposed representations.

The POS tagging task is a token classification task that predicts the part-of-speech of each word in context. It is a convenient way to evaluate a system that has to deal with morphological diversity. As presented in the previous section, POS tagging is crucial for the dependency parsing task. Most state-of-the-art parsers require the text to be tagged before parsing. We will thus investigate how well additional contextualized representations produce syntactically consistent tagging outputs. Second, we test our contextualized representations through parsing, to see whether our contextualized representation is positive for parsing. Finally, we report our results of the CoNLL 2018 shared task using this parser.

The structure of this chapter is as follows. We first describe sub-word and LM representation methods (Section 5.1 and 5.2) and then present our POS tagger (Section 5.3) and our parser (Section 5.4). Our parser is open source and available at: https://github.com/jujbob/.

5.1 Multi-Attentive Character-Level Representations

We want to add sub-word information to our parser, because this is relevant to represent inflections, including common prefixes and suffixes, and is thus well-suited for dependency parsing.

A character-level **word** representation is a word embedding produced by character representations for a word. This is an essential component of NLP tools because of their ability to capture potentially complex morphological information (Kim et al.,

2016; Yu and Vu, 2017). Let's remind the readers that, traditionally, a character-level word representation learned using Long Short-Term Memory (LSTM) units takes a sequence of characters as input and returns an encoded vector (Ballesteros et al., 2015). Recently, studies on character models have focused on enriching feature representations by stacking more neural layers (Shi et al., 2017a), applying an attention mechanism (this will be presented in the following section) (Cao and Rei, 2016), and appending a Multi-Layer Perceptron (MLP) to the output of recurrent networks (Dozat et al., 2017b). This approach has obtained the best performance for POS tagging and dependency parsing in the CoNLL 2017 (Zeman et al., 2017a) and 2018 (Zeman et al., 2018c) shared task. However, despite their benefits, most of these systems also have clear shortcomings, like their (lack of) representation of unknown words. Moreover, the application of several character models, capable of capturing different lexical characteristics, has not been fully explored so far. This is because most of the time when two character models such as LSTM and BiLSTM-based character representations are learned separately, they mostly capture the same kind of features as other methods, and thus do not have a real positive influence on the results.

Here we propose a new approach that aims at offering a more accurate representation. This is done through two complementary devices: i) a sub-word analysis, geared to recognize morpheme-like information and ii) a contextual model taking into consideration the sentential framing of a word, which is especially useful for the analysis of unknown words (context is sometimes enough tot predict accurately the meaning of an unknown word). In order to do this, we need to combine two different character embeddings. One is a context independent word-based character representation (Shi et al., 2017a), and the other is a context sensitive sentence-based character representation (Alberti et al., 2017; Bohnet et al., 2018a) (These will be presented in the following sub-section). We use joint training techniques to induce two character embeddings focusing on different aspects of sub-word information. This new technique has the advantage of capturing not only locally optimized character features but also globally optimized features, regardless of the language type. In the following

sub-sections, we introduce two LSTM-based character models with our self-attentive approach.

Basic notions

- ***A character(-level) representation:*** an embedding for a character.
- **A character-level word representation:** a word embedding generated from character representations.
- **A sentence-based character representation:** a character-level word representation generated from a sequence of characters in a sentence.
- **A word-based character representation:** a character-level word representation generated from a sequence of characters in a word.

For example, given an input sentence s of length n with characters s=(ch_1, . , ch_n), our system creates a sequence of sentence-based character embeddings $ch^s_{1:n}$, initially encoded as random vectors. Since a sentence s is composed of m words such that s=(w_1, . , w_m), and each word w_i can be decomposed into a sequence of characters w_i=(ch^i_1, . , ch_k), the system also creates a set of sequences of word-based character embeddings $ch^{1:m}_{1:k}$. Note that two character embeddings, such as $ch^s_{1:n}$ and $ch^{1:m}_{1:k}$, do not refer to the same vector since the system is initialized randomly. A character can thus be represented by two different embeddings.

In this section, we will use lowercase italics for vectors and uppercase italics for matrices. The characters w and W denote parameters that the system has to learn. Also, semicolons denote the concatenation of two vectors, and $ConcatRow$ denotes the concatenation of matrices by rows. We maintain this convention when indexing and stacking; so h_i is the i-th vector of matrix H, and matrix H is the stack of all vectors h_i.

Context Insensitive Word-based Character Model

A sentence consists of a sequence of characters; likewise a word also consists of a sequence of characters. Therefore, there are at least two ways to build character-level word embeddings using LSTM. Let's call a word-based character model a method that generates a representation based on a word (and thus not on the full sentence). In general, word-based character vectors are obtained by running a BiLSTM (Dozat et al., 2017b) over the k characters $ch^i_{1:k}$ of a word w_i:

$$f^{(wc)}_j, b^{(wc)}_j = BiLSTM(r^{(wc)}_0, (ch^i_1, .., ch^i_k))_j$$
$$h^{(wc)}_j = [f^{(wc)}_j; b^{(wc)}_j]$$

Here, $f^{(wc)}_j$ is the forward-pass hidden layer of the BiLSTM for character j of a word, $b^{(wc)}_j$ the backward pass, and $h^{(wc)}_j$ the concatenation of the two. Previous studies have shown that the last encoded character $f^{(wc)}_k$ represents a summary of all the information from the input character sequence (Shi et al., 2017a) because the output of the LSTM keeps track of the contextual information (see Section 2.3). However, taking the last encoded character as an embedding is often omitted in the earlier parts of the sequence once the entire sequence has been processed. This happens because the last encoded embedding $f^{(wc)}_k$ (vector) is a fixed size of the vector and becomes a bottleneck to summarize long sequences into a single vector. The attention mechanism was born to address this problem. The idea of attention is to use all the intermediate states $H^{(wc)}_i$ to build the context vector. Generally, an attention method establishing relations between different parts of a single sequence to extract a specific representation is called self-attention. The self-attention method involves applying a linear transformation (Cao and Rei, 2016) over the matrix of character encodings

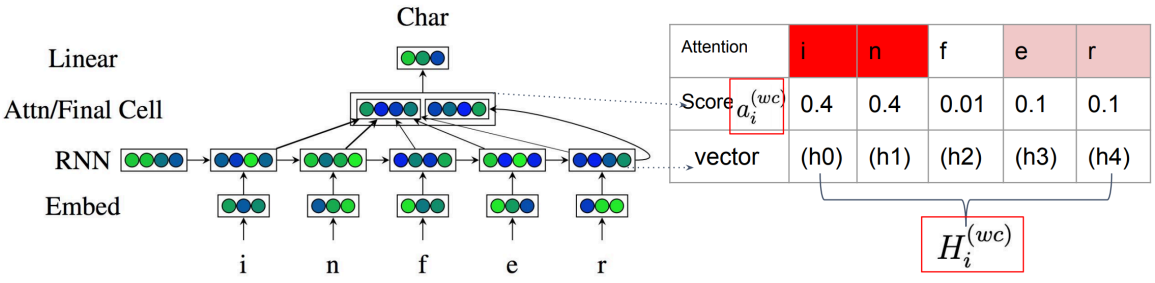


Figure 5-1: An example of the word-based character model with a single attention representation (Dozat et al., 2017b)

$H_i^{(wc)} = h_{1:k}^{(wc)}$, for which attention weights $a_i^{(wc)}$ are calculated as follows[4]:

$$a_i^{(wc)} = Softmax(w^{(wc)} H_i^{(wc)})$$
$$c_i^{(wc)} = a_i^{(wc)} H_i^{(wc)}$$

Here $w^{(wc)}$ is a linear transformation parameter. The self-attention weight $a_i^{(wc)}$ intuitively corresponds to the most informative characters of word w_i for the task being learned. Passing the encoded character vector $H_i^{(wc)}$ of each word through its attention weights $a_i^{(wc)}$, we obtain the character-level word-vector as $c_i^{(wc)}$. Figure 5-1 is an illustration of the word-based character model, including the attention weights $a_i^{(wc)}$ and the encoded character vector $H_i^{(wc)}$. Dozat et al. (2017b) suggest to concatenate the last encoded vector $f_k^{(wc)}$ with the attention vector $a_i^{(wc)} H_i^{(wc)}$ in order to capture both the summary and sub-word information in one go for tagging (see Figure 5-3-(A)). However, as Lin et al. (2017) suggest, self-attention based representations tend to focus on a specific component of the sequence. To alleviate this, we propose multi-head attention character-level word embeddings, which reflect various character-level features of a word by applying multiple attention weights as a matrix

[4]Here, we use lowercase italics for vectors and uppercase italics for matrices. So a set of hidden state $H_i^{(wc)}$ is a matrix stacked on m characters.

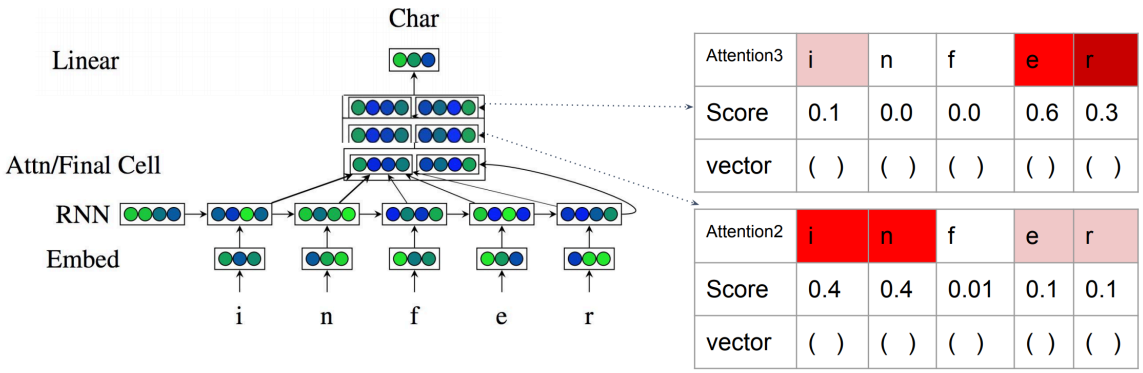


Figure 5-2: An example of the word-based character model with three attention representations.

$A_i^{(wc)}$ rather than as a vector $a_i^{(wc)}$:

$$A_i^{(wc)} = Softmax(W^{(wc)} \tanh(D^{(wc)} H_i^{(wc)}))$$
$$c_i^{(wc)} = ConcatRow(A_i^{(wc)} H_i^{(wc)}) \quad (5.1)$$

By applying an attention parameter matrix $W^{(wc)}$, rather than a vector $w^{(wc)}$, and a non-linear function with a weight parameter $D^{(wc)}$, the attention weight can reflect several aspects of sub-word information. For example, a successfully trained attention weight $W^{(wc)}$ could recognize two different morphemes: "in" and "er" from the word "infer", as presented in Figure 5-2. We, however, do not know which sub-word will exactly be captured during training because the system only tries to adjust the attention parameters W based on the prediction errors (Lin et al., 2017). The effectiveness of the multi-attentive model will be discussed in Section 5.3.

Context Sensitive Sentence-based Character Model

The model we have just described is effective at capturing sub-word information, but cannot capture contextual information beyond word boundaries (e.g. because the model just takes a word as input, it cannot take into account the context of this word). The overall context can be modeled by considering the whole sentence as a sequence of characters. The sentence-based character model is a model that builds a word representation based on the sequence of characters corresponding in a sentence.

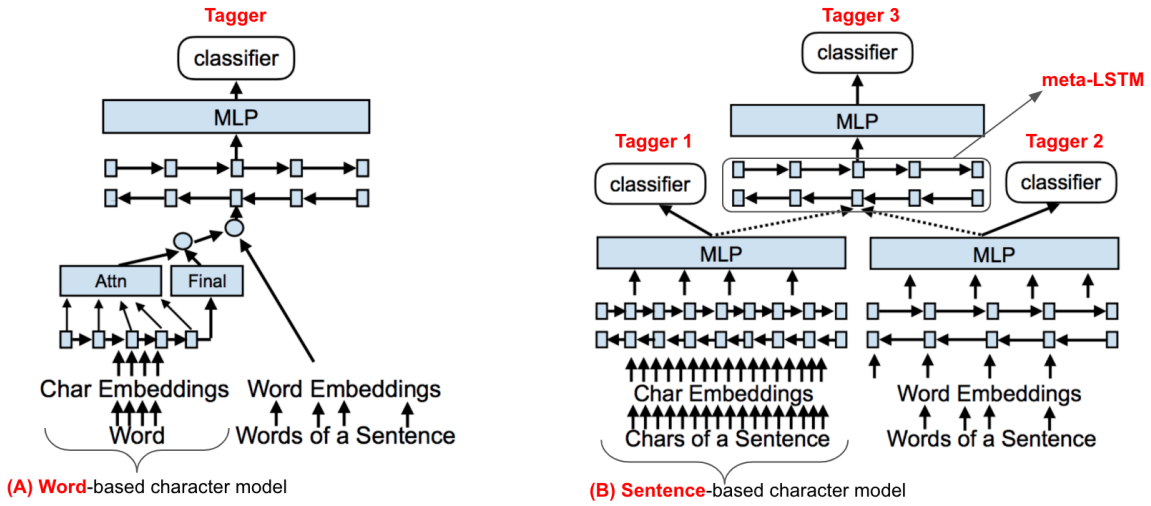


Figure 5-3: (A) Structure of the tagger proposed by Dozat et al. (2017b) using a word-based character model and (B) structure of the tagger proposed by Bohnet et al. (2018a) using a sentence-based character model with meta-LSTM.

The sentence-based character model is thus a context sensitive model (Bohnet et al., 2018a).

Alberti et al. (2017) used a sentence-based character representation trained by a LSTM model for dependency parsing and achieved state of the art results for morphologically rich languages. In tagging, Bohnet et al. (2018a) showed that a sentence-based character model that processes all the characters of a sentence at once is better at keeping context information for unseen data than a token-based one for tagging. Figure 5-3-(B) shows the structure of sentence-based model. This model obtained the best POS parsing results during the 2018 CoNLL shared task.

We propose to extend these previous approaches with a self-attention sentence-based word embedding, composed of three parts:

1. **Encoding.** A single encoding is generated from the entire sequence of characters corresponding to a sentence using a BiLSTM:

$$h_j^{(sc)} = BiLSTM(r_0^{(sc)}, (ch_1^s, .., ch_n^s))_j$$

2. **Slicing.** The output of the BiLSTM is sliced from the start index $sidx(w_i)$ to

the end index *eidx(w$_i$)* of each word. A matrix $H_i^{(sc)}$ is produced by stacking the encoded character vectors of a word:

$$H_i^{(sc)} = (h_{sidx(w_i)}^{(sc)}, .., h_{eidx(w_i)}^{(sc)})$$

3. **Attention.** $H_i^{(sc)}$ is transformed into a multi-attention representation $c_i^{(sc)}$, as with the word-based model in (5.1):

$$A_i^{(sc)} = Softmax(W^{(sc)} \tanh(D^{(sc)} H_i^{(sc)}))$$
$$c_i^{(sc)} = ConcatRow(A_i^{(sc)} H_i^{(sc)})$$

Our approach is distinct from that of Bohnet et al. (2018a), who proposed the concatenation of only the first and last BiLSTM outputs as $c_i^{(sc)} = MLP([h_{sidx(w_i)}^{(sc)}; h_{eidx(w_i)}^{(sc)}])$. This concatenation method can capture a summary of all the information contained in the input character sequence but can be a bottleneck, as explained in the word-based character model section. To solve this problem, we have adopted the multi-head attention model described in the previous section with $H_i^{(sc)}$. We believe this multi-attention model is more accurate in capturing the context.

5.2 Deep Contextualized Representation (ELMo)

It is well known that word meaning changes according to the context. However, traditional pre-trained word embeddings (used with our BASELINE parser for example) do not take contextual information into consideration. This is, of course, a major limitation for natural language processing applications.

In order to address this problem, we need to model the entire sentence as a source of contextual information. This is the goal of deep contextualized word embeddings, that aim at modeling word semantics according to the context. As presented in Section 2.2.3, representing the sentence via a LSTM is a popular method to transform a word vector into a contextualized representation because of its memory cell.

ELMo (Embedding from Language Model) is a deep contextualized word representation that aims at modeling complex characteristics of word use such as syntax and semantics (Peters et al., 2018). These word embeddings are learned functions of the internal states of LSTM, pre-trained on a large text corpus as explained in Section 5.1. This contextualized embedding is a new technique for word representation that has achieved state-of-the-art performance across a wide range of language understanding tasks. This approach is able to capture both subword and contextual information. From a technical point of view, ELMo can be used as a function that provides a deep contextualized word representation based on the entire input sentence using pre-trained LSTM.

Following Peters et al. (2018), we trained our deep contextualized word representations with a BiLSTM using the officially provided ELMo trainer[5] and used ELMo embeddings as an additional word embedding. Our ELMo embeddings have been trained as follows:

$$\begin{aligned} R_i &= \{\mathbf{x}_i^{LM}, \overleftrightarrow{\mathbf{h}}_{i,j}^{LM} | = 1, ..., L\} \\ &= \{\mathbf{h}_{i,j}^{LM} | = 0, ..., L\} \end{aligned} \tag{5.2}$$

$$ELMo_i = E(R_i; \Theta) = \gamma \sum_{j=0}^{L} s_j \mathbf{h}_{i,j}^{LM} \tag{5.3}$$

To train ELMo embeddings, large quantities of raw text, as well as a pre-trained word embedding, are required. We used the permitted pre-trained word embeddings and raw texts provided by the CoNLL shared task organizer[6]. The transformation of a sentence given the pre-trained word embedding is the first step of training. In (5.2), $\mathbf{x}_i^{LM}$ and $\mathrm{h}_{i,0}^{LM}$ are pre-trained word embeddings corresponding to the tokens of a sentence. We then contextualize the sequence of embeddings using BiLSTM. $\overleftrightarrow{\mathbf{h}}_{i,j}^{LM}$ denotes a contextualized LSTM vector consisting of a multi-layered bidirectional LSTM and $\mathbf{h}_{i,j}^{LM}$ is a concatenated vector composed of $\mathbf{x}_i^{LM}$ and $\overleftrightarrow{\mathbf{h}}_{i,j}^{LM}$. Here,

[5]https://allennlp.org/elmo

[6]http://universaldependencies.org/conll17/data.html

each $\mathbf{h}_{i,j}^{LM}$ is an individual contextualized embedding so we need to transform it as a unified embedding. Finally, we compute our model with all the BiLSTM layers weighed to generate a unified embedding using softmax. In (5.3), s_j denotes the softmax weight and γ is the scalar parameter to scale the embedding during training. Following Peters et al. (2018), we used a 1024 dimensions ELMo embedding for our tagger and parser.

5.3 Deep Contextualized Tagger

Since our input is raw text, it is first necessary to implement or have access to pre-processing tools such as a tokenizer and a POS tagger. It is, in particular, crucial to get an accurate POS tagger since POS tags are often used as a non-lexical feature (Che et al., 2018). It has also been observed that tagging accuracy directly affects parsing performance. We thus first investigate a POS tagger to see the impact of our proposed contextualized representations and then introduce our parser in the following section.

In this section, we describe our POS tagger, integrating the contextualized representations we have just detailed, using Joint Many-Task learning (JMT). JMT is a subfield of machine learning in which multiple learning tasks are solved at the same time. JMT enriches context-sensitive feature representations by learning different tasks with shared parameters (Hashimoto et al., 2016). For example, we can train a tagger and parser at the same time with shared word representations in order to capture two different task-specific word representations. This approach may also consist in training several classifiers for the same task. For example, Figure 5-3-(B) shows the structure of a meta-Tagger that applies a JMT approach to a single POS tagging task (Bohnet et al., 2018a). The Meta-Tagger separately trains a word-based and a character-based POS tagger without sharing parameters and then joins the two models via another middle-layer BiLSTM and MLP, which is used as the final classifier. The system thus integrates three different taggers trained from different kinds of information (character, word, character+word). However, the concatenation method

(that concatenates character and word features before contextualizing them, see Figure 5-3-(A)), has been the most popular approach recently. This model generally has only one tagger.

The concatenation method often tends to rely on a specific feature (e.g. word) and ignores the other features (e.g. character) during training (Lin et al., 2017). In this context, the Meta-Tagger offers the advantage of learning contextual information because each tagger struggles to identify the best features within the limited character and word features. Because the middle-layer BiLSTM has access to two different contexts that are captured by two different taggers, it is called meta-BiLSTM. The meta-BiLSTM approach seems to be particularly effective at balancing the application of word- and sentence-based features.

Following Bohnet et al. (2018a), we train two character-level taggers and then combine them through a meta-BiLSTM tagger. As said above, we use each sentence and word-based character embedding rather than only one ultimate embedding: this makes it possible to take advantage of both the meta-BiLSTM model and JMT since we are then using two character-level models. Since each separate tagger trained on an individual classifier, each tagger struggles to identify the best features within the limited sentence and word-based character features. Figure 5-4 shows the overall structure of our contextualized tagger.

5.3.1 Two Taggers from Character Models

To take advantage of the meta-LSTM, our system builds two POS taggers using the two different word embeddings generated from the sentence ($c_i^{(sc)}$) and the word-based ($c_i^{(wc)}$) character model, as described in Section 5.1. To enrich word-level information, for each character model, the system concatenates a shared word embedding $w_i^{(e)}$ initialized with a pre-trained word embedding (Bojanowski et al., 2016a) and an ELMo embedding $e_i^{(el)}$ (Peters et al., 2018) in case we have one available, and then passes it through another BiLSTM layer, whose output is $g_i^{(sc)}$ and $g_i^{(wc)}$ for sentence-based and word-based representations respectively. Finally, for sentence-based embeddings, we apply a MLP classifier with a weight parameter $Q^{(sc)}$ including a bias term $b^{(sc)}$

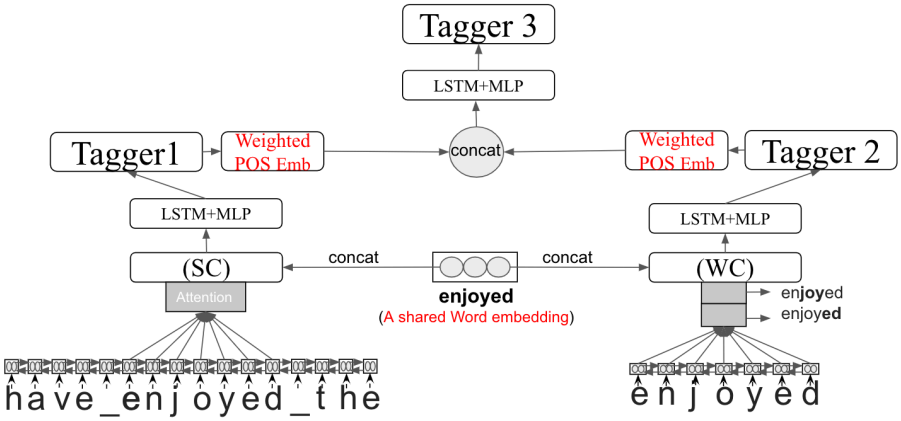


Figure 5-4: Overall structure of our contextualized tagger with three different classifiers.

to classify the best candidate POS:

$$
\begin{aligned}
p_i^{(sc)} &= Q^{(sc)} MLP(g_i^{(sc)}) + b^{(sc)} \\
y_i^{(sc)} &= \arg\max_j p_{i,j}^{(sc)}
\end{aligned}
\tag{5.4}
$$

$$
\begin{aligned}
p_i^{(wc)} &= Q^{(wc)} MLP(g_i^{(wc)}) + b^{(wc)} \\
y_i^{(wc)} &= \arg\max_j p_{i,j}^{(wc)}
\end{aligned}
\tag{5.5}
$$

Performing the same operation for the word-based embeddings as well, we predict two POS tags $y_i^{(sc)}$ and $y_i^{(wc)}$.

5.3.2 Joint POS Tagger

To create joint representations that learn to combine the output of the two taggers, we transform the two tagging results as a weighted POS label embedding $h_i^{(pos)}$ as follows:

$$
\begin{aligned}
l_i^{(sc)} &= \sum_{j=1}^{U} P(y_i^{(sc)} = j | p_i^{(sc)}) pos(j) \\
h_i^{(pos)} &= [l_i^{(sc)}; l_i^{(wc)}]
\end{aligned}
\tag{5.6}
$$

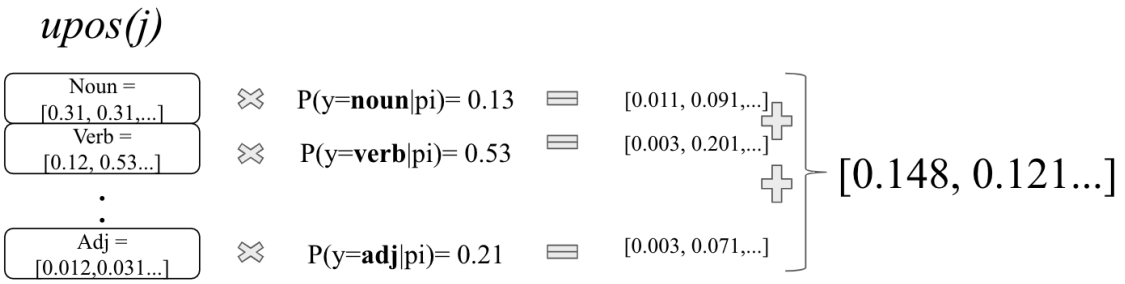


Figure 5-5: An example of the procedure to generate a weighted POS embedding.

Here U is the number of possible POS tags, $P(y_i^{(sc)} = j|p_i^{(sc)})$ denotes the probability that the j-th POS tag is assigned to a word w_i, and $pos(j)$ is a randomly initialized POS vector (presented in our BASELINE model). For example, Figure 5-5 shows a weighted POS embedding for a token p_i. A weighted POS embedding for p_i is the weighted sum of POS embedding based on its probability $P(y_i^{(sc)} = j|p_i^{(sc)})$. We generate a joint embedding $h_i^{(pos)}$ by concatenating two weighted POS features $[l_i^{(sc)}$; $l_i^{(wc)}]$. With the classifier proposed in (5.4) taking the joint vector $h_i^{(pos)}$ in input, the system predicts another POS tag $y_i^{(pos)}$ from two weighted POS features. Note that the system only uses tokenized sentences as input, and the weighted POS are predicted at training time. Where meta-Tagger (Bohnet et al., 2018a) trains three taggers using separate optimizations, we trained our taggers simultaneously using a single *Adam*-optimizer (Kingma and Ba, 2014)[7], with a summed cross-entropy loss for each tagger. This approach has the advantage of passing error propagation directly to the shared word embedding $w^{(e)}$.

5.3.3 Experiments and Results

In this section, we present our experimental setting and the results of our model on the CoNLL 2018 shared task (ST) dataset. This is a similar shared task to the one presented in Section 3.2 (CoNLL 2017) but, for 2018, the organizers expanded the number of languages from 49 to 57. The focus of the task was not only the evaluation of syntactic dependency parsers but also included the evaluation of POS

[7]This is a stochastic approximation of gradient descent optimization, https://en.wikipedia.org/wiki/Stochastic_gradient_descent

tagger. Moreover, it is obvious that POS tagging directly affects parsing (a word with a wrong tag cannot be rightly analyzed during parsing). We compare our UPOS[8] results with the official CoNLL 2018 results for this task.[9]

Data Sets

We evaluate our model on the Universal Dependency 2.2 corpora provided for the CoNLL ST (the development set is issued only for parameter tuning with the provided evaluation metric) (Zeman et al., 2018a). In order to compare our experiments with the official 2018 CoNLL results, we use here the permitted pre-trained word embeddings for Japanese and Chinese[10] and other languages (Bojanowski et al., 2016a), and ELMo embeddings trained by Lim et al. (2018a). We tested our approach on 12 test treebanks from 8 different languages with different character sets to investigate the impact of these character sets on our approach.

Since the input of the shared task was raw texts (plain texts), it is thus necessary to first implement a word tokenizer. After the shared task, the tokenization results of the best performing team have been officially provided by the ST organizer for further investigation[11]. By using the tokenized results of each team as an input, it is directly possible to compare the tagging results of each team. As our input test data, we use the word tokenization result of the best performing model for each treebank in order to compare with them directly. Note that when the baseline tokenizer (Straka et al., 2016) is used for preprocessing, this largely affects the results since tokenization has a direct and massive impact on tagging performance. Among our dataset, five treebanks have no training data available, but for these cases at least one large training treebank in a different domain is available. This offers an excellent opportunity to explore the ability of our joint character model to deal with unseen data. Also, note that ELMo has been trained by a sentence-based character model using external resources. In the end, this gives us the opportunity to investigate three different character models

[8]Universal Part-Of-Speech tags presented in Section 2.1.1
[9]http://universaldependencies.org/conll18/results-upos.html
[10]http://hdl.handle.net/11234/1-1989
[11]http://hdl.handle.net/11234/1-2885

Table 5.1: Hyperparameter Details

Component	**value**
ch_i (char) Dim.	100
$h_i^{(pos)}$ (weighed POS) Dim.	200
W, Q, D (parameters) Dim.	300
$e_i^{(el)}$ (ELMo) Dim.	1024
$h^{(wc)}$ (word-based) output Dim.	300
$h^{(sc)}$ (sentence-based) output Dim.	300
No. BiLSTM layers	2
MLP output Dim.	300
Dropout	0.3
Learning rate	0.002
β_1, β_2	0.9, 0.99
Epoch	300
Batch size	32
Gradient clipping	5.0

effectively.

Experimental Setup

We applied the same hyperparameter settings as Smith et al. (2018a) for BiLSTM dimensions, the MLP, the optimizer including β, and the learning rate to compare our results with them on the similar environments. Table 5.1 presents our hyperparameter settings. We set 300 dimensions for the parameters W and D in (5.1) and Q in (5.4). The same dimensionality is applied to the sentence-based character model and the word-based model. In training, we run over the entire training data as an epoch with a batch size of 32 randomly chosen sentences. We save the model with the best performance on the dev set within 300 epochs.

Results

Table 5.2 shows the results on the test sets of each treebank, compared with the best performance WINN as reported in the official ST results. The JOIN column represents our model jointly trained by the two different character-level representations described in Section 5.3.2, and the JOINE column is the JOIN model enhanced with ELMo

Table 5.2: universal part-of-speech (UPOS) tagging results compared with the best performing team (WINN) of each treebank for the ST. Columns denotes the size of training corpus **Size**, and our joint (JOIN), joint with ELMo (JOINE), concatenated (CONC) and ELMo only (ELMO) models. The symbols * represents the result applied the ELMo embedding and + represents the result applied an ensemble.

Test set	**Train set**	**Size**	WINN	JOINE	ELMO	JOIN	CONC
zh_gsd (Chinese)	zh_gsd	3997	91.94*	**93.29**	92.47	91.97	91.81
ja_gsd (Japanese)	ja_gsd	7164	92.97*	**93.12**	93.01	92.99	92.83
en_ewt (English)	en_ewt	12543	95.94*+	**95.99**	95.81	95.65	95.39
en_lines	en_lines	1022	97.06*+	**97.45**	96.76	96.57	96.39
en_gum	en_gum	981	96.44*+	**96.45**	96.25	96.08	95.95
fr_gsd (French)	fr_gsd	14554	96.97	**97.18**	97.04	97.04	96.85
ko_gsd (Korean)	ko_gsd	27410	96.33*	**96.58**	96.15	96.21	96.17
en_pud (English)	en_ewt	0(12543)	**96.21***+	96.08	96.17	95.90	95.78
ja_mod (Japanese)	ja_gsd	0(7125)	54.60	**54.70**	54.61	54.67	54.55
cs_pud (Czech)	cs_pdt	0(68495)	97.17	-	-	**97.21**	96.81
sv_pud (Swedish)	sv_l+t	0(7479)	94.28+	-	-	**94.29**	94.09
fi_pud (Finnish)	fi_tdt	0(12217)	97.65+	-	-	**97.67**	97.50

embeddings, as described in Section 5.3.1.

Overall, our JOINE model achieves state-of-the-art results compared with the official results published for the ST, except in the case of en_pud, where the best performing model applied both ELMo and an ensemble of different models (Lim et al., 2018a). Even without the application of ELMo, our JOIN model shows comparable results with models which did use ELMo embeddings (marked *) (Che et al., 2018) and an ensemble (marked +) (Lim et al., 2018a).

As one can see in Table 5.2, the last five test treebanks have no training data, but there exist large treebanks in different domains for these languages. For example, the en_pud (genre: news) test treebank does not have specific training treebanks but has alternative training treebanks from a different domain such as en_ewt (genre: blog, reviews). We can thus investigate to which extent our joint character model is helpful for handling unseen data. We tested those five PUD treebanks with models trained on other training corpora (en_ewt, ja_gsd, cs_pdt, sv_l+t (sv_talbanken+sv_lines), and fi_tdt), in line with other approaches to the ST (Lim et al., 2018a; Smith et al., 2018a). We can see that our results are comparable for handling cross-domain data when compared to other systems on the PUD treebanks.

Impact of the joint learning mechanism. To investigate whether our joint model brings some benefit compared to a simple concatenation approach, we test a disjoint model CONC where a word embedding is defined simply as a concatenation of embeddings for different levels of representation:

$$h_i^{(pos)} = [c_i^{(sc)}; c_i^{(wc)}; w_i^{(e)}]$$

This model then trains a single tagger without our joint learning method (please refer to Figure 5-3-(A)). As our empirical result demonstrate in Table 5.2, the JOIN model always yields better performance than the CONC model.

It should be noted that the shared word embedding $w^{(e)}$ produced by our joint learning procedure leads to consistent improvements not only for the joint model but also for the two character-based models. When we use the shared word embedding only for the sentence-based or word-based character models, the performance decreases by an average of 0.05-0.20 absolute points over the three taggers. We observe almost identical results with the multi-task learning approach for training a tagger and a parser simultaneously with or without shared embeddings (Hashimoto et al., 2016).

Impact of ELMo. Although the best performing system (Smith et al., 2018a) for universal part-of-speech (UPOS) tagging in ST outperformed the macro-average score over all the treebanks, with a 0.72 gap over the second-ranked team, some teams who have used ELMo got the best score on many languages. It is thus necessary to extend the evaluation by using the same ELMo embedding, as applied in ST[12]. To investigate the performance of previously proposed taggers with ELMo, we evaluated the ELMO model, which is a simple concatenation model with a single classifier presented in Figure 5-3-(A). This model produces a single tagger based on concatenation of ELMo,

[12]https://github.com/jujbob/multilingual-models

word-based character, and word embedding as:

$$h_i^{(pos)} = [c_i^{(wc)}; e_i^{(el)}; w_i^{(e)}] \tag{5.7}$$

In Table 5.2, the ELMO model generally yields better performance than our JOIN model but not for JOINE. We found a relatively significant gap between ELMO and JOINE in tagging Chinese and Korean but not the same in English and French. As reported by (Smith et al., 2018b), we assume that languages that have a bigger character set benefit more from the character embeddings, especially when it is trained with external data.

There is some indication that in the less-resourced conditions, ELMo is more influential than the dynamically trained character embeddings. This is because ELMo is trained on various resources, external to the task; in contrast, our character models are trained only on limited training data, and thus struggle to learn deep contexts (see the size and performance gaps between JOIN and JOINE on zh_gsd).

Impact of the self-attention approach. Table 5.3 demonstrates the effectiveness of the multi-head attention component for the word and sentence-based character models (as described in Eq.(5.1)). Here, N represents the number of attention heads presented in Figure 5-2 (the number of rows allocated to the matrix A_i), with additional columns providing traction for the model to focus on different semantic components of the word under study.

We see at least marginal improvements when expanding from a single-head N=1 to double-head N=2 for all models, and then to triple-head N=3 for the WORD and JOIN models. Here, the applied model N=1 is the popular single head model proposed by (Dozat et al., 2017b). We observe a negative impact when expanding beyond 5 rows for all models. This is because, as Lin (Lin et al., 2017) shows, each additional attention-score $a_i^{(wc)}$ tends to focus on the same part of a sequence, even though it requires an N-times higher dimensional space.

Table 5.3: eu_bdt (Basque) tagging results by the number of attention heads N of the word and sentence-based character embedding. Here, WORD and SENT denote models which trained taggers only word and sentence-based character representations (as described in (5.1))

# of head	N=1	N=2	N=3	N=5
WORD	96.04	96.17	**96.19**	96.12
SENT	96.24	**96.26**	96.21	96.17
JOIN	96.39	96.40	**96.43**	96.35

5.4 A Deep Contextualized Multi-task Parser

In the previous section, we have presented an approach based on contextualized word representations for POS tagging. We have seen that two lexical representations (character-based and ELMo representations) play a crucial role for the task. We can thus assume that, beyond tagging, these representations will also be helpful for parsing. A common approach consists then in chaining these two components: first a tagger is applied to assign a POS tag to each word, then the parser use s this information to parse the sentence (i.e. provide s syntactic analysis of the sentence). We can however ask ourselves whether there is a better way to deal with the two tasks at the same time, or not. In this section, we present a multi-task learning scenario that handles tagging and parsing simultaneously.

Multi-task learning is a machine learning approach in which several learning tasks are solved at the same time. Recent breakthroughs in multi-task learning have made it possible to effectively perform different tasks with a shared lexical representation model (Hashimoto et al., 2016). In NLP, this approach has been widely used to learn joint models performing tagging and parsing simultaneously, and most state-of-the-art (SOTA) parsing models now use a multi-task strategy (Che et al., 2018; Smith et al., 2018a; Lim et al., 2018a).

In general, given an input sentence s and a set of gold labels $y = (l_1, l_2...l_n)$, where each l_i consists of gold labels for tagging ($pos^{(gold)}$) and parsing ($head^{(gold)}, dep^{(gold)}$), the goal of the multi-task structure is to train a joint model that can provide at the same time a POS tagger and a dependency parser.

The multi-task architecture of our parser is based on the multilingual BASELINE

parser presented in the previous chapter, with the addition of the two feature representations presented in section 5.1 (character-level models) and 5.2 (ELMo). Let's remind the reader that the basic token representations for our multi-task parser is as follows. Given a sentence of tokens $s = (t_1, t_2, ..t_n)$, the i^{th} token t_i can be represented by a vector x_i, which is the result of the concatenation ($\circ$) of a word vector w_i and a word-based character-level vector c_i of t_i:

$$x_i = c_i \circ w_i$$
$$c_i = CHAR(t_i; \theta_c)(seeEq(5.1))$$
$$w_i = WORD(t_i; \theta_w)$$

when the approach is monolingual, w_i corresponds to the external word embeddings provided by Facebook (Bojanowski et al., 2016b). We have also seen in the previous chapter (see Section 4.2.1) an alternative approach based on multilingual embeddings that have proven useful for example when only little data was available for training. To enhance the system and be able to capture sub-word information, we propose now to concatenate a character-level word embedding c_i with word embedding w_i. For our parsing task, we applied word-based character representations presented in Section 5.1 for character-level word vector c_i. On top of the character and word embedding, we want to enhance our word representation with three different information here:

- ***ELMo representation***: we concatenate ELMo embedding directly to word embedding x_i from the encoding layer as:

  $e_i = ELMo_i$ (see Eq(5.3))

  $x_i = c_i \circ w_i \circ e_i$

  we want to enhance our parser with deeply contextualized word embeddings to handle unknown words. The ELMo embedding trained with raw texts is a word representation that is known to handle accurately unknown words, as presented in Section 5.3.

- ***Treebank Representation***: Following the strategy used for our BASELINE

parser, we use a treebank representation strategy to encode language-specific features. In other words, each language has its own set of specific lexical features. For languages with several training corpora (e.g., French-GSD and French-Spoken) available in the Universal Dependency repository, our parser computes an additional feature vector taking into account corpus specificities at the word level. Following the recent work of Stymne et al. (2018), who proposed a similar approach for treebank representation and showed a 12 dimensional vector is sufficient for treebank representation, we chose to use the same size of treebank representation. This representation tr_i is concatenated with the token representation x_i:

$tr_i = Treebank(t_i; \theta_{tr})$

$x_i = c_i \circ w_i \circ e_i \circ tr_i$

We used this approach (treebank representation) for 24 corpora, and its effectiveness will be discussed in the evaluation section.

- ***Multilingual Representation***: As presented in Section 4.2, our BASELINE parser can take multilingual word embedding to train multilingual dependency models. Thanks to the multilingual word embedding, we have shown in the previous chapter that we can train a multilingual parsing model even for low-resource languages with no or very little data available for training. For this kind of situation, our approach makes it possible to infer knowledge from other related languages. We concatenate multilingual word embeddings with word representation w_i as follows:

  $mw_i = Multilingual(t_i; \theta_{mw})$ (please refer to $e1_i$ in Section 4.2.2)

  $x_i = c_i \circ w_i \circ e_i \circ tr_i \circ mw_i$

  We used this multilingual embedding approach mostly to train the nine low-resource languages of the Universal Dependency 2.2 data sets (Nivre et al., 2018), for which only a handful of annotated sentences were provided in the CoNLL 2018 shared task.

Finally, we generate an encoded token representation x_i. This representation contains different features depending on the resource availability for each language, as presented in Table 5.6.

5.4.1 Multi-Task Learning for Tagging and Parsing

In this section, we describe our Part-Of-Speech (POS) tagger and dependency parser using the encoded token representation x_i implementing a Multi-Task Learning (MTL) strategy (Zhang and Yang, 2017). To build our multi-task-based tagger and parser, we first need to predict a POS tag since it is among the most important features for our parser.

Part-Of-Speech Tagger

We apply the ELMO model POS tagger that has a single classifier presented in Eq(5.7) of Section 5.3.3. This tagger is based on a combination of features (a word-based character embedding, a word embedding, and an elmo embedding). However, the attention mechanism for this word-based character embedding c_i and word w_i embedding are focusing only on a limited number of features within the token, it is thus needed to contextualize by a BiLSTM, as a way to capture the overall context of the sentence. Finally, a token is encoded as a vector g_i:

$$g_i = BiLSTM^{(pos)}(g_0, (x_1, .., x_n))_i$$

We transform the token vector g_i into a vector of the desired dimensionality by a MLP with a bias term to classify the best candidate of universal part-of-speech (UPOS):

$$\hat{p}_i = W^{(p)} MLP(g_i) + b^{(p)}$$
$$\hat{y}_i^{(pos)} = \arg\max_j \hat{p}_{ij}$$

Finally, we randomly initialize the UPOS embedding as p_i and map the predicted

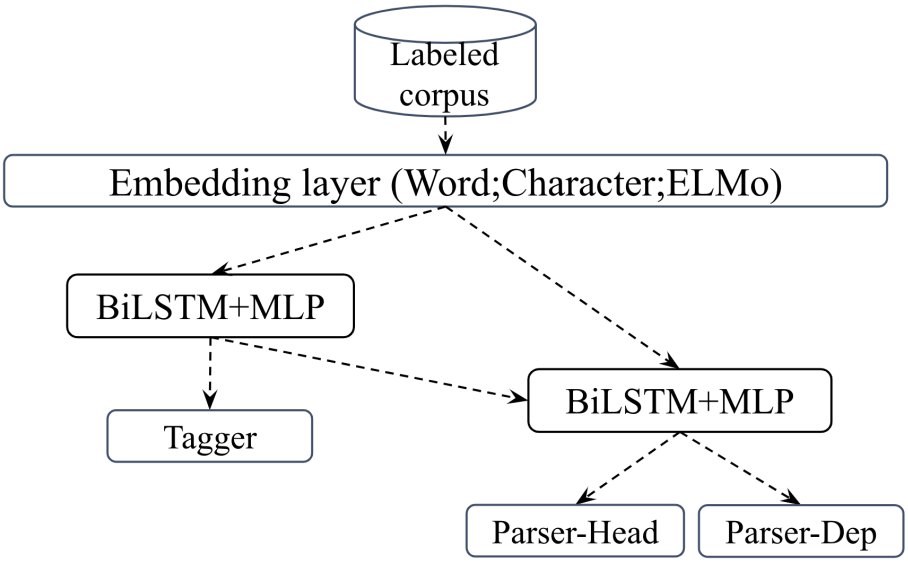


Figure 5-6: Overall structure of our multi-task dependency parser.

UPOS $\hat{y}_i^{(pos)}$ as a POS vector:

$$p_i = POS(\hat{y}_i^{(pos)}; \theta_{pos}) \tag{5.8}$$

the overall structure of the tagger is presented in Figure 5-6.

Dependency Parser

We want to build our parser that considers predicted POS tagging results in a multi-task manner. To take into account the predicted POS vector for parsing, we concatenate the predicted POS vector p_i with the token representation x_i and then we encode the resulting vector via a BiLSTM. This enriches the syntactic representations of the token by using POS information during training:

$$x_i = x_i \circ p_i$$

$$v_i = BiLSTM^{(parse)}(v_0, (x_1, .., x_n))_i$$

$$\hat{head}_i = Biaffine(MLP^{(arc-head)}(v_i), MLP^{(arc-dep)}(v_i))$$

v_i is the final contextualized embedding that is only used for the dependency parsing task. In order to predict a parsed tree following a graph-based parsing approach, we need to know the probability of word i being the head of word j given the contextualized embedding $v_{i:n} = V$. Since word i can be both the head of word j and a modifier of j, we transform the representation v_i into two different representations using MLP as $MLP^{(arc-head)}(v_i)$ (a vector to represent the head) and $MLP^{(arc-dep)}(v_i)$ (a vector to represent the modifier). Following Dozat and Manning (2016), we use a $Biaffine$[13] classifier (Appendix B) to score all the possible **h**ead and **m**odifier pairs $Y = (h,m)$. We then select the best dependency graph based on Eisner's algorithm (Eisner and Satta, 1999). This algorithm tries to find the Maximum Spanning Tree (MST) among all the possible graphs (a more detailed example described in Section 2.2.2):

$$\arg \max_{valid\ Y} \sum_{(h,m) \in Y} Score^{MST}(h, m)$$

With this algorithm, it has been observed that parsing results (for some sentences) can have multiple roots, which is not a desirable feature. We thus follow an empirical method in order to select a unique root based on the word order of the sentence, as already proposed in Section 3.1 to ensure tree well-formedness. After the selection of the best-scored tree, another bi-affine classifier is applied for the classification of relation labels, based on the predicted tree:

$$\hat{dep}_i = Biaffine(MLP^{(rel-head)}(v_i), MLP^{(rel-dep)}(v_i))$$

The overall structure of the parser is presented in Figure 5-6. To train our parser with a supervised learning approach, we need to have an objective (loss) function to feedback (backpropagate) errors by comparing the correct label and the predicted label. We train our tagger and parser simultaneously using a single objective function

[13]Here we use a usual linear transformation such as $Wx + b$, where W is a weight matrix, x is an input vector and b is a bias. $Wx + b$ is an affine transformation, and it can be applied twice, as $W(Wx + b) + b$. This corresponds to a biaffine.

with penalized terms:

$$\begin{aligned} loss = \alpha CrossEntropy(\hat{p}, p^{(\text{gold})}) \\ + \beta CrossEntropy(\hat{head}, head^{(\text{gold})}) \\ + \gamma CrossEntropy(\hat{dep}, dep^{(\text{gold})}) \end{aligned}$$

where $\hat{head}$ and $\hat{dep}$ refer to the predicted head (*Head*) and dependency label (*Dep*) results. $CrossEntorpy$[14] measures the performance of a classification model by comparing two probability distributions such as $\hat{head}$ and $head^{(gold)}$ whose output is a probability value between 0 and 1.

Since UAS (a score that considers only the head search procedure) directly affects LAS, we assume that focusing on UAS would be more relevant than focusing on LAS for parsing unseen data, as well as other corpora from low-resource languages. Therefore, we gave more weight to the parameters predicting $\hat{head}$ than $\hat{dep}$ and $\hat{p}$, because $\hat{head}$ directly affects UAS. We set $\alpha = 0.1$, $\beta = 0.7$ and $\gamma = 0.2$.

5.4.2 Experiments on The CoNLL 2018 Shared Task.

The goal of the CoNLL 2018 shared task (ST) was to evaluate dependency parsers following a real-world setting. For example, input for the task was just raw text without annotation. The task was also intended to evaluate parsing many typologically different languages, including low resource ones. We participated in this *CoNLL 2018 UD Shared Task* on "Multilingual Parsing, from Raw Text to Universal Dependencies" (Zeman et al., 2018b). As presented in Section 3.2, the task offered a very relevant testbed for comparing our results with systems developed by other competing teams. In 2018, 7 languages were added to the task compared to 2017. The task concerned 82 UD treebanks, covering over 57 languages.

[14]https://en.wikipedia.org/wiki/Cross_entropy

Implementation Details

Following the CoNLL 2017 shared task, we chose to train both monolingual and multilingual models, not only for parsing but also for tagging. In the monolingual case, we simply used the available Universal Dependency 2.2 corpora for training (Zeman et al., 2018a). In the second case, for the multilingual approach, as both multilingual word embeddings and corresponding training corpora (in the Universal Dependency 2.2 format) were needed for our approach as presented in the previous chapter, we concatenated the corresponding available Universal Dependency 2.2 corpora in order to artificially create multilingual training corpora.

The number of epochs was set to 200, with one epoch processing the entire training corpus in each language and with a batch size of 32. We then picked the best two performing models to parse the test corpora on the TIRA (Potthast et al., 2014) evaluation platform (see Section 3.2.1). The two models were used as an ensemble run (this will be described in the Testing subsection).

Hyperparameters. Each deep learning parser has a number of hyperparameters that can boost the overall performance of the system. In our implementation, most hyperparameter settings are identical to those of our BASELINE parser, except, of course, those concerning the additional features we have just introduced. We use 100 dimensional character-level word representations with a 300 dimensional MLP, as presented in Section 5.4.1, and for treebank representation, we use a 12 dimensional vector. We set the learning-rate to 0.002 with Adam optimization.

Multilingual Embeddings. With the same approach as the one presented in the previous chapter, we trained multilingual embedding models for nine low-resource languages. Table 5.7 gives the list of languages for which we adopted this approach, along with the language used for knowledge transfer. We selected language pairs based on previous studies (Lim and Poibeau, 2017b; Lim et al., 2018b; Partanen et al., 2018a) for *Buryat (bxr), Kazakh (kk), Kurmanji (kmr), North Sami (sme),* and *Upper Sorbian (hsb)*, and the others where chosen based on the public availability of bilingual dictionaries (this explains why we chose to map several languages with

English, even when there was no real linguistically motivated reason to do so). Since we could not find any pre-trained embeddings for *Naija (pcm_nsc)*, for this case, we applied a delexicalized parsing approach (see Section 4.2) based on an English monolingual model.

ELMo. We applied ELMo embeddings to train specific models for five languages: Korean, French, English, Japanese, and Chinese. ELMo embeddings were pre-trained using the CoNLL resources provided[15]. We used AllenNLP[16] which is a publicly available piece of software allowing to train ELMo models. We included ELMo only at the level of the input layer to make use of an additional feature representation for both training and inference as shown in Figure 5-6. We set up dropout to 0.5 and used 1024 dimensions for the ELMo embedding layer in our model to prevent overfitting based on our empirical experiments[17] on our training data.

Testing with an Ensemble

All the tests were done on the TIRA platform provided by the shared task organizers. Since the input of the shared task is raw text (plain text), it is thus necessary to first implement or have access to pre-processing tools such as a sentence boundary detector and tokenizer. UDPipe baseline models Straka et al. (2016) were provided (esp. for pre-processing) for teams who did not wish to develop their own pre-processing modules. We chose this option and all our preprocessing modules (a sentence boundary detector and tokenizer) were taken from UDPipe except for the UPOS tagger and dependency parser.

During the test phase, an ensemble mechanism needs what is called "seeds". The seeds are integers randomly produced by the Python *random* library and used to initialize the parameters used during training as θ:

$\hat{y} = softmax(\sum_{seed_i \in V} P(\hat{y}^{seed_i}|x, \theta^{seed_i}))$.

We chose to train our models with two different "seeds". Generally, an ensemble

[15]http://hdl.handle.net/11234/1-1989

[16]https://github.com/allenai/allennlp

[17]Overfitting is a modeling error which occurs when a model is too closely fit to a training set of data than a testing set

Corpus	UAS	LAS	Rank(UAS)	Rank(LAS)	BASE(LAS)
Overall (82)	**78.71**	**73.02**	**2**	**4**	65.80
Big treebanks only (61)	85.36	80.97	4	7	74.14
PUD treebanks only (5)	76.81	72.34	3	3	66.63
Small treebanks only (7)	75.67	68.12	2	3	55.01
Low-resource only (9)	37.03	23.39	4	5	17.17

Table 5.4: Overall experiment results based on each group of corpora.

mechanism combines the best performing models obtained from different seeds, so as to ensure robustness and efficiency.

In our case, due to a lack of GPU, we selected two best performing model on the development set based on the use of two different seeds, respectively. Finally, the two best performing models produced by each seed were put together to form the ensemble model. This improved the performances by up to 0.6 points, but further improvements could be expected by testing with a larger set of seeds. There could be a further performance increase by using only the best performing models trained using different seeds (This will be discussed in the next chapter).

Hardware Resources

The training process for all the dependency parsing models with i) the ensemble and ii) ELMo was done using respectively 32 CPUs and 7 GPUs (Geforce 1080Ti), in approximately two weeks. The memory usage of each model depends on the size of the external word embeddings (3GB RAM by default plus the amount needed for loading the external embeddings). In the testing phase on the TIRA platform, we submitted our models separately, since testing with a model trained with ELMo takes around three hours. Testing took 46.2 hours for the 82 corpora using 16 CPUs and 16GB RAM.

5.4.3 Results and Analysis

In this section, we discuss the results of our system and the relative contributions of the different features to the global results.

Corpus	Method	UAS(Rank)	LAS(Rank)
af_afribooms		87.42 (7)	83.72 (8)
grc_perseus	*tr*	79.15 (4)	71.63 (8)
grc_proiel	*tr*	79.53 (5)	74.46 (8)
ar_padt		75.96 (8)	71.13 (10)
hy_armtdp	*tr, mu*	**53.56 (1)**	**37.01 (1)**
eu_bdt		85.72 (7)	81.13 (8)
br_keb	*tr, mu*	43.78 (3)	23.65 (5)
bg_btb		92.1 (9)	88.02 (11)
bxr_bdt	*tr, mu*	36.89 (3)	17.16 (4)
ca_ancora		92.83 (6)	89.56 (9)
hr_set		90.18 (8)	84.67 (9)
cs_cac	*tr*	93.43 (2)	91 (2)
cs_fictree	*tr*	**94.78 (1)**	91.62 (3)
cs_pdt	*tr*	92.73 (2)	90.13 (7)
cs_pud	*tr*	89.49 (7)	83.88 (9)
da_ddt		85.36 (8)	80.49 (11)
nl_alpino	*tr*	90.59 (2)	86.13 (5)
nl_lassysmall	*tr*	87.83 (2)	84.02 (4)
en_ewt	*tr, el*	**86.9 (1)**	84.02 (2)
en_gum	*tr, el*	**88.57 (1)**	**85.05 (1)**
en_lines	*tr, el*	**86.01 (1)**	81.44 (2)
en_pud	*tr, el*	**90.83 (1)**	**87.89 (1)**
et_edt		86.25 (7)	82.33 (7)
fo_oft	*tr, mu*	48.64 (9)	25.17 (17)
fi_ftb	*tr*	89.74 (4)	86.54 (6)
fi_pud	*tr*	90.91 (4)	88.12 (6)
fi_tdt	*tr*	88.39 (6)	85.42 (7)
fr_gsd	*tr, el*	**89.5 (1)**	86.17 (3)
fr_sequoia	*tr, el*	**91.81 (1)**	**89.89 (1)**
fr_spoken	*tr, el*	79.47 (2)	73.62 (3)
gl_ctg	*tr*	84.05 (7)	80.63 (10)
gl_treegal	*tr*	78.71 (2)	73.13 (3)
de_gsd		82.09 (8)	76.86 (11)
got_proiel		73 (6)	65.3 (8)
el_gdt		89.29 (8)	86.02 (11)
he_htb		66.54 (9)	62.29 (9)
hi_hdtb		94.44 (8)	90.4 (12)
hu_szeged		80.49 (8)	74.21 (10)
zh_gsd	*tr, el*	71.48 (5)	68.09 (5)
id_gsd		85.03 (3)	77.61 (10)
ga_idt		79.13 (2)	69.1 (4)

Table 5.5: Official experiment results for each corpus, where *tr (Treebank)*, *mu (Multilingual)* and *el (ELMo)* in the column Method denote the feature representation methods used (see Section 5.4.1).

Corpus	Method	UAS(Rank)	LAS(Rank)
it_isdt	*tr*	92.41 (6)	89.96 (8)
it_postwita	*tr*	77.52 (6)	72.66 (7)
ja_gsd	*tr, el*	76.4 (6)	74.82 (6)
ja_modern		29.36 (8)	22.71 (8)
kk_ktb	*tr, mu*	39.24 (15)	23.97 (9)
ko_gsd	*tr, el*	88.03 (2)	84.31 (2)
ko_kaist	*tr, el*	**88.92 (1)**	86.32 (4)
kmr_mg	*tr, mu*	38.64 (3)	27.94 (4)
la_ittb	*tr*	87.88 (8)	84.72 (8)
la_perseus	*tr*	75.6 (3)	64.96 (3)
la_proiel	*tr*	73.97 (6)	67.73 (8)
lv_lvtb	*tr*	82.99 (8)	76.91 (11)
pcm_nsc	*tr, mu*	18.15 (21)	11.63 (18)
sme_giella	*tr, mu*	**76.66 (1)**	**69.87 (1)**
no_bokmaal		91.4 (5)	88.43 (11)
no_nynorsk	*tr*	90.78 (8)	87.8 (11)
no_nynorsklia	*tr*	76.17 (2)	68.71 (2)
cu_proiel		77.49 (6)	70.48 (8)
fro_srcmf		91.35 (5)	85.51 (7)
fa_seraji		89.1 (7)	84.8 (10)
pl_lfg	*tr*	95.69 (8)	92.86 (11)
pl_sz	*tr*	92.24 (9)	88.95 (10)
pt_bosque		89.77 (5)	86.84 (7)
ro_rrt		89.8 (8)	84.33 (10)
ru_syntagrus	*tr*	93.1 (4)	91.14 (6)
ru_taiga	*tr*	**79.77 (1)**	74 (2)
sr_set		90.48 (10)	85.74 (11)
sk_snk		86.81 (11)	82.4 (11)
sl_ssj	*tr*	87.18 (10)	84.68 (10)
sl_sst	*tr*	63.64 (3)	57.07 (3)
es_ancora		91.81 (6)	89.25 (7)
sv_lines	*tr*	85.65 (4)	80.88 (6)
sv_pud	*tr*	83.44 (3)	79.1 (4)
sv_talbanken	*tr*	89.02 (4)	85.24 (7)
th_pud	*tr, mu*	0.33 (21)	0.12 (21)
tr_imst		69.06 (7)	60.9 (11)
uk_iu		85.36 (10)	81.33 (9)
hsb_ufal	*tr, mu*	54.01 (2)	43.83 (2)
ur_udtb		87.4 (7)	80.74 (10)
ug_udt		75.11 (6)	62.25 (9)
vi_vtb		49.65 (6)	43.31 (8)

Table 5.6: Official experiment results for each corpus, where *tr (Treebank)*, *mu (Multilingual)* and *el (ELMo)* in the column Method denote the feature representation methods used (see Section 5.4.1).

Overall results.

The official evaluation results are given in Table 5.4. Our system achieved 73.02 LAS (4^{th} out of 26 teams) and 78.71 UAS (2^{nd} out of 26). The comparison of our results with those obtained by other teams shows that there is room for improvement regarding preprocessing. For example, our system is 0.86 points below HIT-SCIR (Harbin) for sentence segmentation and 1.03 for tokenization (HIT-SCIR obtained the best overall results). Those two preprocessing tasks (sentence segmentation and tokenization) affect tagging and parsing performance directly. As a result, our parser ranked second on small treebanks (LAS), where most teams used the default segmenter and tokenizer, avoiding the differences in this aspect. In contrast, we achieved 7^{th} on the big treebanks, probably because there is a more significant gap (1.72) when compared to the best performing team at the tokenization level. Also, during the testing phase, we chose not to adjust the weight parameters (α, β, γ) of the objective function presented in the previous section. We set $\alpha = 0.1$, $\beta = 0.7$ and $\gamma = 0.2$ because we assumed that focusing on UAS (β) would be helpful for low-resource languages. This choice made our results on big treebanks suffer a bit (7^{th}) compared to those we obtained on Small and PUD treebanks (3^{th}) regarding LAS. This also explains the gap between the UAS and LAS scores in our overall results. When we set $\alpha = 0.1$, $\beta = 0.2$ and $\gamma = 0.7$ to focus more on LAS score, we get better LAS performance and we are then ranked 5^{th} on the big treebanks.

Effect of Treebank Representation on Performance.

Results with treebank representation (corpora marked *tr* in column Method in Table 5.6) exhibit relatively better performance than those without it, since *tr* makes it possible to capture corpus-oriented features. Results were positive not only for small treebanks (e.g., *cs_fictree* and *ru_taiga*) but also for big treebanks (e.g., *cs_cac* and *ru_syntagrus*). Treebank representation with ELMo is the best for parsing English and French.

Language	Corpus	Projected languages	UAS	LAS
(Armenian)	*hy_armntdp*	Greek	1	1
(Breton)	*br_keb*	English	3	5
(Buryat)	*bxr_bdt*	Russian	3	4
(Faroese)	*fo_oft*	English	9	17
(Kazakh)	*kk_ktb*	Turkish	15	9
(Kurmanji)	*kmr_mg*	English	3	4
(Naija)	*pcm_nsc*	-	21	18
(North Sami)	*sme_giella*	Finnish+Russian	1	1
(Thai)	*th_giella*	English	21	21
(Upper Sorbian)	*hsb_ufal*	Polish	2	2

Table 5.7: Languages trained with multilingual word embeddings and their ranking.

Effect of Multilingual Approach on Performance.

As described in Section 5.4.1, we applied our multilingual approach to most of the low-resource languages. Table 5.7 shows results of our multilingual models. The best result is obtained for *hy_armtdp*, while *sme_giella* and *hsb_ufal* also gave satisfactory results. We only applied the delexicalized approach to *pcm_nsc* since we could not find any pre-trained embeddings for this language. We got a relatively poor result for *pcm_nsc*, despite testing different strategies and different feature combinations (we assume that the English model is not fit for it).

Additionally, we found that character-level representation is not always helpful, even in the case of some low-resource languages. When we tested *kk_ktb* (Kazakh) trained with a Turkish corpus, with multilingual word embeddings and character-level representations, the performance dramatically decreased. We suspect this has to do with the writing systems (Arabic versus Latin), but this should be further investigated.

North Sami (*sme_giella*) is another exceptional case since we chose to use a multilingual model trained with three different languages. Although Russian and Finnish do not use the same writing system, applying character and treebank representation improved the results. This is probably because the size of the training corpus for *sme_giella* is around 900 sentences, which seems to be enough to capture its main characteristics.

Representation Methods	UAS	LAS
baseline	81.79	78.45
+em	83.39	80.15
+em, tr	83.67	80.64
+em, el	85.47	82.72
+em, tr, el	85.49	82.93

Table 5.8: Relative contribution of the different representation methods on the overall results.

Effect of ELMo Representation on Performance.

We used ELMo embeddings for five languages: Korean, French, English, Japanese and Chinese (marked with *el* in the method column in Table 5.6). The experiments with ELMo models showed excellent overall performance. All the English corpora, *fr_gsd* and *fr_sequoia* in French, and Korean *ko_kaist* obtained the best UAS scores. We also obtained the best LAS score for English *en_gum* and *en_pud*, and for *fr_sequoia* in French.

Contributions of the Different System Components to the General results.

In this chapter, we have presented several alternative representations. The primary goal of our study is to investigate the effect of each proposed representation. In order to do so, we evaluate four different models with different representations using the English treebanks (en_ewt). We set our baseline model with a token representation as $x_i = w_i \circ c_i \circ p_i$, where w_i is a randomly initialized word vector, c_i is a character-level word vector and p_i is a POS vector predicted by UDpipe1.1 (note that we did not apply our 2018 POS tagger here, since it is trained jointly with the parser and that affects the overall feature representation). We then initialized word vector w_i with external word embeddings provided by the CoNLL shared organizers. We also re-run the experiment by adding treebank and ELMo representations. The results are shown in Table 5.8 (*em* denotes the use of the external word embedding and *tr* and *el* denotes treebank and ELMo representations, respectively.). We observe that each representation improves the overall results. This is especially true regarding the LAS score with ELMo (*el*), which means this representation has a positive effect on

Table 5.9: UAS and LAS on English(en_ewt) corpus for each model, with ELMo (ELMO), character (CHAR), and pre-trained word embeddings (EXT) over only unknown words.

Representation Methods	UAS	LAS
BASELINE	70.7	64.9
+CHAR	72.4	66.7
+EXT	73.2	68.0
+ELMO	75.2	70.6
+CHAR+EXT	73.6	68.8
+ELMO+EXT	75.1	70.5
+ELMO+CHAR	75.6	71.1
+ELMO+CHAR+EXT	75.8	71.1

relation labeling.

Does Our Model Help Handle Unknown Words?

As presented in the introduction of this chapter, we want to enrich our parser with contextualized word representations: we expect that these representations will help handle issues related to Out-Of-Vocabulary (OOV) words. A more detailed OOV analysis of the LAS scores is available in Table 5.9, based on a specific English corpus (en_ewt) taken as an example. This corpus contains 204,585 tokens over 12,543 sentences for training and 25,096 tokens over 2,077 sentences for testing. Among the tokens, 3.54 percent (889) is OOV, including letters, punctuation and sequences such as "alt.animals.cat" and "ekrapels@esaibos.com". We produced a unique parsing model only trained with ELMo (ELMO), character (CHAR), and pre-trained word (EXT) representations to see the impact of each of these representations on the task. In the end, we calculate the accuracy of the system only for OOV words (889) among all tokens (25,096) based on the test treebank.

Among the three representations, ELMo always outperforms the baseline model, and two proposing representations also improve performance: improvement of 5.7 LAS points from ELMo, 1.8 from char, and 3.1 from the pre-trained word representations.

We can make three observations here. First, we observe that the model with the lower performance, namely CHAR in our example, always improves the overall perfor-

Task	Precision	Recall	F1(Rank)
Event Extraction	58.93	43.12	**49.80 (1)**
Negation Resolution	99.08	41.06	58.06 (12)
Opinion Analysis	63.91	56.88	60.19 (9)

Task	LAS	MLAS	BLEX
Intrinsic Evaluation	84.66 (1)	72.93 (3)	77.62 (1)

Table 5.10: Official evaluation results on three EPE task (see `https://goo.gl/3Fmjke`).

mance when it is concatenated with other representations. For instance, CHAR+ELMO and CHAR+EXT always yield better performance than the models trained without CHAR. This is because both ELMo and pre-trained word embeddings are trained on corpus resources external to the task; in contrast, our character models are trained only on the limited training data. Our system thus learns from both treebank-dependent and independent (sub-) word information based on these representations. Second, applying ELMo and pre-train word embedding at the same time does not always bring a positive effect on the overall performance. We observe a slight drop in performance when applying the two features at the same time rather than just using one of them. We assume that they mostly capture the same kind of information, and thus do not have a real positive influence on the results when they are applied together. Finally, the absolute performance gain increases when we use less training data. We trained three models that use 50, 25, and 10 percent of training sentences, respectively, and compared our contextualized parser (ELMO+CHAR) and BASELINE. We found that the performance gaps between the two models increase when using less training data. We conjecture that the exposure to diverse vocabularies based on ELMO and EXT is more influential in low-resource scenarios.

Extrinsic Parser Evaluation (EPE 2018)

When evaluating a parser, one should not take into account only intrinsic metrics (such as the LAS score) but also consider real-world applications. Thus, participants in the CoNLL shared task were invited to participate in downstream tasks, known as

the 2018 Extrinsic Parser Evaluation (EPE) campaign[18] (Fares et al., 2018a), as a way to confirm the applicability of the developed methods to practical tasks. Three downstream tasks were proposed: biomedical event extraction, negation resolution and opinion analysis (each task was run and evaluated independently from the others). Related corpora were all in English. This part of the evaluation did not take into account the ability of the different systems to deal with multiple languages at the same time.

For this evaluation, participants were only required to send back to the organizers a parsed version of the different corpora received as input, using a UD-type format (the organizers then ran the different scripts related to the different tasks and computed the corresponding results). We trained one single English model for the three tasks using the three English corpora provided (*en_lines*, *en_ewt*, *en_gum*) without treebank embeddings (*tr*), since we did not know which corpus embedding would perform better. In addition, we did not apply our ensemble process on TIRA since it would have been too time consuming.

Our results are listed in Table 5.10. They include an overall evaluation (overall performance of the parser on the different corpora considered as a whole) (Nivre and Fang, 2017) and three task-specific evaluations (i.e. results for the three different tasks). In the intrinsic evaluation, we obtained the best LAS score among all the participating systems, which confirms the portability of our approach across different domains. As for the task-specific evaluations, we obtained the best result for event extraction, but our parser did not perform so well on negation resolution and opinion analysis. This means that specific developments would be required to properly address the two tasks under consideration. Probably one way to get better results for these tasks would be to take more semantic information into consideration.

[18] `http://epe.nlpl.eu/`

5.5 Summary

In this chapter, we have presented two different systems based on a contextualized approach: a tagger and a parser.

On the one hand, we have developed a tagger, integrating two different character-level components: the first one limited to word boundaries, the second able to take into account sentence-level information. By training two individual character models, we have produced a tagger taking into account not only locally optimized character information but also globally optimized information, regardless of the language types. We have detailed our three main innovations: (*1*) A Multi-attention character model, which makes the system able to capture several aspects of sub-word information. (*2*) Joint POS representations to combine the two models' states as a feature for final tagger and (*3*) Contextual representation to capture contextual information from external resources. This method is effective, leading to better results compared to previously reported ones.

On the other hand, we described a deep contextualized parser that has been tested over the 82 UD corpora provided for the CoNLLL 2018 shared task. Our system was an extension of our baseline system, presented in the previous chapter, with three additional contextual representations (multilingual word representation, character-level representations, ELMo representation). It also included a multi-task learning process able to simultaneously handle tagging and parsing. In this chapter, we have described our three main innovations: (*1*) Multilingual word representations, which makes the system to work both with a monolingual model and with a multilingual one. (*2*) character-level representation to model subword-oriented lexical representations and (*3*) Contextual representation to capture context information from external resources.

Our parser achieved 73.02 LAS score (4^{th} over 26 teams), and 78.72 UAS score (2^{nd} out of 26), over the 82 test corpora of the evaluation. This shows that the approach is accurate and effective in handling language diversity and different parsing situations (with variable training conditions in particular).

Chapter 6

A Co-Training Parser on Meta Structure

In the course of this thesis, we have proposed a multilingual transfer learning approach, along with contextualized representations, to get a high accuracy dependency parser, especially in low-resource scenarios. However, while the amount of labeled data is small in low-resource languages, we often have access to larger sets of unlabeled data. The question is then: how to leverage our supervised model using unlabeled data. In this chapter, we expand our contextualized parser with a semi-supervised and a multi-view learning approach.

Multi-view data consist of different manifestations of the same data, often in the form of different features, and such data are abundant in real-world applications (Xu et al., 2013). Color and texture information can be viewed as examples of multi-view data in image processing whereas character-level representations, stem, prefix, and suffix representations are examples of multi-view data in Natural Language Processing (NLP). The use of multi-view data has resulted in considerable success in various NLP problems. Combining different word representations at the character, token, or sub-word levels has proven to be helpful for dependency parsing (Botha et al., 2017; Andor et al., 2016), Part-of-Speech (POS) tagging (Plank et al., 2016), and other NLP tasks.

As shown in the previous chapter, a simple but popular approach is to unify multi-

ple representations into a combined one through concatenation, averaging, or pooling. For instance, our baseline model concatenates character and word embeddings before contextualizing them via a LSTM. This approach is especially popular with neural networks as it is very straightforward to concatenate multiple representations without any modification of the model. All the aforementioned work also considered this approach. However, the major problem of the simple input concatenation approach is that it can lead to overfitting problems in low-resource conditions as the model might ignore the specific statistical property of each view (Zhao et al., 2017).

As discussed in the previous chapter (in Section 5.3), recently, META-BILSTM (Bohnet et al., 2018b) was proposed to extend the naive solution of concatenating input representations in the context of POS tagging, and it showed superior performance compared to simple view concatenation on input representations. META-BILSTM builds a single-view model of each view (lower layer) and concatenates the series of single-view-model outputs (i.e., the output of LSTMs) to form an input to the meta layer, as shown in Figure 6-3. All the components of META-BILSTM (per-view models and meta layer) are trained jointly, as expressed in Eq.(6.2).

In this chapter, we first examine whether META-BILSTM can be beneficial in the context of more complex tasks, namely multi-tasking for joint POS tagging and dependency parsing. The study then proposes Co-meta, a semi-supervised approach, to improve each single-view model through the consensus promotion of the multiple single-view models on unlabeled data. The proposed Co-meta is motivated by co-training (Blum and Mitchell, 1998), a classic approach similar to multi-view learning, which enables the exploration of unlabeled data and is known to be helpful in low-resource settings. Overall, co-training and many of its variants improve the multi-view models by maximizing agreement between the multi-view models on unlabeled data, and thus can improve performance in low-resource settings.

Thus, this study raises the question of whether classical co-training style approaches can further improve the META-BILSTM model in low-resource settings. Specifically, we explore two questions: (1) can respective models from different views learn from each other on unlabeled data? Moreover, (2) can this help the perfor-

mance of low-resource models? We study whether improving each multi-view model by promoting the consensus in a Semi-Supervised Learning (SSL) fashion can lead to learning better meta models in the context of joint tagging and dependency parsing.

Once we apply META-BILSTM, we obtain several parsing models trained by each view. Then the main challenge that arises with regard to our SSL approach (co-training) is to make a decision about which view teaches others. We suggest three different methods for learning from each other, namely, Entropy, Voting, and the Ensemble-based approach. We employ our SSL methods and META-BILSTM on top of the graph-based parser with a bi-affine classifier proposed by (Dozat et al., 2017b) (see Section 5.4), and investigate the effectiveness of our approach. To test the hypothesis, we create both low- and high-resource scenario experiment setups using the Universal Dependency 2.3 dataset (Zeman et al., 2018a). The proposed model shows consistent improvement across the test cases, with an average of $-0.9 \sim +9.3$ Labeled Attachment Score (LAS) gains in low-resource and $0.2 \sim 1.1$ in high-resource settings, respectively. The study also investigates whether the proposed method varies unlabeled data by changing the amount and varying the domains of unlabeled data, and its effect on the proposed model. To sum up, our objectives in this study include:

1. The Proposal of a new formulation Co-meta that leverages consensus promotion on top of a META-BILSTM model.

2. An Analysis of the relation of each multi-view model performance to that of the meta model.

3. The Exploration of different semi-supervised scenarios, where the amount of unlabeled data and the domains of unlabeled data are varying.

4. The Generalization of META-BILSTM and Co-meta by expanding an additional-view model on top of the existing model using external word embedding.

Basic Notions

We define here a few notions that will play a crucial role in the remaining of this chapter.

- **A view:** a feature
- **Multi-view:** several features (e.g. word, character, subwords, POS, etc)
- **Multi-view learning:** a machine learning approach that learns one function to model each view and jointly optimizes all the functions to improve the generalization performance (Zhao et al., 2017).
- **Multi-view model:** a model trained by multi-view learning.
- **meta-BiLSTM:** a middle-layer BiLSTM that has access to two different contexts that are captured by two different views. It is a specific structure of Multi-view learning.
- **Co-training:** a semi-supervised learning approach that trains multiple learners (parsers in our case) based on different views, then these learners teach each other using **unlabeled** data.

6.1 Parsing on Meta Structure

As discussed in Section 2.2.1, typically, the goal of dependency parsing is to derive a tree structure for a sentence following a given dependency grammar (Nivre et al., 2016a). Recent breakthroughs in multi-task learning have made it possible to effectively perform different tasks with the same model. The multi-task approach enriches context-sensitive feature representations by learning different tasks using shared parameters (Hashimoto et al., 2016). In NLP, this approach has been widely used to learn joint models performing tagging and parsing simultaneously, and all state-of-the-art (SOTA) models now use a multi-task structure. In general, given an input sentence $x = (w_1, w_2 ...w_n)$ and a set of gold labels $y = (l_1, l_2...l_n)$, where each l_i

consists of labels for tagging (l^{POS}) and parsing (l^{Head}, l^{Dep}), the goal of the multi-task structure is to train a joint model that can provide at the simultaneously a POS tagger and a dependency parser.

There are many variants of multi-task learning for tagging and parsing. These variants consist in models sharing LSTM parameters between the tasks (Straka, 2018; Che et al., 2018; Lim et al., 2018a). On top of this, recent systems trained with Language Model (LM) representations have shown even better results. One of these models, ELMo (Peters et al., 2018), which is trained with unsupervised textual representations using BiLSTM (see Section 5.2). Models with ELMo obtained the best performance in the 2018 CoNLL shared task (Che et al., 2018; Lim et al., 2018a). Another more-recent and cutting-edge LM, BERT (Devlin et al., 2018), which is trained by bidirectional transformers with a masked language model strategy, shows outstanding results in parsing (Kondratyuk, 2019; Kulmizev et al., 2019). While many variants exist, all these models basically produce a single parser and tagger based on a single concatenated view. In contrast, (Bohnet et al., 2018b) proposed an approach to build several POS taggers trained by individual lexical representations and generated a multi-view model only for POS tagging. This multi-view model proved that each model trained by individual views struggles to learn the best possible parameters because the information it has access to is limited. At the opposite, because of the amount of information captured by the different parameters, the multi-view model outperforms the concatenation model for tagging.

We cannot know the exact nature of the captured information but we can conjecture what is captured by the individual views. Figure 6-1 shows an example of similar words captured by different views (word, char, and char+word sequence), given an input word based on a LM task (ELMo). Given an input "richard", each word (LSTM-Word), char (LSTM-Char), and word+char (LSTM-Char)[1] model predicts "jonathan", "hard", and "eduard" as the most similar word, respectively. We observe that each word, char, and word+char model focus on semantic, syntactic, and both features, respectively. We want to make full use of the three information

[1]This model consists two LSTM that model a token as a character and as a word sequence.

	In Vocabulary				
Input:	*while*	*his*	*you*	*richard*	*trading*
LSTM-Word	*although*	*your*	*conservatives*	*jonathan*	*advertised*
	letting	*her*	*we*	*robert*	*advertising*
	though	*my*	*guys*	*neil*	*turnover*
	minute	*their*	*i*	*nancy*	*turnover*
LSTM-Char (before highway)	*chile*	*this*	*your*	*hard*	*heading*
	whole	*hhs*	*young*	*rich*	*training*
	meanwhile	*is*	*four*	*richer*	*reading*
	white	*has*	*youth*	*richter*	*leading*
LSTM-Char (after highway)	*meanwhile*	*hhs*	*we*	*eduard*	*trade*
	whole	*this*	*your*	*gerard*	*training*
	though	*their*	*doug*	*edward*	*traded*
	nevertheless	*your*	*i*	*carl*	*trader*

Figure 6-1: An example of word similarity captured by different Views (from CS224N Stanford Lecture: `http://web.stanford.edu/class/cs224n/`)

rather than only using a single concatenated information for our multi-task parser.

In this section, we first consider the baseline model introduced in the previous chapter as a deep contextualized parser and extend it so as to get a multi-view model structure following (Bohnet et al., 2018b).

6.1.1 The baseline Model

As it is known that using information from multiple views yield better performance, most SOTA multi-task parsers use both word-level and character-level views to get a lexical embedding $v_{1:n}^{(wc)}$ from a sequence of n words $w_{1:n}$. Most of these approaches simply concatenate a word embedding $v_i^{(w)}$ and the character-level embedding $v_i^{(c)}$ of w_i to form $v_i^{(wc)}$. For example, Figure 6-2 shows the multi-task parsing architecture for low-resource scenarios proposed in the previous chapter. It obtained good results on the CoNLL 2018 shared task (Zeman et al., 2018c). Specifically, the parser transforms the sequence of shared lexical representation $v_i^{(wc)}$ into a context-sensitive

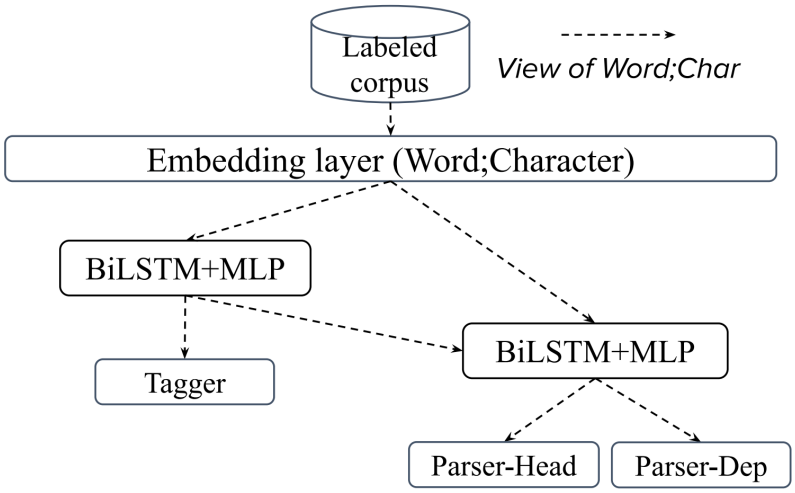


Figure 6-2: Overall structure of our baseline model. This system generates word- and character-level representation vectors, and concatenates them as a unified word embedding for every token in a sentence. To transform this embedding into a context-sensitive one, the system encodes it based on the individual BiLSTM for each tagger and parser.

vector contextualized by a BiLSTM with a hidden layer r_0 as:

$$h_i^{(pos)} = BiLSTM(r_0^{(pos)}, (v_1^{(wc)}, .., v_n^{(wc)}))_i$$
$$h_i^{(dep)} = BiLSTM(r_0^{(dep)}, (v_1^{(wc)}, .., v_n^{(wc)}))_i$$

The system uses vector $h_i^{(pos)}$ to predict POS with a Multi-layer Perceptron (MLP) classifier, and $h_i^{(dep)}$ for $Head$ and Dep with a bi-affine classifier (Dozat and Manning, 2016) (see Section 5.4). During training, it learns the parameters θ of the network that maximize the probability $P(y_j|x_j, \theta)$ from the training set T based on the conditional negative log-likelihood loss B_loss(θ). Thus,

$$\text{B\_loss} = \sum_{(x_j,y_j)\in T} -\log P(y_j|x_j, \theta) \tag{6.1}$$
$$\hat{y} = \arg\max_y P(y|x_j, \theta)$$

where $(x_j, y_j) \in T$ denotes an element from the training set T, y is a set of gold labels (l^{POS}, l^{Head}, l^{Dep}), and $\hat{y}$ is a set of predicted labels. This model[2] is subsequently

[2]As presented in the previous section, the parser achieved the 2nd and 4th ranks with regard to

used as the BASELINE model.

6.1.2 Supervised Learning on Meta Structure (meta-base)

In order to examine whether a multi-view learning approach similar to that of (Bohnet et al., 2018b) would also be helpful to perform tagging and parsing jointly, we propose the meta structure shown in Figure 6-3. We use BASELINE's multi-task structure of tagging and parsing as our default single-view model and call the overall system META-BASE.

We define a model M^{vi} for each view $vi \in V$, where V is the set of all the views. For example, Figure 6-3 contains different views for word, character, and meta levels, and V is expressed as $V = \{\text{word,char,meta}\}$. Each model M^{vi} consists of a BiLSTM^{vi} that contextualizes its view with a representation h_i^{vi} for word w_i, and an MLP classifier to predict POS tag and a bi-affine classifier (Dozat and Manning, 2016) to predict parsing outputs *Head* and *Dep*. As the input of each view, M^{word} and M^{char} consume the word- and character-level embedding, respectively, and M^{meta} consumes the concatenation of two models' contextualized outputs as $[h_i^{word};h_i^{char}]$. Each M^{vi} is parameterized by the network parameter θ^{vi}, and the overall network parameter θ is defined as the union of the network parameters of all views, that is, $\theta = \cup_{vi \in V}\theta^{vi}$.

During the supervised learning phase, we train θ to maximize the probability $P(y_j|x_j,\theta)$ for the input and labeled instance pair (x_j, y_j) in the training set T by optimizing over the supervised loss (S_loss) as follows:

$$\text{S\_loss} = \sum_{(x_j,y_j)\in T} -\log P(y_j|x_j,\theta) \tag{6.2}$$

which is simply the standard cross entropy loss, where $\log P(y_j|x_j,\theta)$ stands for $\sum_{vi\in V}\log P(y_j|x_j,\theta^{vi})$ for brevity. Note that the predicted POS results are added to the parser's classifier as an embedding (learnable parameters) during training.

UAS and LAS, respectively, out of 26 teams in the CoNLL 2018 shared task.

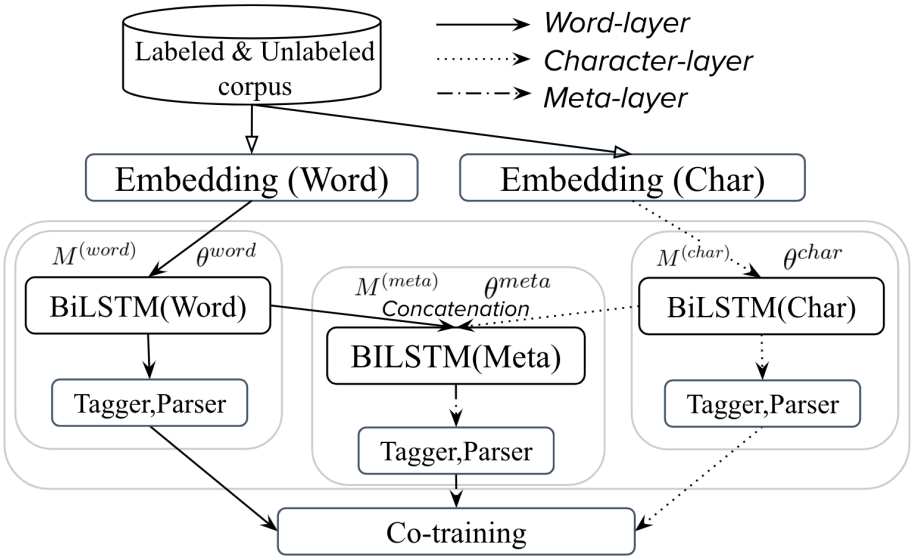


Figure 6-3: Overall structure of our `Co-meta` model. The system consists of three different pairs of taggers and parsers that are trained using limited context information. Based on the input representation of the word, character, and meta, each model draws a differently shaped parse tree. Finally, our co-training module induces models to learn from each other using each model's predicted result.

6.2 Parsing on Co-Training

The standard multi-view learning approaches try to learn a model by jointly optimizing all the multi-view models arising from different views as opposed to combining input level multi-view data. The most representative and one of the earliest multi-view learning methods is co-training Blum and Mitchell (1998). Co-training is a semi-supervised learning method that trains multiple models with different sets of features (e.g. words and characters) and generates labeled examples for one another using unlabeled data. It first trains a supervised model based on labeled data only. It then makes some predictions for the unlabeled data to generate more labeled examples as input for the supervised learning algorithm. Since co-training generates several predictions for a task, co-training and many of its variants (Nigam and Ghani, 2000; Muslea et al., 2002; Yu et al., 2011) try to maximize the mutual agreement of multi-view models on unlabeled data promoting a *consensus* principle. The unified model is said to have improved when each view provides some knowledge that the other views do not possess; that is, when different views hold *complementary* informa-

tion. In this section, we propose a new semi-supervised learning (SSL) approach on top of META-BASE and call it Co-meta. We detail the proposed loss function (Section 6.2.2) for co-training while taking into account the provided meta structure.

6.2.1 Co-meta

Co-meta stands for the co-training approach on the meta structure. The main idea of co-training is to augment training data with each model's confident prediction on unlabeled data so that each model can learn from other models' predictions. While not exactly following the co-training algorithm, we adopt the idea of one model teaching other models. We propose to extract the best possible parsing result using the predictions from all the models as $\hat{y}^*$ on a given instance x in unlabeled set U, and make each single-view model learn from $\hat{y}^*$ by optimizing over the proposed unsupervised loss (C_loss) as follows:

$$\text{C\_loss} = -\sum_{vi \in V \setminus \{\text{meta}\}} \sum_{x \in U} g(\hat{y}^*, \hat{y}^{vi}) \log P(\hat{y}^* | x, \theta^{vi}). \tag{6.3}$$

Here, $\hat{y}^{vi} = \arg\max_y P(y|x, \theta^{vi})$ stands for the best output for view vi and the $g(\hat{y}^*, \hat{y}^{vi})$ stands for the confidence score, which measures the confidence of $\hat{y}^{vi}$ with respect to $\hat{y}^*$. The ways to obtain $\hat{y}^*$ can be divided into three variants depending on how one extracts $\hat{y}^*$. We detail the notions of Entropy-based, Voting-based, and Ensemble-based extraction.

- **Entropy-based extraction** selects the entire prediction of one model in one view vi^*, as $\hat{y}^* = \hat{y}^{vi^*}$, which has the highest confidence for its prediction score, i.e. $vi^* = \text{argmax}_{vi \in V} P(\hat{y}^{vi} | x, \theta^{vi})$. In the entropy-based approach, the corresponding view for $\hat{y}^*$ *only teaches other views and does not teach itself.*

- **Voting-based extraction** selects the most popular label among the three models for each word w_m. When there is no agreement between the output of each model, we select the prediction of $M^{(meta)}$.

- **Ensemble-based extraction** selects $\hat{y}^*$ using an ensemble method, that is, $\hat{y}^* = softmax(\sum_{vi \in V} P(\hat{y}^{vi}|x, \theta^{vi}))$.

In addition, we scale the loss function with the confidence score $g(\hat{y}^*, \hat{y}^{vi})$, which measures the similarity between the two arguments. The idea is to assess how much confidence one should have in updating model θ^{vi} with instance $\hat{y}^*$. We hypothesize that if the prediction $\hat{y}^{vi}$ has a similar structure to the extracted $\hat{y}^*$, then the vi-view model is aligned with the extracted output and thus can confidently learn from $\hat{y}^*$. In more detail, the confidence score $g(\hat{y}^{vi}, \hat{y}^{vj})$ is a simple agreement measure between $\hat{y}^{vi}, \hat{y}^{vj}$ normalized by the sentence length to range from 0 to 1. If two models predict an identical output, the confidence score is 1. Note that we update the parameters of each view but do not update the parameters of $M^{(meta)}$ using C_loss to avoid overfitting.

A similar idea was explored by (Dong and Schäfer, 2011) in the context of self-training but without the confidence score. In our experiments, all the models without a confidence score showed a decrease of performance for all the three variants of $\hat{y}^*$.

6.2.2 Joint Semi-Supervised Learning

While labeled data T is small in low-resource scenarios, we often have larger unlabeled data U. We thus need to leverage the supervised model Eq.(6.2) using unlabeled data. Since our C_loss only requires prediction result $\hat{y}$, we can train both T and U as a joint loss (J_loss) as follows:

$$\begin{aligned} \text{J\_loss} = & \sum_{(x_j, y_j) \in T} -\log P(y_j|x_j, \theta) \\ & - \sum_{vi \in V} \sum_{x_k \in U} g(\hat{y}^*_k, \hat{y}^{vi}_k) \log P(\hat{y}^*_k|x_k, \theta^{vi}) \end{aligned} \tag{6.4}$$

where $T \subseteq U$ might apply to U, T when using T without labels. During the joint learning phase, we use the individual $CrossEntropy$ objective function to compute all

the losses with an *Adam*-optimizer presented in the previous Chapter. In what follows, let's call Co-meta the training process with J_loss on the meta-LSTM structure.

6.3 Experiments

6.3.1 Data Sets

We evaluate Co-meta on the Universal Dependency 2.2 (Zeman et al., 2018a) test set, which is applied in the previous section (Section 5.4.2), for nine languages. Our testing languages are Ancient Greek, Chinese, Czech, English, Finnish, Greek, Hebrew, Kazakh, and Tamil, following the criteria from de Lhoneux et al. (2017), with regard to typological variety, geographical distance, and the quality of the treebanks. During training, we use pre-trained word embeddings[3] and unlabeled data[4] from the CoNLL 2018 shared task to initialize our word embedding $v^{(w)}$ and the SSL presented in the previous section. When we use Language Models, we take the pretrained models provided by Lim et al. (2018a) for ELMo and Google[5] for BERT. We use the gold segmentation result for the training and test data.

6.3.2 Evaluation Metrics

We use the Unlabeled Attachment Score (UAS) and the Labeled Attachment Score (LAS) to evaluate our parsing performance (see Section 2.2.5). As for POS tagging, we measure the percentage of words that are assigned the correct POS label. We evaluate our tagger and parser based on the official evaluation metric provided by the CoNLL 2018 shared task[6].

[3]http://hdl.handle.net/11234/1-1989
[4]https://lindat.mff.cuni.cz/repository/xmlui/handle/11234/1-1989#
[5]https://github.com/google-research/bert
[6]https://universaldependencies.org/conll18/evaluation.html

Table 6.1: Hyperparameter Details

Component	**value**
$v^{(c)}$ (char) Dim.	100
$v^{(w)}$ (word) Dim.	100
$v^{(elmo)}$ Dim.	1024
$v^{(bert)}$ (multi) Dim.	768
$v^{(bert)}$ (base) Dim.	200
$h^{(word)}$ (word) output Dim.	400
$h^{(char)}$ (char) output Dim.	400
No. BiLSTM layers	2
MLP output (arc) Dim.	300
MLP output (dep) Dim.	300
MLP output (pos) Dim.	100
Dropout	0.3
Learning rate	0.002
Learning rate (BERT)	0.00001
β_1, β_2	0.9, 0.99
Epoch	1,000
Batch size (Base)	2
Batch size (High-resource)	32
Batch size (High-resource+BERT)	10
Gradient clipping	5.0

6.3.3 Experimental Setup

For our evaluation, We sample the first 50 instances of the treebank for each language from labeled data as a training set to test the low-resource scenario following (Guo et al., 2016). In addition, we test our models on extremely low-resource scenarios that use 5∼50 training sets to investigate the effect of our semi-supervised approach. We borrow hyperparameter settings from the BASELINE and apply them on the single-view layers in the META-BILSTM structure. Table 6.1 shows our hyperparameter settings with the learning rate. In each epoch, we run over the training data with a batch size of 2 and run only a batch from randomly chosen unsupervised data. We evaluate our models on the test sets, and report the average of the three best performing results, trained with different initial seeds, within 1,000 epochs. All the reported scores without any mention are based on the scores from the meta-layer output.

6.4 Results and Analysis

Our study has different goals: (1) study the impact of multi-view based learning, META-BASE Co-meta, on tagging and parsing in low-resource scenarios, (2) check whether Co-meta can increase the consensus between single-view models and the effect of this promoted consensus on the performance of each-view model and on the overall META-BILSTM system, (3) study the effect of unlabeled data on Co-meta, and finally (4) investigate to what extent the efficacy of Co-meta remains when the approach is applied to high-resource scenarios.

Table 6.2: LAS and UPOS scores of $M^{(meta)}$ model output on the test set using 50 training sentences and unlabeled sentences based using `Co-meta`, META-BASE, and our BASELINE model (Lim et al., 2018a). We report META-BASE to decompose the performance gain into the gains due to META-BASE (supervised) and `Co-meta` (SSL). *Kazakh only has 31 labeled instances. Thus we use only 31 sentences and its unlabeled data are sourced from Wikipedia whereas other languages take the unlabeled data from the given training corpus after removing label information.

		VOTING		ENTROPY		ENSEMBLE		META-BASE		BASELINE	
corpus	unlabeled	LAS	POS	LAS	POS	LAS	POS	LAS	POS	LAS	POS
cs_cac (Czech)	23478	47.4	79.4	47.4	79.7	**48.7**	**81.4**	45.9	79.0	39.4	74.6
fi_ftb (Finnish)	14981	21.7	43.2	22.0	44.7	21.8	43.5	21.9	**44.6**	**22.6**	39.2
en_ewt (English)	12543	45.1	75.7	46.3	**76.7**	**46.5**	76.3	45.4	75.2	42.8	71.1
grc_perseus (Ancient Greek)	11460	30.8	70.1	**31.7**	**70.9**	31.3	70.7	30.9	70.4	29.5	65.8
he_htb (Hebrew)	5240	47.9	76.9	47.8	77.2	**48.4**	**77.4**	47.6	76.7	45.1	75.2
zh_gsd (Chinese)	3997	36.1	70.7	35.1	70.8	**36.9**	**71.1**	35.1	70.6	34.8	68.7
el_bdt (Greek)	1162	60.0	84.3	**60.6**	83.2	60.5	**84.2**	57.8	82.6	51.7	80.0
ta_ttb (Tamil)	400	38.1	69.1	39.0	**69.7**	**40.0**	69.3	38.3	67.3	34.0	61.9
kk_ktb (Kazakh)*	12000*	27.6	56.9	27.9	57.0	**28.7**	57.1	27.8	**57.7**	26.2	53.0
Average	-	39.4	69.6	39.8	70.0	**40.3**	**70.1**	39.0	69.3	36.2	65.5

Table 6.3: LAS and UPOS scores of $M^{(meta)}$ model on the test set using **100** training sentences. We see that `Co-meta` takes over BASELINE for Finnish, unlike the results in Table 6.2 (50 sentences used)

		ENTROPY		ENSEMBLE		VOTING		META-BASE		BASELINE	
corpus	SSL-size	LAS	POS	LAS	POS	LAS	POS	LAS	POS	LAS	POS
cs_cac (Czech)	23478	54.9	82.9	**56.3**	**84.6**	55.0	83.6	54.1	84.0	50.8	81.6
en_ewt (English)	12543	**57.9**	**82.5**	**57.9**	82.0	56.7	81.3	56.5	82.3	55.1	80.6
fi_ftb (Finnish)	14981	29.0	50.9	**29.2**	**51.1**	28.5	50.7	29.0	50.5	27.6	49.7
grc_perseus (Ancient Greek)	11460	**38.1**	**78.0**	37.0	77.8	36.5	77.1	36.0	77.4	34.9	76.2
zh_gsd (Chinese)	3997	43.5	76.2	**45.3**	**76.9**	44.5	76.5	42.9	76.2	41.0	74.1
el_bdt (Greek)	1162	**69.1**	88.2	69.0	88.5	68.5	**88.7**	67.4	87.4	66.2	86.7

Table 6.4: LAS on the Greek(el_bdt) corpus for each model, with the average confidence score $g(\hat{y})$ comparing $M^{(word)}$ and $M^{(char)}$ over the entire test set using 100 training sentences.

Method	WORD	CHAR	META	CONFIDENCE
ENTROPY	**61.8**	66.7	**69.1**	0.871
ENSEMBLE	61.4	**66.9**	69.0	**0.879**
WITHOUT	57.6	65.2	67.4	0.799

6.4.1 Results in Low-Resource Settings

Impact of Multi-View Learning. Table 6.2 and Table 6.3 show the experimental results of $M^{(meta)}$ on the test data of each language, with 50 and 100 training sentences, respectively. We see that the proposed co-training method shows average performance gains of $-0.9 \sim +9.3$ LAS points in parsing and $+1.7 \sim +6.9$ points in tagging compared to BASELINE.

Note that the proposed META-BASE approach also shows a LAS improvement of $-0.6 \sim +6.5$ for BASELINE as well. Breaking down the contribution of improvement, Co-meta shows $-0.3 \sim +2.8$ LAS improvement over META-BASE and this improvement is comparable to the improvement of META-BASE over BASELINE.

Comparison of `Co-meta` Variants. When we compare the three proposed co-training approaches, one can see that the ENSEMBLE approach seems to work better than ENTROPY, and VOTING is always worst. This is because the best-voted labels for each token do not guarantee to get an optimal structure over the parse tree at the sentence-level, since the VOTING model has a relatively high chance of learning from the inconsistent graph that has multi-roots and cycling heads among tokens (Kiperwasser and Goldberg, 2016a). Figure 6-4 describes the label selection method of ENSEMBLE and VOTING for a token. ENSEMBLE makes a decision by taking into account the probability of each possible label from the three models. On the contrary, VOTING makes a local decision and selects the most popular label. We found that both two methods make a local decision but VOTING made a lot more errors during training.

Lastly, we also try running Co-meta experiments without confidence scores, i.e.,

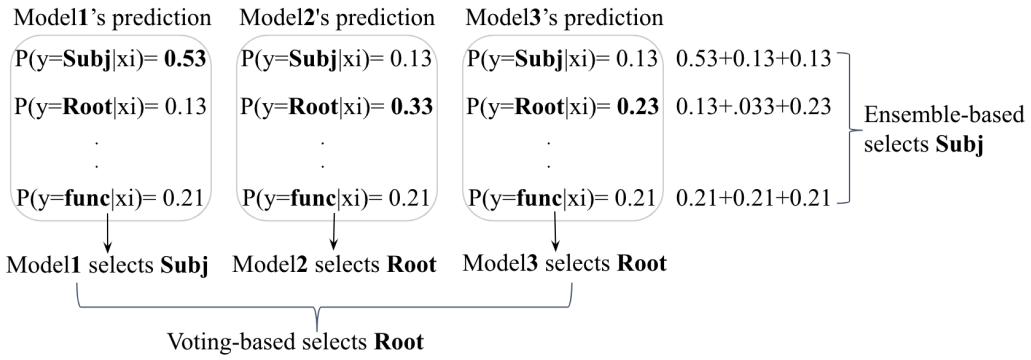


Figure 6-4: An example of the label selection method for ENSEMBLE and VOTING.

we set the confidence score as 1. We find that, with this configuration, performance always decreases in comparison to META-BASE, and thus, we conclude that the proposed confidence score plays a major role in stabilizing the Co-Train approach. Figure 6-5 presents the impact of our confidence score based on the size of unlabeled sentences. We see positive gains using our confidence score when the number of unlabeled sentences is more than 1200.

Interaction among the layers. More detailed per-layer analysis of the LAS scores is available in Table 6.4 for the case of the Greek corpus. Among the three views, CHAR always outperforms WORD, and all the three views improve after using Co-meta: improvements of +1.6-1.7 LAS point for META, +1.5-1.7 for CHAR and +3.8-4.2 for WORD.

We can make three observations. First, we note that the model with lower performance, namely WORD view in our example, always benefits the most from other better-performing views. Second, the evolution of low-performing views towards better results has a positive effect on META view, and thus on the overall performance. While the score CHAR increases by +1.5, META increases by +1.7. If the lower-performing-view model was not helping, then the improvement would be upper-bounded by the performance gain of the higher-performing model. Note that we do not update the META layer $\theta^{(meta)}$ when using Co-meta, and all the gains result from the improvements of the single-view layers. Lastly, the CONFIDENCE column shows that the consensus increases, and thus, we can confirm that promoting consensus-philosophy

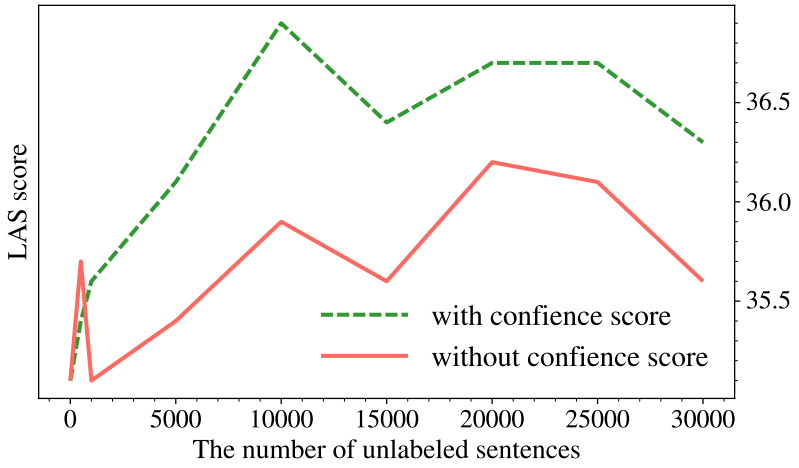


Figure 6-5: Evaluation results for Chinese (zh_gsd) based on different sizes of the unlabeled set and proposed models. We apply ENSEMBLE-based `Co-meta` with the fixed size of 50 training sentences while varying the unlabeled set size.

of Co-Train works as intended in Co-meta. In other words, higher CONFIDENCE denotes that models predict a similar tree structure by learning from each other.

Sensitivity to the Domain of the Unlabeled Set. In Table 6.5, we investigated a more realistic scenario for our semi-supervised approach for two languages, Chinese and Greek, by using out-of-domain data: Wikipedia and a crawled corpus. In the case of Chinese, the crawled out-domain corpus shows better results than the in-domain corpus for both ENTROPY-based and ENSEMBLE-based Co-meta, by up to +1.1 UAS and +0.9 POS points. In contrast, for Greek, the in-domain corpus (el_bdt) shows a better result than the out-domain corpus even when the size of el_bdt is only about 13% of the others. We conjecture that as the Chinese has large character sets, the exposure to diverse characters helps learning regardless of the domain.

Effect of Training Size on Performance. Table 6.2 shows positive results for Co-meta given fixed size train data. However, would Co-meta be useful even with extremely low resource scenarios (<50 sentences)? And also in a more favorable scenario, when more resources are available for training (e.g. >1000 sentences)?

To answer these questions, we conducted an experiment using the zh_gsd (Chi-

Table 6.5: Scores of `Co-meta` with the ENSEMBLE method on different domains of unlabeled data with 100 training sentences.

Labeled	**Unlabeled**	size	LAS	UAS	POS
el_bdt	el_bdt	1162	**69.0**	**75.6**	88.5
(Greek)	wikipedia	12000	68.7	75.1	**88.7**
	crawl	12000	68.3	74.8	88.4
zh_gsd	zh_gsd	3997	45.3	57.9	76.9
(Chinese)	wikipedia	12000	**46.3**	**59.1**	77.6
	crawl	12000	46.1	59.0	**77.8**

nese) corpus with training sets of different sizes, but with a fixed set of 12k unlabeled data. The results are visible in Figure 6-6-(A,B).

Figure 6-6-(A) shows our results for the lower resource scenario (with less than 50 sentences for training). Co-meta outperforms META-BASE and BASELINE except when only five sentences are used for training. We conjecture that this result is attributable to the fact that too little vocabulary (5 sentences) is used to allow meaningful generalization. A similar behavior was observed for fi_ftb in Table 6.2: in this experiment, there are only 241 tokens available for fi_ftb, whereas other languages had on average ∼1388. However, as observed in Figure 6-6, that once we expand the labeled instances (>20 sentences), Co-meta and META-BASE always outperform the BASELINE, both in lower (Figure 6-6-A) and higher resource (Figure 6-6-B) settings. Also note that Co-meta always outperforms META-BASE, including when one only has 5 labeled instances for training.

We can refine our analysis by examining the different layers of META-BASE and Co-meta that appear on Figure 6-6-A-1. META-BASE is detailed on Figure 6-6-C-2 and Co-meta on Figure 6-6-C-1. In most cases, META stays close to the highest performing view (the WORD layer for most cases). One interesting fact is that the WORD as well as meta layer of META structures outperform the BASELINE which is built on a combined view.

The biggest contrast between Co-meta and META-BASE is the gap between the performances of the WORD and the CHAR layers. A closer look at META-BASE(Figure 6-6-C-2) seems to indicate that the performance of the META layer cannot differ too much from the lower-performing layer (CHAR in our case). When the gap between

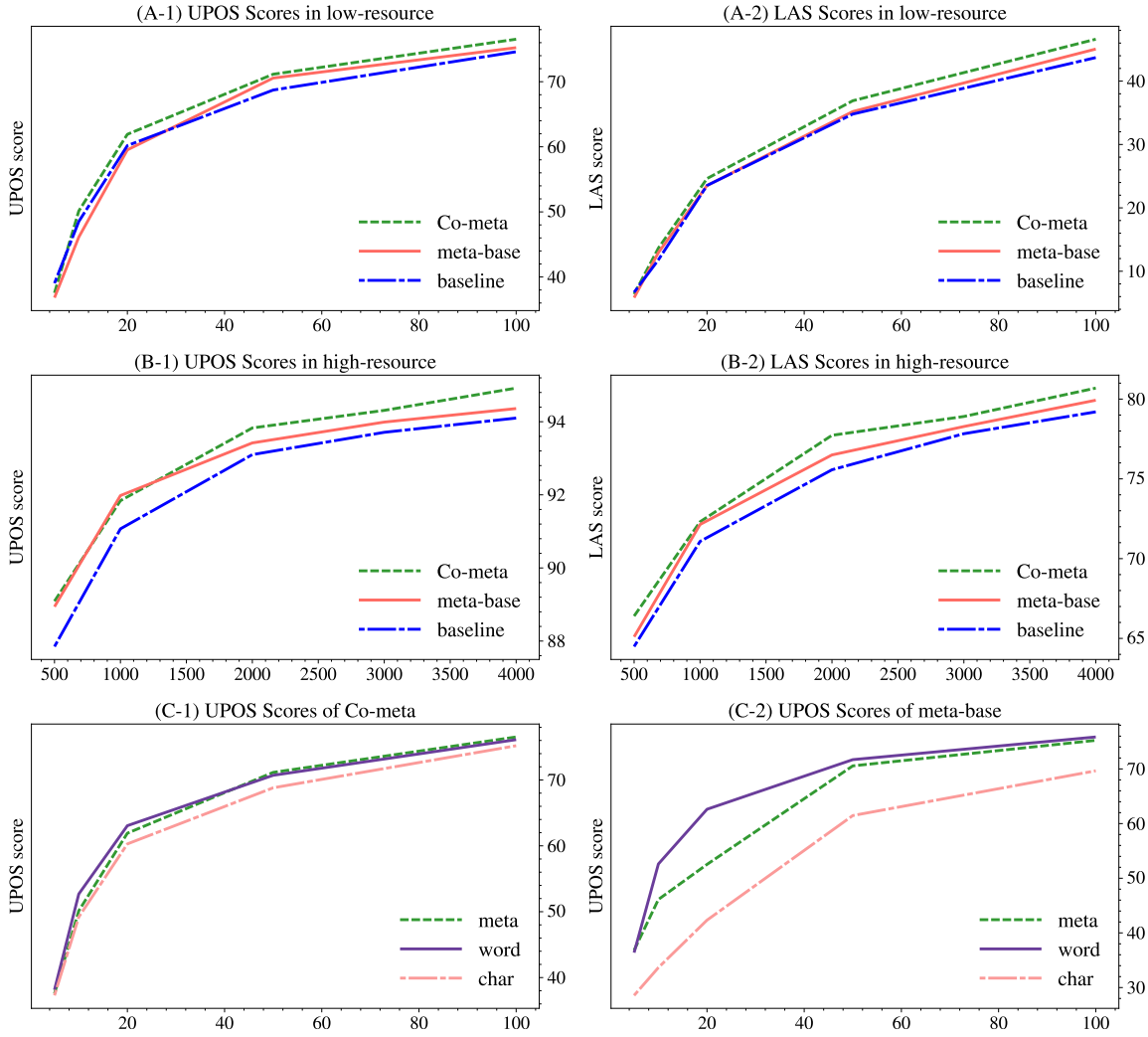


Figure 6-6: Evaluation results for Chinese (zh_gsd) based on the different sizes of the train set and proposed models. We apply ENSEMBLE based `Co-meta` with the fixed size of 12k unlabeled sentences while varying training set size.

WORD and CHAR becomes too large (>5 points), then the performance gain of META layer is parallel to that of CHAR layer for train size of 10–50 even when the WORD layer makes steeper performance gains. In contrast, the Co-meta's META layer from Figure 6-6-C-1 shows more stable performance as the gap between CHAR and WORD is minimal as the two layers learn from each other.

To summarize from Table 6.2 and Figure 6-6, the proposed SSL approach is always beneficial for the META-BILSTM structure when comparing the LAS scores between Co-meta and META-BASE. However, the META-BILSTM structure itself might not

Table 6.6: LAS for the English (en_ewt) corpus for each model, with the external language models with the entire train set.

Model	**LM**	LAS	UAS	POS
UDPIPE (Kondratyuk, 2019)	-	86.97	89.63	96.29
BASELINE (Lim et al., 2018a)	-	86.82	89.63	**96.31**
METABASE	-	86.95	89.61	96.19
CO-META	-	**87.01**	**89.68**	96.17
BASELINE (Lim et al., 2018a)	ELMo	88.14	91.07	96.83
METABASE	ELMo	88.28	91.19	96.90
CO-META	ELMo	88.25	91.19	96.84
UDIFY (Kondratyuk, 2019)	BERT-MULTI	88.50	90.96	96.21
UUPARSER (Kulmizev et al., 2019)	BERT-MULTI	87.80	-	-
BASELINE	BERT-MULTI	89.34	91.70	96.66
METABASE	BERT-MULTI	89.49	92.01	96.75
CO-META	BERT-MULTI	89.52	91.99	96.80
CO-META	BERT-BASE	**89.98**	**92.25**	**97.03**

benefit when too few tokens exist in the train set. In general, we hypothesis that for the META-BILSTM structure to be useful, the train set should consist of more than 300 tokens (more than 20 sentences) to provide enough generalization information.

6.4.2 Results in High-Resource Settings

Although the lack of annotated resources for many languages has given rise to low-resource approaches, there are also several languages for which we have plenty of resources. We can thus examine whether our approach is also effective in more favorable settings, when large scale resources are available. A comprehensive overview is shown in Table 6.6, 6.7, where different systems using no language model (first part of the table), or ELMo (Peters et al., 2018) or BERT (Devlin et al., 2018) language models are evaluated.

Table 6.6 includes a comparison of our results using the approach presented in this chapter with four state-of-the-art systems. The first system is our BASELINE (introduced in Section 6.1.1), which obtained the best LAS measure for English in the 2018 CoNLL shared task. The second is UDPIPE (Straka, 2018; Kondratyuk, 2019) which was one of the best performing systems during the 2018 CoNLL shared task (best

Table 6.7: LAS for the **Chinese (zh_gsd)** corpus for each model, with BERT–Multilingual embedding using the entire training set. We observe much higher improvements than for English showed (see Table 6.6), probably because zh_gsd has a relatively small training set (3,997) and larger character sets than the training set (12,543) of en_ewt.

Model	**LM**	LAS	UAS	POS
UDPIPE	-	80.50	84.64	**94.88**
BASELINE	-	79.70	84.28	94.41
METABASE	-	80.32	84.58	94.72
CO-META	-	**80.71**	**84.99**	94.81
UDIFY	BERT-MULTI	83.75	87.93	95.35
UUPARSER	BERT-MULTI	83.7	-	-
METABASE	BERT-MULTI	83.90	88.07	**96.07**
CO-META	BERT-MULTI	**84.21**	**88.39**	**96.07**

MLAS score, that combines tagging and parsing, and 2nd for the average LAS score). UDPIPE uses a multi-task learning approach with a loosely-joint LSTM layer between tagger and parser. The third system is UDIFY (Kondratyuk, 2019) (derived from UDPIPE), where the LSTM layer is replaced with BERT embedding, which is in turn fine-tuned during training. The fourth system is UUPARSER wherein concatenated word, character and BERT embedding serves as an input, e.g., $h_i = [v^{(wc)}; v^{(bert)}]$.

Effect of `Co-meta` On High-Resource Settings without LMs. By expanding the baseline with our meta-LSTM and SSL approach, we observe a slight improvement of up to 0.19 and 0.04 points against the BASELINE and UDPIPE, respectively. In contrast, we find that both META-BASE and Co-meta slightly underperform the BASELINE in tagging, which goes against our intuition. One possible reason might be that there is enough data to get accurate results using a supervised learning approach while SSL suffers from unexpected surface sequences. Another evidence of this is that SSL did not bring further improvement when using more than 10,000 training sentences. In contrast, interestingly, Chinese (Table 6.7) for which we had a relatively small train set (3,997), is positively affected by the SSL approach, with a gain of up to +0.21 LAS points compared to UDPIPE, +1.12 points compared to BASELINE. We assume that the main reason for this is the character set. Languages with a bigger

character set size and little training data gain more influence with SSL.

Effect of `Co-meta` On High-Resource Settings with LMs. While we train our model with a LM, we concatenate the last layer of the LM embedding with the input of the $BiLSTM^{(meta)}$ presented in the previous section. Finally, the input of our meta model consists of three different contextualized features as $[h_i^{(word)};h_i^{(char)};v_i^{(lm)}]$.

On average, adding a LM provides excellent results both for dependency parsing and POS tagging, outperforming by large margins previous results obtained without LMs (up to +1.27 LAS for ELMo and +2.97 for BERT). Furthermore, our parser with Co-meta globally shows better results than the state-of-the-art parsers that use ELMo (Lim et al., 2018a) and the BERT-Multilingual model (Kondratyuk, 2019). However, it should be noted that the UDIFY model used by (Kondratyuk, 2019) (that includes Bert-Multilingual as a LM) was first trained with 75 different languages using Universal Dependency corpora and then tuned for English, and it is not clear how this training process affects the performance. Thus, we add the results of UUPARSER and BASELINE with BERT to represent fine-tuning in a monolingual way only and still found that CO-META+BERT-MULTI yields better performance.

We generalized Co-meta by adding an additional view: *LM* embedding. We conclude that Co-meta can, surprisingly, result in positive effects by more than +1–+1.7 points compared to competing models and by +0.2 compared to the BASELINE even in a high-resource setting, especially when a LM embedding is present.

6.5 Summary

In this chapter, we have proposed Co-meta, a SSL on multi-view learning strategy using co-training methods. The proposed model is evaluated on the multi-task of POS tagging and dependency parsing. In this setting, multi-view learning shows a large improvement in comparison to a single model with a combined view in the input level on all levels: low-, mid-, and high-resource settings with or without a LM embedding. Furthermore, Co-meta is more stable and yields significant gains on low-,

and mid-resource settings and marginal gain in high-resource settings compared to META-BASE, a multi-view learning model without SSL. The proposed entropy and ensemble-based methods yield the best prediction among multi-views and update the individual-view model based on a confidence score. This strategy is especially well suited for low-resource scenarios, when only a very small sample of annotated data is available, along with larger quantities of unlabeled data. Our experiment shows statistically significant gains ($-0.9 \sim +9.3$ points compared to the baseline), largely due to the proper integration of unlabeled data in the learning process. Finally, this chapter shows the performance of Co-meta varies as we change the size of labeled and unlabeled dataset in the case of the el_bdt and zh_gsd corpora, so that we were able to provide some comments on the chance that Co-meta would succeed or fail.

Chapter 7

Multilingual Co-Training

In Sections 4 and 6, we discussed two main bootstrap methods, multilingual transfer learning and co-training. Although these two approaches have yielded outstanding performance compared to the supervised monolingual model in low-resource scenarios, several questions remain, including whether two bootstrap methods can work together. No attempts have yet been made to apply both multilingual and semi-supervised learning simultaneously owing to structural limitations. Because the proposed transfer learning method based on multilingual token representations takes several treebanks from several languages in input, some difficulties were encountered when applying the semi-supervised learning approach using unlabeled data. For example, we need to adjust the ratio between labeled and unlabeled data and also between languages to avoid overfitting, especially when the languages have different character sets. Recently, Kondratyuk (2019) proposed a multilingual approach based on the multilingual BERT model. This parser can simultaneously learn from 75 languages using 142 annotated treebanks and, of course, also parse 75 languages. Interestingly, the parser showed state-of-the-art performance in low-resource languages because it can capture sub-word information from similar languages by tuning the BERT language model (parameter tuning). However, this approach does not consider the use of unlabeled data for training.

In this chapter, we investigate how to integrate the two proposed methods and we analyze the effect of this integration for parsing. This chapter is structured as

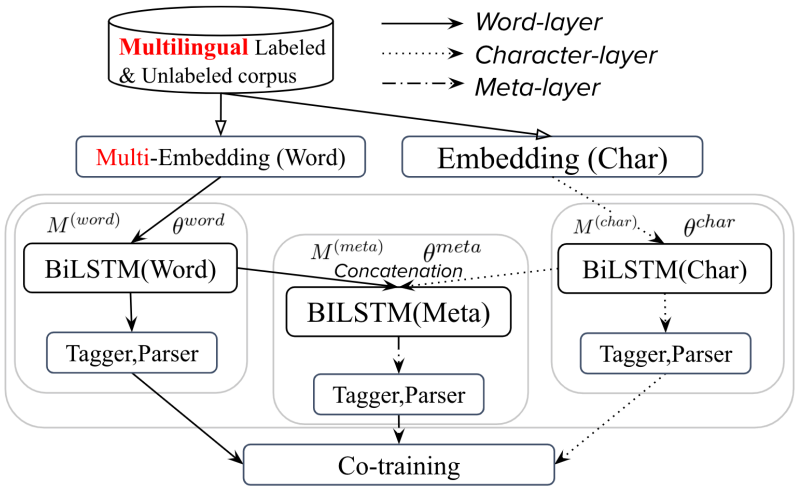


Figure 7-1: The overall structure of our `Co-metaM` model. This system generates word- and character-level representation vectors and concatenates them into a unified word embedding for every token in a sentence. The word-level representation can be a multilingual embedding as proposed in Section 4.2. Thus, this system can train a dependency model, using both labeled and unlabeled resources from several languages.

follows: we describe an approach that uses simultaneously multilingual and transfer learning (presented in Chapter 4) and co-training (presented in Chapter 6) in Section 6.1. The evaluation results are presented in Section 6.3.

7.1 Integration of Co-Training and Multilingual Transfer Learning

To evaluate the benefit of co-training, we use the same structure with Co-meta as presented in Section 6.3. This model thus integrates three individual parsers based on three different views (CHAR, WORD, and META-BILSTM), and produces three predicted parse trees ($\hat{y}^{word}, \hat{y}^{char}, \hat{y}^{meta}$) using unlabeled data. When the parser integrates the co-training approach (Semi-supervised learning), the best (predicted) possible tree $\hat{y}^*$ is generated using an ensemble, voting, and entropy-based method applied on the predictions of the three based parsers. To apply multilingual approaches to Co-meta, a function that considers multilingual representations is required. As mentioned in Section 4.2, a possible option is to use a cross-lingual word embedding obtained after the projection of two monolingual embeddings via a bilingual dictio-

nary. The resulting cross-lingual embeddings are supposed to have similar vectors for words with a similar meaning in two languages (e.g., English "dog" and French "chien"). When a cross-lingual word representation is built using two languages, A and B, the embedding can be directly applied to train the cross-lingual dependency parser based on two training corpora from language A and B. Figure 7-1 shows the structure of our system expanded from Co-meta with multilingual word representations. Since the system uses a multilingual word embedding, it can also take several training corpora in the input. Notably, the character-level representation would be monolingual when different writing systems are considered (e.g., Korean and French). Hereinafter, we will call this multilingual Co-meta Co-metaM (Co-metaM is the multilingual variant of Co-meta).

7.2 Experiments

To quantify the effectiveness of Co-metaM in low-resource scenarios, we select Sami and the cross-lingual word embeddings used in Section 4.3. Sami was one of the low-resource languages proposed in the CoNLL shared task 2017 and only 20 annotated sentences were provided fro training. However, in 2018, the number of training sentences was expanded to 1,662 to ensure efficient testing for both high- and low-resource scenarios. We used the same environmental settings presented in Section 6.4 (Co-meta), i.e. the hyper-parameter settings, dimension of LSTM, and learning rate were kept the same.

7.2.1 Preparation of Language Resources

We used the lexical resources presented in Chapter 4, including the bilingual dictionaries and word embeddings. Table B.1 shows the sizes of the dictionaries used.

We used the pretrained Finnish FastText word embedding published by Facebook (Bojanowski et al., 2016b), as presented in Section 4.3. As the Sami Wikipedia is relatively small, we also trained larger word embeddings using FastText. When co-training (presented in Section 6.2) was applied using unlabeled data, the unlabeled

Bilingual pairs	Bi-dictionary	Bi-embedding
FinnishNorth Sami	12,398	2.4GB
North SamiEnglish	8,746	7.5GB
North SamiFinnish	10,541	2.4GB

Table 7.1: Dictionary sizes and size of bilingual word embeddings generated from each dictionary.

data provided by the shared task organizer was used[1]. This unlabeled data also used for training word embeddings as well.

7.2.2 Experiments strategies

We conducted a series of experiments on Sami. We tested different language combinations to get a cross-lingual parsing model. All the experiments were carried out using the 20 Sami sentences provided for training for the 2017 CoNLL Shared Task. Therefore, these results can be compared to the ones in the official CoNLL evaluation.

As presented in Section 4.3, when training a model with multilingual data, the size of the training corpora for low-resource languages is smaller than that for high-resource languages. Following our previous work presented in Section 4.3, we iterated for additional 20 times for low-resource training data as compared to the scenario of high-resource. For example, when iterating 20 times using 20 Sami sentences, the system iterates only one time using 12,543 Finnish sentences. When applying co-training, we used the unlabeled data with batch size 2, as presented in the previous section.

7.3 Results

Impact of the multilingual approach. Table 7.2 shows our experimental results based on the different pairs of training data with the gold-tokenized input. The multilingual approach outperforms every monolingual approach. Additionally, the choice of the language pairs is significant: compare for example sme+eng and sme+fin,

[1]https://lindat.mff.cuni.cz/repository/xmlui/handle/11234/1-1989

Case	Training corpus	Model	LAS	UAS
1	sme (20)	Co-metaM without Co-training	32.96	46.85
2	eng (12,217)	Co-metaM without Co-training	32.72	50.44
3	fin (12,543)	Co-metaM without Co-training	40.74	54.24
4	sme (20) + eng (12,217)	Co-metaM without Co-training	46.54	61.61
5	**sme (20) + fin (12,543)**	Co-metaM without Co-training	**51.57**	**63.06**
4-1	sme (20) + eng (12,217)	Co-metaM	46.97	61.44
5-1	**sme (20) + fin (12,543)**	Co-metaM	**53.80**	**66.76**

Table 7.2: Labeled attachment scores (LAS) and unlabeled attachment scores (UAS) for Northern Sami (sme) based on the use of the training corpora

which yielded LAS scores of 46.54 and 51.57, respectively. In addition to the multilingual approach, co-training has a positive effect on the overall performance, especially for sme+fin (note though that this is not the case for sme+eng). We assume that this difference is due to the different character sets and word order between the two languages.

Comparison with the CoNLL Shared Task. We used the same environmental settings in these experiments as for the CoNLL Shared Task (same training sets, no development set and application of the baseline tokenizer). Table 7.3 reports the official 2017 CoNLL results with our multilingual model trained for Sami and Finnish. C2L2 (Cornell Univ.) obtained the best performance for Sami with a delexicalized transfer approach (using a Finnish training corpus and a corpus of 20 Sami sentences as a development set for parameter tuning without lexicalized features). IMS (Stuttgart) used a delexicalized transfer approach with an exceptionally large training corpus based on 40 different training corpora in UD, thereby obtaining the second-best result. Compared with the result of the Shared Task, our approach without co-training (lexicalized cross-lingual transfer parsing with resources from relevant languages) can be effective for parsing low-resource languages when observing the "Co-metaM without co-training" model. When our multilingual parser is used with the co-training approach (Co-metaM), the performance dramatically improves compared to the other model, with an average LAS gain of $+2.23 \sim 7.25$. Interestingly, it seems that the multilingual approach is more important than co-training for Sami, if we compare the

Model	LAS	UAS
C2L2 (Ithaca) (Shi et al., 2017a)	48.96	58.85
IMS (Stuttgart) (Björkelund et al., 2017a)	40.67	51.56
HIT-SCIR (Harbin) (Che et al., 2017a)	38.91	52.51
LATTICE (Paris) (Lim and Poibeau, 2017b)	28.39	42.72
`Co-metaM`	**49.73**	**59.89**
`Co-metaM` without Co-training (unlabeled data)	47.50	58.94
`Co-metaM` without multilingual training	45.16	57.17
`Co-metaM` without Co-training and multilingual training	41.48	53.61

Table 7.3: Comparison with top four results for Sami from the CoNLL 2017 Shared Task and our multilingual model trained on Sami and Finnish corpora.

individual contribution of each technique to Co-metaM.

7.4 Summary

In this chapter, we have presented a multilingual co-training approach for parsing that is effective for languages having limited resources for training. We demonstrated that our Co-metaM (Multilingual Co-training) model yields better results compared to monolingual ones. We also found that a multilingual word embedding derived from carefully selected related languages is more crucial than co-training (Semi-supervised learning) for low-resource scenarios. With the careful selection of training data, it is possible to enhance parsing results for low-resource languages.

Chapter 8

Conclusion

The present thesis mainly focused on bootstrapping methods for accurate dependency parsing under low-resource conditions. Two approaches, namely, multilingual transfer learning and co-training, were proposed.

8.1 Summary of the Thesis

In the course of this thesis, we have examined the different resources available for parsing, including labeled treebanks, unlabeled treebanks, pre-trained word representations, and pre-trained language embeddings (ELMo, Bert). Our monolingual and multilingual systems (described in chapter 3 and 4) make full use of these resources in high resource scenarios. We also examined how knowledge can be transferred from several languages to train low-resource languages. Additionally, co-training enabled the use of **unlabeled data** as a training set.

In Chapter 4, we extended a monolingual parser to make it multilingual, based on multilingual lexical representations. We showed that the bilingual word mapping approach is effective with multilingual training sets. This approach is simple yet powerful for creating a dependency parsing model when no annotated corpus or parallel corpus is available for training. Our approach requires only a small bilingual dictionary and the manual annotation of a handful of sentences. We showed that the performance one can obtain with this approach depends largely on the set of languages

used for training. This was done by investigating several models using genetically related and non-related languages to gain a better understanding of the limitations or possibilities of model transfer across different language families. For example, we presented three multilingual models, namely, Komi-English, Komi-Finnish (genetically related languages), and Komi-Russian (geographically related languages) models for parsing. The best results were obtained with the Komi-Finish and Komi-Russian models, which shows that language typology and geography play a role.

In Chapter 6, we proposed a co-training parsing model that can infer information from unlabeled data. The primary idea was to augment the quantity of labeled data with automatic methods. We showed that an automatic approach based on the combination of different "views" (character-based analysis, token-based analysis, etc.) provides good enough predictions to be able to generate a highly accurate combined result, that in turn can be used as training data. To compute the confidence of the predicted labels when the views are combined, we proposed three different methods, namely, the entropy-, voting-, and ensemble-based score. This strategy is especially well suited for low-resource scenarios, when only an exceedingly small sample of annotated data is available, along with larger quantities of unlabeled data. The proposed model showed consistent improvement across the different test cases used. Moreover, the evaluations on various domains and languages demonstrated the effectiveness and robustness of the proposed approach.

Based on our experiments, we can conclude by examining the different questions raised in the introduction.

8.2 Discussion over the Research Questions of the Thesis

(A) In the course of this thesis, we have shown that a multilingual approach provides accurate results for parsing. This approach is especially suited for low resource scenarios as it makes it possible to transfer knowledge from

a well-resourced language to a low resource one. However, the conditions under which these experiments are carried out must be examined in detail.

We have shown that the multilingual transfer learning approach, which utilizes annotated data from several languages, is advantageous for low-resource languages. However, we also found that a careful selection of the related languages used for the experiments is important for transfer learning. Specifically, in Section 4.1, we investigated the multilingual transfer approach as a substitute for the more typical monolingual approach. We proposed a method that compensates the lack of training data with transfer learning, which enabled us to use different corpora in different languages as training data. In most cases, for instance, in the CoNLL 2017 shared task (Zeman et al., 2017a), the teams that adopted this approach used a multilingual delexicalized parser (i.e. a multi-source parser trained without considering lexical features). However, it is evident that delexicalized parsing cannot capture contextual features that depend on the meaning of the words within the sentence. This led to the creation of multilingual lexical representations. As discussed in Section 4.4, the multilingual transfer learning approach based on multilingual word representations showed better results than the delexicalized one under low-resource conditions. In addition, the results on the CoNLL shared task demonstrated the good performance of our multilingual approach for a wide variety of languages.

(A-1) Is parallel data required for multilingual parsing?

- We believe that parallel corpora are no longer needed when using a transfer learning approach. Instead, monolingual raw texts can be used to train monolingual word embeddings. As presented in Section 4.1, once we integrate a multilingual transfer learning approach to produce multilingual lexical resources, we only need to map lexical resources among the languages. Traditionally, a large parallel corpus or a bilingual dictionary is required to map two different word embeddings into a joint distributional space (Artetxe et al., 2016a; Guo et al., 2015b). However, (Artetxe et al., 2017) proposed a method for mapping two different embeddings based on a linear transformation and using only 25

pairs of words, with almost no decrease of the quality of the result.

(A-2) How can we bootstrap a system when no parallel corpus is available?

- To answer this question, we have presented two different case studies, around Komi (a Finno-Ugric language spoken in Russia) and five different low resource languages used for evaluation during the CoNLL 2017 shared tasks (these languages were called "Surprise" languages because the languages and the data were provided only a few days before the evaluation). In Sections 4.3 and 5.4 we suggested the use of a bilingual word embedding (integrating the vocabulary of the language to be parsed and the vocabulary of another, linguistically related language, for which different resources including a treebank is available). However, it must be noted that even for low-resource languages, raw texts are required as the minimum resource to train a word embedding. This multilingual lexicalized approach based on transfer learning achieved good results during the CoNLL 2017 evaluation. In practice, larger bilingual dictionaries can be used to improve the result; however, only 25 pairs of words are sufficient to align the embeddings reasonably well.

(B) In this thesis, we also examined whether using unlabeled data for parsing, especially in low resource scenarios, can improve the results.

There have been several semi-supervised learning (SSL) algorithms proposed for parsing, and these algorithms generally obtained better results than the typical supervised learning approach. Among these approaches, self-training (see Section 2.4), which is based on concatenated lexical representations (e.g. concatenation of char and word embeddings), is especially interesting. However, the main problem of this simple concatenation approach is that it can lead to overfitting in low-resource conditions, as the model may ignore the specific statistical properties of each lexical representation.

As presented in Chapter 6, we suggest the application of co-training on individual models trained with limited features. Co-training is a semi-supervised approach that trains multiple learners (parsers in our case) based on different features (views). The

views in our case refer to the word and character-level representations. Subsequently, a single-view model is constructed that concatenate single-view-model outputs to form the input of the meta layer. Because each parser struggles to identify the best features within the limited character and word features, this method maximizes the use of lexical features under low-resource conditions.

(B-1) Can traditional Co-Training approaches further improve dependency parsing in low-resource scenarios?

- Based on our experimental results presented in Section 6.4, we see that the proposed co-training approach is always advantageous for the META-BILSTM structure that trains several different parsers simultaneously. We found up to +9.3 LAS gains when comparing the LAS scores between our co-training model and the baseline model. However, the META-BILSTM structure itself may not benefit when extremely few tokens exist in the training set. In general, we hypothesize that for the co-training structure to be useful, the training set should include more than 300 tokens (more than 20 sentences) to provide meaningful generalizations.

(B-2) Can co-training models that consider different views globally (i.e. at the sentence level) learn from each other on unlabeled data? Does this improve the performance for low-resource languages?

- To answer this question, we set three different parsers that consume individual features (views) as input, namely CHAR, WORD, and META and subsequently allowed these parsers teach each other using unlabeled data (in Section 6.3). We found that the three models improved in terms of performance after using co-training: improvement was 1.6-1.7 LAS point for META, 1.5-1.7 for CHAR, and 3.8-4.2 for WORD for Chinese.

  We report two observations. First, we note that the model (parser) with the lowest performance, namely the WORD model in this example, always benefits

the most from the better-performing models. Second, the transition of low-performing models into those yielding better results has a positive effect on META view, and consequently on the overall performance. While the score CHAR increases by 1.5, META increases by 1.7. Without the assistance of low-performing-view model, the improvement would have been upper-bounded by the performance gain of the high-performing model.

(B-3) How many labeled and unlabeled sentences are needed for co-training to be beneficial?

- To answer this question, we presented an experiment in Section 5.4 using the zh_gsd (Chinese) corpus with training sets of different sizes, but with a fixed set of 12k unlabeled data. Our co-training model shows the best performance over the BASELINE except when only five sentences were used for training. We believe that this is attributable to the fact that an extremely small vocabulary was used for meaningful generalization. However, once we expand the labeled examples (>20 sentences), our co-training model always outperforms the other models, both in low and high (<500 sentences) resource settings.

  In Section 6.3, we investigated the performance gains depending on the use of different domains of semi-supervised corpora. We evaluated on two languages, Chinese and Greek, using out-of-domain data: Wikipedia and a crawled corpus. In the case of Chinese, the crawled out-domain corpus shows better results than the in-domain corpus by up to 1.1 UAS and 0.9 POS points. In contrast, for Greek, the in-domain corpus (el_bdt) shows a better result than the out-domain corpus even when the size of el_bdt is only approximately 13% of the others. We determine that as Chinese has large character sets, the exposure to diverse characters is advantageous during learning regardless of the domain.

(C) What is the effect on the results of our parser when the two proposed approaches, (A) multilingual and (B) SSL, are simultaneously applied as a multilingual SSL model?

- As discussed in Section 6.3, Co-metaM show much better results than the other models, (1) without co-training, with 2.23 LAS, (2) without multilingual representations, with 4.57 LAS, and (3) both co-training and multilingual approach, with 8.29 LAS. Based on these experimental results, we determine that the two proposed approaches lead to a performance improvement. Additionally, the two methods demonstrated a positive synergy when working in cooperation with one another.

8.3 Perspectives

In this thesis, we have shown that multilingual word embeddings can be used to train a model that combines data from multiple languages. This seem to be particularly useful for low-resource scenarios. We have for example conducted different experiments around Komi: the strategy was mainly to use a knowledge transfer approach, where some information is automatically derived from corpora in different languages. We have designed experiments with different language pairs, and we have observed that the language pair Finnish–Russian is one of the most accurate one for Komi. This work has however some important limitations, the main one being that we do not know in advance which language combination will give the best results in the end. Although it is theoretically possible to build truly multilingual models (e.g., Finnish-Komi-Russian), we found that a bilingual Finnish-Komi model performed best, based on our tests on Komi. It could thus be useful to look at language typologies and see if these typologies contain usable data and information for parsing.

Apart from the multilingual approach, co-training methods also improved performance for dependency parsing in low-resource scenarios. However, it does not mean that this approach always brings some benefit, because semi-supervised learning is highly sensitive to parameter settings. For example, we observed that, with our co-training method, the ratio of labeled vs unlabeled data for training should be adjusted very precisely. More specifically, the method is prone to overfitting when one uses too much unlabeled ones (vs labeled one). It would be both interesting and useful to

investigate this issue, and try to determine what proportion of labeled and unlabeled date should be used for an optimal result, according to the context.

Appendix A

Universal Dependency

A.1 The CoNLL-U Format

Universal Dependencies (UD) is a framework for consistent annotation of grammar and the annotation format is called CoNLL-U. The format contains parts of speech, morphological features, and syntactic dependencies. The description of tagsets and examples of tagging are based on the official website[1].

In the CoNLL-U format, words are indexed with integers, while multiword tokens are indexed with integer ranges like 1-2 or 4-7. Lines representing such tokens are inserted before the first word in the range. Figure A-1 shows an example of tokenized output of a sentence with multiword tokens.

Observing an example of syntactic annotation (Figure A-2), the UPOS field con-

[1]https://universaldependencies.org/format.html

```
1-2     vámonos     _
1       vamos       ir
2       nos         nosotros
3-4     al          _
3       a           a
4       el          el
5       mar         mar
```

Figure A-1: An example of tokenization of Universal Dependency

```
1    They     they    PRON    PRP    Case=Nom|Number=Plur                2    nsubj    2:nsubj|4:nsubj
2    buy      buy     VERB    VBP    Number=Plur|Person=3|Tense=Pres     0    root     0:root
3    and      and     CONJ    CC     _                                   4    cc       4:cc
4    sell     sell    VERB    VBP    Number=Plur|Person=3|Tense=Pres     2    conj     0:root|2:conj
5    books    book    NOUN    NNS    Number=Plur                         2    obj      2:obj|4:obj
6    .        .       PUNCT   .      _                                   2    punct    2:punct
```

Figure A-2: An example of syntactic annotation of Universal Dependency

tains a part-of-speech tag from the universal POS tag set, while the XPOS optionally contains a language-specific part-of-speech tag, normally from a traditional, more fine-grained tagset. If the XPOS field is used, the treebank-specific documentation should define a mapping from XPOS to UPOS values (which may be context-sensitive and refer to other fields as well). If no language-specific tags are available, the XPOS field should contain an underscore for all words. The FEATS field contains a list of morphological features, with vertical bar (|) as list separator and with underscore to represent the empty list. All features should be represented as attribute-value pairs, with an equals sign (=) separating the attribute from the value.

The HEAD (the 7th column in Figure A-2) and DEPREL (the 8th column in Figure A-2) fields are used to encode a dependency tree over words. The DEPREL value should be a universal dependency relation or a language-specific subtype of such a relation (defined in the language-specific documentation). As in the case of morphology, syntactic annotation is only provided for words, and tokens that are not words have an underscore in both the HEAD and DEPREL fields.

The HEAD and DEPREL values define the basic dependencies which must be strictly a tree. However, in addition to these basic dependencies, treebanks may optionally provide an enhanced dependency representation that specifies additional dependency relations, for example, when dependencies propagate over coordinate structures. The enhanced dependency representation, which in general is a graph and not a tree, is specified in the DEPS field, using a list of head-relation pairs. We use colon (:) to separate the head and relation and (as usual) vertical bar (|) to separate list items and underscore for the empty list. The list is to be sorted by the index of the head: 4:nsubj|11:nsubj.

A.2 Tagsets

The Universal Dependency has 37 unified (standard) dependency relation tag sets as follows:

1. acl: clausal modifier of noun (adjectival clause)
2. advcl: adverbial clause modifier
3. advmod: adverbial modifier
4. amod: adjectival modifier
5. appos: appositional modifier
6. aux: auxiliary
7. case: case marking
8. cc: coordinating conjunction
9. ccomp: clausal complement
10. clf: classifier
11. compound: compound
12. conj: conjunct
13. cop: copula
14. csubj: clausal subject
15. dep: unspecified dependency
16. det: determiner
17. discourse: discourse element
18. dislocated: dislocated elements

19. expl: expletive
20. fixed: fixed multiword expression
21. flat: flat multiword expression
22. goeswith: goes with
23. iobj: indirect object
24. list: list
25. mark: marker
26. nmod: nominal modifier
27. nsubj: nominal subject
28. nummod: numeric modifier
29. obj: object
30. obl: oblique nominal
31. orphan: orphan
32. parataxis: parataxis
33. punct: punctuation
34. reparandum: overridden disfluency
35. root: root
36. vocative: vocative
37. xcomp: open clausal complement

The Universal Dependency has 17 Universal Part-Of-Speech (UPOS) tag set as follows:

1. ADJ: adjective
2. ADP: adposition
3. ADV: adverb
4. AUX: auxiliary
5. CCONJ: coordinating conjunction
6. DET: determiner
7. INTJ: interjection
8. NOUN: noun
9. NUM: numeral
10. PART: particle
11. PRON: pronoun
12. PROPN: proper noun
13. PUNCT: punctuation
14. SCONJ: subordinating conjunction
15. SYM: symbol
16. VERB: verb
17. X: other

Appendix B

Résumé en français de la thèse

B.1 Introduction

Le développement de systèmes automatiques, pouvant analyser avec succès des langues faiblement dotées, est une question cruciale pour le traitement automatique des langues (TAL). La plupart des systèmes d'analyse sont en effet fondés sur des techniques d'apprentissage supervisé nécessitant de grandes quantités de données annotées : la disponibilité de tels corpus est une des conditions principales pour obtenir des performances correctes, quelle que soit la tâche visée. Ce type de techniques est donc bien adapté pour les quelques langues pour lesquelles on dispose de nombreuses ressources en ligne (dictionnaires et surtout corpus annotés), mais l'approche laisse aussi de nombreuses autres langues de côté, du fait de l'absence des ressources nécessaires. Par ailleurs, produire des données annotées en grandes quantités demande beaucoup de moyens (que ce soit au niveau humain ou financier). C'est évidemment un problème majeur pour quantité de langues pour lesquelles ces données sont quasi inexistantes et pour lesquelles on ne dispose pas des moyens nécessaires pour y remédier.

Nous nous intéressons dans cet article au cas de l'analyse syntaxique (cet article reprend en partie la présentation du système développé par le LATTICE pour la tâche d'évaluation CoNLL 2017 (Lim and Poibeau, 2017a; Lim et al., 2018c))[1]. L'analyse

[1]Le code source correspondant aux réalisations présentées dans cet article est intégralement

syntaxique est une tâche classique, fondamentale pour le TAL et nécessaire pour de nombreuses applications dérivées. Les systèmes d'analyse syntaxique récents les plus performants ou les plus emblématiques du domaine (Weiss et al., 2015b; Straka et al., 2016; Ballesteros et al., 2016b), pour n'en citer que quelques-uns, reposent tous sur l'approche décrite dans le paragraphe précédent, c'est-à-dire sur une approche par apprentissage supervisé à partir de grands corpus annotés de la langue visée, souvent l'anglais.

La communauté a toutefois bien conscience qu'il faut aller au-delà des quelques langues bien dotées pour lesquelles on dispose de ressources en masse. D'une part parce qu'il y a des besoins concrets pour d'autres langues : différentes communautés linguistiques, en particulier celles liées à des langues minoritaires ou en danger, ont conscience que l'avenir passe entre autres par l'informatisation des langues et la mise au point d'outils performants, y compris pour le grand public. D'autre part, parce que les langues moins bien dotées posent souvent des questions extrêmement intéressantes sur le plan linguistique, et qui ont été trop longtemps négligées jusqu'ici. Les systèmes entraînés seulement sur l'anglais ne donnent qu'une vision étriquée du TAL, visant l'analyse d'une langue analytique à la morphologie extrêmement pauvre. Au-delà de la quantité de données disponible, la prise en compte de la complexité linguistique, notamment morphosyntaxique, est un autre élément fondamental.

Pour prendre un exemple récent, la tâche d'évaluation lors des conférences *Computational Natural Language Learning* 2017 et 2018 (*CoNLL shared task*) (Zeman, D. *et al.*, 2017; Zeman et al., 2018b) portait sur environ cinquante langues (plus précisément quarante-neuf en 2017 et cinquante-sept en 2018), soit à peu près toutes les langues pour lesquelles des données annotées syntaxiquement sont disponibles en quantité significative au format UD (Universal Dependencies) (Nivre et al., 2016b). C'est probablement le défi d'analyse syntaxique le plus ambitieux jamais organisé de ce point de vue, mais le chiffre de cinquante langues est à considérer en regard des six mille langues estimées dans le monde. Et même si l'on ne considère que les langues pour lesquelles des données écrites sont disponibles, les cinquante-sept langues de

disponible sur le site : `https://github.com/jujbob`.

CoNLL 2018 ne permettent de couvrir qu'un échantillon extrêmement restreint de ce qui existe.

En ce qui concerne l'analyse syntaxique automatique, l'approche monolingue et supervisée (c'est-à-dire par apprentissage automatique à partir de corpus annotés représentatifs) est évidemment la plus répandue (l'alternative étant les systèmes reposant sur des grammaires entièrement élaborées à la main). Des chercheurs essaient toutefois depuis un certain temps de concevoir des systèmes multilingues. L'approche multilingue a donné des résultats encourageants aussi bien pour les langues faiblement dotées (Guo et al., 2015a, 2016) que pour les langues déjà bien dotées, et disposant déjà de ressources comme des dictionnaires et des corpus représentatifs (Ammar et al., 2016a,d). Dans ce dernier cas, l'idée est de n'avoir à maintenir qu'un seul modèle d'analyse et de pouvoir l'appliquer ensuite aux différentes langues constitutives du modèle. L'approche multilingue a de plus un avantage, même pour les langues bien dotées : en mettant ensemble plusieurs langues, on peut espérer mieux analyser certains mots ou certaines constructions rares sans dégrader les performances sur des phénomènes plus classiques. Il semble donc y avoir toujours un gain possible.

Ainsi, Ammar et ses collègues (cf. références déjà citées) ont proposé des études portant sur des langues indo-européennes pour lesquelles on dispose déjà de ressources importantes. Ils ont démontré que l'approche *via* un modèle multilingue donne généralement de meilleurs résultats que les modèles monolingues correspondants pour les langues visées.

D'une manière générale, c'est surtout pour les langues moins bien dotées que l'approche multilingue est intéressante. Cette approche peut en fait être mise en œuvre de deux façons différentes. La première consiste à projeter des annotations disponibles d'une langue donnée vers une langue peu dotée *via* un corpus parallèle. Cette approche a été utilisée à plusieurs reprises (notamment dans les références déjà citées (Guo et al., 2015a; Ammar et al., 2016d)), mais elle nécessite de disposer de données parallèles en quantité suffisante, ce qui est souvent problématique. Le transfert de connaissances nous semble aussi problématique en soi, dans la mesure où cela suppose une relative similarité de structure entre les deux langues visées. Si les deux

langues sont trop différentes, l'approche fonctionnera mal, ce qui est insatisfaisant à la fois sur le plan pratique et sur le plan théorique. La seconde approche, celle que nous adoptons ici, vise à produire directement un modèle multilingue, pouvant fonctionner pour plusieurs langues, tout en relâchant les contraintes de structure (voir aussi Scherrer et Sagot 2014 pour une expérience visant l'étiquetage morphosyntaxique de langues non dotées par transfert depuis une langue dotée, sans utilisation de corpus parallèles).

Dans cet article, nous proposons une approche d'analyse syntaxique utilisant des méthodes à l'état de l'art pour des langues disposant de très peu de ressources structurées (mais pour lesquelles des corpus bruts, c'est-à-dire non annotés, sont disponibles). Notre approche ne nécessite qu'un petit dictionnaire bilingue (ou, *a minima*, une liste élaborée manuellement de mots de la langue visée avec leur traduction dans la langue cible) et l'annotation syntaxique (au format UD) manuelle d'une poignée de phrases de la langue visée. Ces données peuvent être mises au point en quelques heures seulement (moins d'une journée) par une personne connaissant la langue en question. Comme souvent dans ce type de schéma, l'hypothèse que nous faisons est qu'il est possible de transférer des connaissances d'une langue à l'autre entre langues apparentées, mais nous ne faisons pas pour autant l'hypothèse d'une similarité de structure stricte entre les langues. Le point principal est d'identifier des éléments communs au niveau lexical, *via* des plongements de mots (*word embeddings*) multilingues. La source première de comparaison entre une phrase en langue source et une phrase en langue cible est donc lexicale et sémantique, plus que syntaxique (même si la syntaxe joue aussi un rôle primordial, bien évidemment ; c'est d'ailleurs pour cela que les langues choisies pour élaborer le modèle d'analyse doivent être sélectionnées avec attention).

Nous faisons aussi l'hypothèse que les performances dépendent largement des langues utilisées pour élaborer le modèle d'analyse. *A priori*, des langues de même famille et, au sein d'une même famille, des langues étroitement apparentées sont évidemment les meilleurs candidats *a priori*, mais les contacts linguistiques peuvent aussi jouer un rôle. Il existe en effet de nombreux cas de langues où les locuteurs sont

tous au moins bilingues et s'expriment le plus souvent dans la langue « dominante », ce qui peut affecter largement leur langue maternelle. Ces phénomènes sont connus, mais relativement peu étudiés, et le TAL peut aider à donner une base statistique et quantitative à l'étude de ces phénomènes d'emprunts et de contagion linguistique. Au cours de l'étude, nous détaillerons plusieurs modèles mettant en jeu des langues génétiquement apparentées et non apparentées, afin de mieux comprendre les limites ou les possibilités de transfert de modèles entre différentes familles de langues.

Afin de mener à bien nos expériences, nous nous penchons sur deux langues finno-ougriennes peu dotées et ayant fait l'objet de peu de recherches en TAL jusqu'ici. Le same du nord[2] est une langue parlée par environ 20 000 personnes au nord de la péninsule scandinave (Suède, Norvège, Finlande). Il existe une dizaine de langues sames (25 000 à 30 000 locuteurs environ au total), mais le same du nord est de loin la langue la plus répandue et celle qui est la mieux supportée par les autorités et les médias (il existe des journaux, ainsi qu'une radio et des émissions de télévision soutenues publiquement). Nous nous intéressons par ailleurs au komi-zyriène[3] (parfois abrégé en komi par la suite), une langue finno-ougrienne de Russie assez éloignée du same. Quasiment tous les locuteurs komis parlent aussi le russe, qui est leur langue essentielle de communication (souvent même entre locuteurs komis). Il y a environ 150 000 locuteurs komis.

Les deux langues (same du nord et komi) sont dans des situations différentes mais possèdent aussi de nombreux points communs pour leur avenir : tous les locuteurs sont bilingues, ils utilisent essentiellement une autre langue de communication (le russe pour les Komis, le finnois, le suédois ou le norvégien pour les Sames du nord) et le komi comme le same du nord étaient dévalorisés jusqu'à récemment. La situation a toutefois changé depuis les années 1980 : les communautés ont pris conscience de l'importance de la préservation de leur langue maternelle, des campagnes de numérisation ont permis de rendre disponibles les écrits existants (la production écrite disponible s'étend sur un siècle environ) et surtout la langue est transmise

[2] glottolog.org/resource/languoid/id/nort2671
[3] glottolog.org/resource/languoid/id/komi1268

activement aux enfants, au moins dans certaines régions et dans certaines communautés. Les Sames comme les Komis sont aujourd'hui convaincus de l'importance de développer des outils informatiques pour aider à maintenir et développer leur langue.

Sur le plan informatique, la situation des deux langues n'est pas la même. Le centre d'analyse linguistique de l'université de Tromsø (projet Giellatekno[4]) développe depuis plusieurs années des outils permettant la description des langues finno-ougriennes en général, et du same en particulier. On dispose donc de dictionnaires électroniques assez complets pour le same du nord, incluant les paradigmes de flexion et de conjugaison, ce qui permet d'un côté de générer l'essentiel des formes de la langue et de l'autre, d'analyser dynamiquement des formes linguistiques complexes. Les outils d'analyse (analyse morphosyntaxique et syntaxique) sont en revanche limités, l'approche de l'équipe de Tromsø reposant uniquement sur des automates à nombre fini d'états (éventuellement pondérés), mais sans recours à l'apprentissage automatique. Pour le komi, la situation est beaucoup moins favorable que pour le same du nord. L'équipe de Tromsø a commencé à décrire le komi mais les données disponibles restent relativement embryonnaires.

Il faut enfin noter que, fin 2017, un corpus annoté au format UD a été rendu disponible pour le same du nord. Les données disponibles pour le same sont donc aujourd'hui suffisamment massives pour pouvoir évaluer précisément des analyseurs pour cette langue, mais aussi pour développer des analyseurs de manière traditionnelle, à partir d'un corpus d'entraînement important, comme lors de la campagne CoNLL 2018. Pour le komi, la situation est très différente et il n'existait, à notre connaissance, aucun corpus syntaxiquement annoté pour cette langue au moment où nous avons commencé nos expériences. Les quelques corpus électroniques disponibles sont liés à des travaux réalisés à des fins de documentation linguistique (Blokland et al., 2015; Gerstenberger et al., 2016) : ces corpus sont relativement petits et difficiles d'utilisation dans une perspective de TAL. Notons enfin que ces langues disposent de données numérisées en quantités relativement importantes, ce qui est utile pour l'élaboration de plongements de mots et permet par ailleurs de compenser en partie

[4] http://giellatekno.uit.no/

le manque de ressources.

L'article est structuré comme suit : nous présentons dans un premier temps l'état de l'art en matière d'analyse syntaxique multilingue (section 2). Nous présentons ensuite le modèle lexical mis au point pour nos expériences (section 3), puis l'architecture du modèle d'analyse à base de réseaux de neurones bidirectionnels, dit BiLSTM (section 4). Nous présentons ensuite le détail des expériences sur le same du nord et le komi-zyriène (section 5), avant de finir par une discussion de ces résultats (section 6), une conclusion et quelques perspectives (section 7). Nous présentons enfin les données mises au point pour le komi-zyriène (embryon de corpus annotés au format Universal Dependencies), ainsi que quelques exemples en annexe à cet article.

B.2 État de l'art

Depuis les travaux pionniers de Hwa *et al.* 2005, de nombreux groupes se sont intéressés à la mise au point d'analyseurs syntaxiques multilingues, et/ou au transfert de connaissances d'une langue à l'autre, que ce soit dans un cadre d'analyse syntaxique ou pour d'autres tâches, par exemple l'analyse morphosyntaxique. La plupart des méthodes supposent un corpus parallèle, avec des annotations d'un côté (langue source), et non de l'autre (langue cible). La tâche repose alors le plus souvent sur une stratégie de transfert d'étiquettes (c'est-à-dire d'annotations) d'une langue à l'autre, en tenant compte des spécificités de chaque langue. D'autres approches évitent le transfert direct en proposant des stratégies plus ou moins élaborées visant tout d'abord à produire des représentations multilingues avancées, pour éviter les problèmes de transfert d'information. L'apprentissage du parseur est alors réalisé directement sur le modèle enrichi ainsi défini.

Comme on l'a dit, les approches reposant sur la projection d'annotations utilisent un corpus parallèle annoté dans la langue source. Ces annotations sont projetées sur le corpus en langue cible, à partir de quoi un analyseur syntaxique peut être inféré par apprentissage automatique (Smith and Eisner, 2009; Zhao et al., 2009; Liu et al., 2013a). Cette approche est efficace mais elle est principalement confrontée à

des problèmes liés à l'alignement des mots lors de l'étape de projection d'annotations. Les méthodes proposées reposent sur des algorithmes de projection robustes prenant en compte un contexte large (Das and Petrov, 2011), ou sur des ressources extérieures comme Wikipédia (Kim et al., 2014) ou WordNet (Khapra et al., 2010), ou bien encore sur la correction *a posteriori* de certaines étiquettes de manière heuristique (Kim et al., 2010).

L'alternative consiste à élaborer directement des modèles d'analyse multilingues grâce aux informations contenues dans des corpus parallèles, ou grâce à des connaissances extérieures, provenant en général de dictionnaires bilingues. L'approche consiste à « apprendre » un modèle d'analyse unique, conjointement pour les deux langues. Des règles, spécifiées ou non à la main, permettent ensuite d'adapter l'analyse et de tenir compte des spécificités des langues considérées. En dehors de l'analyse syntaxique, les modèles multilingues ont été appliqués à d'autres problèmes de traitement automatique des langues, comme la reconnaissance des entités (Zhuang and Zong, 2010) ou l'analyse des rôles sémantique (Kozhevnikov and Titov, 2012).

D'autres méthodes enfin empruntent aux deux approches précédentes pour créer un modèle d'analyse hybride. Il s'agit alors de produire dans un premier temps une représentation en grande partie indépendante des langues (ou plutôt mêlant les différentes langues dans un seul espace de représentation partagé) puis à « apprendre » un analyseur à partir de cette représentation abstraite et « *crosslingue* » (Täckström et al., 2012a). Différents types de ressources peuvent être utilisés dans ce cadre, notamment des corpus parallèles et/ou des dictionnaires bilingues.

Les systèmes plus récents reposent quasi systématiquement sur la notion de plongement de mots (« *word embeddings* » en anglais). Comme précédemment, les systèmes utilisent soit des dictionnaires soit des corpus bilingues, voire des documents parallèles (des légendes d'images ou des pages Wikipédia, par exemple) comme source de connaissances pour inférer un modèle bilingue. Une grande variété d'approches a pu être proposée, mais plusieurs auteurs ont montré que ce sont les données utilisées pour l'apprentissage, plus que l'architecture ou les algorithmes utilisés, qui ont une influence majeure sur le résultat final (Levy et al., 2017; Ruder et al., 2017). En

gros, à partir des mêmes données, on obtient des résultats très similaires avec des approches en apparence différentes, car dans les faits les algorithmes eux-mêmes sont au final relativement similaires, quel que soit leur point de départ.

L'article de Ruder *et al.* 2017 présente en détail les méthodes fondées sur des représentations lexicales riches. Trois approches sont possibles pour obtenir des plongements de mots bilingues (ou multilingues si on généralise l'approche) : *i*) une première approche consiste à obtenir des représentations sous forme de plongements de mots indépendants pour les deux langues visées (selon la technique introduite par Mikolov *et al.* 2013a par exemple), puis à mettre en relation les deux représentations obtenues par projection d'un espace sémantique sur l'autre, comme par exemple dans (Artetxe et al., 2016b) ; *ii*) élaborer directement un modèle bilingue à partir d'un corpus dans lequel des phrases (voire des documents) des deux langues visées sont déjà en rapport direct (corpus parallèle ou similaire) (Gouws and Søgaard, 2015; Gouws et al., 2015) ou *iii*) utiliser un corpus parallèle et un espace sémantique pour chaque langue simultanément (Luong et al., 2015), afin d'obtenir la représentation la plus adéquate en fonction des données fournies en entrée au système.

La mise au point de plongements de mots bilingues et multilingues est un secteur clé de la recherche en TAL à l'heure actuelle. Les tendances visent à réduire les contraintes sur les données en entrée pour obtenir des approches rapides, efficaces et surtout simples à mettre en œuvre. Ainsi, Artexte *et al.* 2017 montrent que quelques dizaines (une cinquantaine environ) de couples de mots bien choisis sont suffisants pour obtenir des plongements de mots bilingues de bonne qualité, au lieu des quelques milliers utilisés dans les expériences précédentes. Une équipe de Facebook a même récemment montré qu'on pouvait produire des plongements de mots bilingues sans données parallèles ni thésaurus bilingue (Conneau et al., 2017). Cet article a eu un relatif retentissement, mais ses conclusions doivent être nuancées, les résultats n'étant satisfaisants que si les corpus utilisés sont très proches stylistiquement et thématiquement (Vulić et al., 2018).

Dans cet article, nous utiliserons la première méthode qui est facile à mettre en œuvre et qui semble obtenir des résultats très satisfaisants malgré sa simplicité. En ce

qui concerne l'architecture du système, nous nous inspirons de Guo *et al.* 2015a. La principale différence est que Guo et ses collègues utilisent une approche délexicalisée pour leur analyse, tandis que, conformément au système de Ammar *et al.* 2016a, nous avons recours à des représentations multilingues riches pour l'analyse.

B.3 Mise au point d'un modèle lexical multilingue

Dans la mesure où les langues que nous souhaitons analyser sont finno-ougriennes, nous nous tournons naturellement vers le finnois pour obtenir des connaissances pertinentes pour l'analyse. Le same du nord a été en contact depuis plusieurs siècles avec le finnois et ce sont surtout deux langues étroitement liées sur le plan génétique (Aikio, 2012, p. 67–69). Le komi est plus éloigné du finnois, mais le finnois reste la langue la plus proche sur le plan linguistique pour laquelle on dispose de ressources importantes. Nous nous sommes également intéressés au russe, sachant que le komi est depuis longtemps en contact avec le russe, et que tous les locuteurs komis sont bilingues (ils parlent aussi russe). On peut donc s'attendre à ce que le russe ait influencé le komi et que ce soit une autre source de connaissances pertinente, les structures copiées du russe étant fréquentes en komi, surtout à l'oral (Leinonen, 2006, p. 241).

Enfin, des expériences avec un corpus anglais seront aussi effectuées : l'anglais n'a pas de lien génétique avec le komi ou le same, ce qui le rend intéressant comme « langue de contrôle » (c'est-à-dire pour comparer les performances obtenues par rapport à des langues de la même famille linguistique, par exemple). Il faut toutefois faire attention aux expériences avec l'anglais : la masse de données disponible pour cette langue permet souvent d'obtenir des résultats relativement corrects malgré tout, la quantité permettant de suppléer partiellement au manque de qualité (ou du moins à l'absence de similarité entre l'anglais et les langues visées lors de l'analyse). L'anglais peut aussi avoir une influence bénéfique en apportant des éléments d'information pertinents pour le niveau lexical-sémantique, ce qui est utile même pour une tâche d'analyse syntaxique.

B.3.1 Préparation de ressources linguistiques

Comme nous l'avons déjà dit, pour les expériences qui suivent nous avons recours aux lexiques bilingues disponibles sur le site Giellatekno[5]. Nous avons par ailleurs utilisé les plongements de mots FastText proposés par Facebook en mai 2017 pour le finnois et le russe (Bojanowski et al., 2016b). Il nous faut ensuite générer des plongements de mots similaires pour le same et le komi. Pour ce faire, nous avons en premier lieu recours au corpus Wikipédia, mais il s'agit d'un corpus relativement petit pour les langues visées. Nous le complétons alors avec des corpus disponibles dans le domaine public[6]. Nous produisons enfin les plongements de mots monolingues pour chacune des langues considérées à partir du module FastText de Facebook.

B.3.2 Projection de plongements de mots pour obtenir une ressource multilingue

Dans la section précédente, nous avons décrit comment nous avons obtenu des plongements de mots monolingues pour chaque langue considérée mais, logiquement, chacun de ces plongements a son propre espace vectoriel. Afin d'obtenir des plongements de mots bilingues (voire multilingues, en répétant l'opération plusieurs fois), c'est-à-dire des plongements de mots partageant un espace vectoriel unique, nous utilisons la méthode de transformation linéaire proposée par Artexte *et al.* 2016b. Pour effectuer cette transformation, il est nécessaire d'avoir un petit lexique bilingue qui va permettre de définir des « points d'attache » entre les deux espaces vectoriels à mettre en regard. Selon les comparaisons présentées dans Artexte *et al.* 2017, p. 457, la taille des dictionnaires que nous utilisons ici est bien supérieure à ce qui est nécessaire pour effectuer la mise en correspondance des deux espaces vectoriels des langues concernées

[5]Les dictionnaires pour le same sont disponibles ici : `http://dicts.uit.no/smedicts.eng.html` et les autres dictionnaires sont disponibles à l'adresse suivante : `https://gtsvn.uit.no/langtech/trunk/words/dicts/`. Tous ces dictionnaires sont relativement complets et disponibles sous forme libre, avec une licence GNU GPLv3.

[6]Notamment les livres numérisés de la collection Fenno-Ugrica (`https://fennougrica.kansalliskirjasto.fi/`) qui ont été corrigés manuellement par le laboratoire d'appui à la production de ressources électroniques pour les langues régionales de Syktyvkar (`http://komikyv.org/`). Pour le same du nord, nous utilisons le corpus gratuit SIKOR (`http://hdl.handle.net/11509/100`), disponible avec une licence CC-BY 3.0.

(tableau 1). Il serait intéressant d'essayer avec de très petits dictionnaires, de quelques dizaines de mots au maximum, afin d'estimer la dégradation des performances dans ce cas de figure, mais comme nous disposons de dictionnaires bilingues contenant plusieurs milliers de mots, nous n'avons pas à ce stade exploré de contextes plus difficiles (mais cela sera nécessaire si l'on doit s'intéresser à d'autres langues ouraliennes, moins bien dotées que le same du nord ou le komi-zyriène).

Paire linguistique	Taille du dictionnaire	Taille des plongements
Finnois-same du nord	12 398	2,4 Go
Same du nord-finnois	10 541	2,4 Go
Same du nord-anglais	1 499	1,4 Go
Finnois-komi	12 879	2,3 Go
Komi-anglais	8 746	7,5 Go
Russe-komi	12 354	5,7 Go

Table B.1: Taille des dictionnaires et des plongements de mots liés générés à partir des différents dictionnaires (il s'agit de dictionnaires de formes fléchies, ce qui explique que la taille du dictionnaire finnois-same du nord soit par exemple différente de celle du dictionnaire same du nord-finnois).

La méthode de projection des deux espaces sémantiques l'un sur l'autre est la suivante. Soit deux plongements de mots différents, l'un X correspondant à la langue cible, et l'autre Y à la langue source, et soit $D=\{(x_i,y_i)\}_{i=1}^{m}$ ($o\grave{u}$ $x_i \in X$, $y_i \in Y$) la ressource obtenue consistant en une collection de plongements de mots bilingues. Le but est, dès lors, de trouver la matrice de transformation W telle que xW soit la meilleure approximation de y. On obtient ce résultat en minimisant la somme des carrés des erreurs, suivant Mikolov *et al.* 2013c:

$$\arg\min_{W} \sum_{i=1}^{m} \|x_i W - y_i\|^2 \tag{B.1}$$

Une dégradation importante des résultats peut se produire si la transformation linéaire est appliquée à deux plongements de mots sans autre contrainte. Pour répondre à ce problème, Artetxe *et al.* 2016b proposent une méthode de correspondance orthogonale qui permet de garder un niveau de performance correct. C'est cette variante de l'algorithme que nous avons utilisée ici.

B.3.3 Corpus annotés au format Universal Dependencies

Nous avons également besoin de corpus annotés pour nos expériences, au moins pour montrer leur apport quand ils sont disponibles. Nous avons utilisé des corpus pour l'anglais, le finnois et le russe : tous provenaient de l'initiative Universal Dependencies et peuvent être trouvés en ligne[7].

B.4 Modèle d'analyse en dépendances *crosslingue*

Les analyseurs syntaxiques traditionnels emploient des méthodes d'apprentissage supervisé fondées sur des séries de traits définis en grande partie manuellement. Le développeur doit en fait définir des combinaisons pertinentes (*feature functions*) de traits et de relations entre ceux-ci, afin que le système soit capable de déterminer les relations entre têtes et dépendants[8]. La définition manuelle de ces combinaisons de traits est une tâche difficile et en grande partie arbitraire, que tous les concepteurs de systèmes cherchent à contourner.

Les systèmes récents à base de réseaux de neurones ont plutôt recours à des méthodes automatiques permettant de simplifier le problème, en laissant le soin à la machine de déterminer les combinaisons de traits pertinentes. Ainsi, Chen et Manning 2014b ont proposé d'utiliser des classificateurs non linéaires intégrés dans un modèle de réseau neuronal. Avec cette méthode, les caractéristiques lexicales et non lexicales sont encodées dans des vecteurs qui peuvent être concaténés pour alimenter un classificateur non linéaire. Cette approche présente deux avantages : *i*) les classificateurs non linéaires ont globalement de meilleures performances que les

[7] Sur le projet Universal dependencies, voir `http://universaldependencies.org`. Nous avons utilisé les corpus arobés suivants, dans leur version 2.1 : `https://github.com/UniversalDependencies/UD_English-EWT` (anglais), `https://github.com/UniversalDependencies/UD_Russian-GSD` (russe) et `https://github.com/UniversalDependencies/UD_Finnish-TDT` (finnois).

[8] "*Traditionally, state-of-the-art parsers rely on linear models over hand-crafted feature functions. The feature functions look at core components (e.g. "word on top of stack", "leftmost child of the second-to- top word on the stack", "distance between the head and the modifier words"), and are comprised of several templates, where each template instantiates a binary indicator function over a conjunction of core elements (resulting in features of the form "word on top of stack is X and leftmost child is Y and ...").*" (Kiperwasser and Goldberg, 2016b).

classifieurs linéaires pour identifier les relations entre les éléments pertinents pour l'analyse, et *ii*) cette approche réduit drastiquement le travail manuel dans la mesure où le réseau de neurones se fonde essentiellement sur les caractéristiques calculées par les classifieurs.

B.4.1 Architecture du système d'analyse

Notre approche est ici similaire à celle de Chen et Manning 2014b et de Kiperwasser et Goldberg 2016b pour la partie analyse, mais nous utilisons des plongements de mots multilingues, alors que nos prédécesseurs s'en tiennent à un système monolingue.

Représentations LSTM bidirectionnelles. Les progrès récents en TAL sont largement dus à des représentations sous forme de traits portant des informations efficaces pour l'analyse des relations entre les mots de la phrase (Cho, 2015; Huang et al., 2015). Une représentation LSTM bidirectionnelle (bi-LSTM) est un type de réseau de neurones récurrent, où chaque élément dans la séquence à analyser est lui-même représenté par un vecteur. L'algorithme procède en produisant des représentations préfixes (dites *forward* car la phrase est analysée de gauche à droite) et des représentations suffixes (dites *backward* car la phrase est alors analysée de droite à gauche). Un item est représenté par la concaténation de ses deux contextes, gauche et droit. Soit par exemple la phrase $t = (t_1,t_2,...,t_n)$, dans laquelle le symbole $\circ$ dénote une opération de concaténation. La fonction LSTM bidirectionnelle correspond à : $\text{BiLSTM}(t_{1:n}, i) = \text{LSTM}_{Forward}(t_{1:i}) \circ \text{LSTM}_{Backward}(t_{i:n})$.

L'architecture est exactement la même que celle du BIST-parser (Kiperwasser and Goldberg, 2016b). Nous renvoyons donc le lecteur à cet article fondateur pour connaître les détails de l'architecture du système qui est de ce point de vue relativement standard. Nous avons juste étendu cet analyseur de manière à le rendre multilingue, ce qui oblige à prendre en compte des représentations contextuelles construites par le module bi-LSTM multilingue (un code pour chaque mot, dit *one hot encoding*, permet de déterminer la langue associée).

Représentation lexicale. Soit une phrase en entrée $t = (t_1,t_2,...,t_n)$, une forme lexicale w, une étiquette morphosyntaxique correspondante p, un plongement de mots

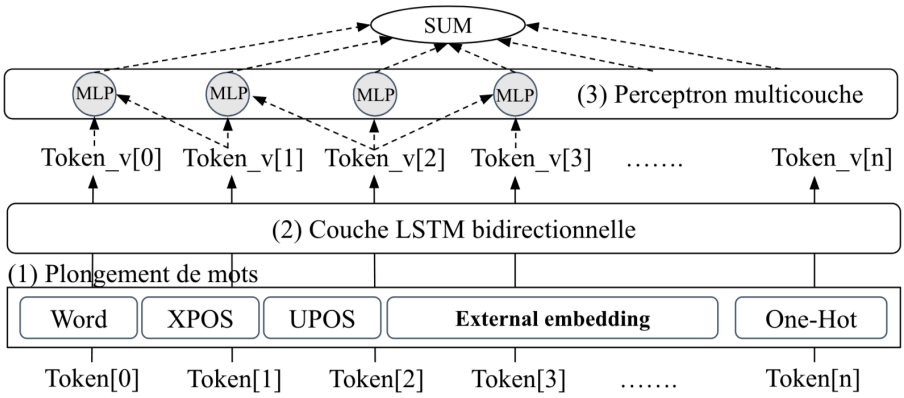


Figure B-1: Architecture du réseau de neurones

obtenu préalablement xw et une valeur de codage de la langue concernée l, un mot t_i (*token*) est défini comme : $t_i = e(w_i) \circ e(p_i) \circ e(xw_i) \circ e(l_i)$, où e réfère au plongement de chaque trait et $e(xw_i)$ est le plongement de mots déjà présenté en section 3. Nous ajoutons un code pour désigner la langue concernée, comme dit précédemment (Naseem et al., 2012; Ammar et al., 2016a). La plupart des analyseurs monolingues utilisent des traits comme $e(w_i)$ et $e(p_i)$, ainsi que d'autres éléments comme la distance entre la tête et le dépendant, ou d'autres traits spécifiques calculables à partir du corpus UD. Notez enfin que t_i de BiLSTM($t_{1:n}$, i) permet de stocker les contextes *forward* et *backward* du LSTM.

B.4.2 Modèle d'analyse

Il existe deux approches principales en matière d'analyse syntaxique en dépendance. La première est fondée sur la notion de transition (Nivre, 2004), l'autre sur la notion de graphe (McDonald et al., 2005c). Nous utilisons ici une approche à base de graphes héritée du BIST-parser. L'approche semble efficace pour les corpus au format Universal Dependencies, et on renverra à Dozat *et al.* 2017a pour une comparaison détaillée et argumentée des deux approches.

À partir des représentations des mots et de leurs annotations dans la couche BiLSTM, le BIST-parser produit un arbre candidat pour chaque couple dépendant-mot-tête. Les scores attachés aux différents arbres candidats sont ensuite calculés à l'aide

d'un perceptron multicouche (MLP), utilisé comme simple fonction de pondération (*scoring function*). Enfin, le système choisit les meilleurs arbres d'analyse en dépendance sur la base de la somme des scores attachés aux différents sous-arbres. Pour plus d'informations sur le modèle à base de graphes et sur le modèle de pondération d'arcs utilisé par le BIST-parser, voir (Taskar et al., 2005) et (McDonald et al., 2005b).

B.5 Expériences

Nous présentons dans cette section les expériences que nous avons menées sur le same du nord et sur le komi-zyriène.

Corpus disponibles. Le same était une des langues dites *surprise language* de la campagne d'évaluation CoNLL 2017 : seulement vingt phrases étaient fournies pour l'entraînement et les participants n'avaient que quelques jours pour produire un système opérationnel. Le komi n'était pas inclus dans l'évaluation CoNLL 2017 mais nous avons choisi cette langue pour des raisons linguistiques (il s'agit d'une langue finno-ougrienne, comme le same) et parce qu'elle correspond à un cas typique de langue sous-dotée, comme on l'a vu dans l'introduction. Pour pouvoir mener à bien nos expériences, nous avons produit un corpus annoté composé de dix phrases komies pour l'entraînement et soixante-quinze phrases pour le test (ce corpus contient aujourd'hui près de trois cents phrases et grossit régulièrement, mais moins d'une centaine de phrases étaient disponibles au moment des expériences rapportées ici). Une présentation du corpus komi et des problèmes d'annotation rencontrés est disponible à la fin de cet article, en annexe.

Étiquettes morphosyntaxiques utilisées. Dans les expériences rapportées ici, nous nous fondons sur les étiquettes (catégories morphosyntaxiques) fournies par UDpipe (Straka et al., 2016) pour le same et, en l'absence d'analyseur morphosyntaxique disponible pour le komi, nous utilisons les étiquettes posées à la main pour cette langue (*gold*). Lors de la campagne CoNLL 2017, l'analyse se fondait aussi sur des étiquettes de référence pour le same du nord, mais nous préférons recourir ici à un

analyseur morphologique pour le same afin de rendre les conditions expérimentales plus proches de la réalité. Nous n'utilisons pas de traits morphologiques autres que ceux du corpus de référence ou ceux fournis par UDpipe pour le same.

Le fait d'utiliser des étiquettes morphosyntaxiques de référence est bien évidemment quelque peu artificiel, mais permet de se focaliser uniquement sur le niveau syntaxique. Il n'en reste pas moins que la production d'analyseurs morphosyntaxiques performants est évidemment une condition nécessaire pour produire des analyses en situation réelle. La tâche commune CoNLL 2018 impliquait de développer une chaîne complète allant du texte brut à l'analyse syntaxique, et l'expérience a montré que les systèmes conservent ainsi des performances satisfaisantes. On renverra donc le lecteur aux actes de la tâche commune CoNLL 2018 sur ce point (Zeman et al., 2018b).

Conditions d'entraînement du système. Comme nous voulons explorer des scénarios pour des langues faiblement dotées, nous avons supposé que l'on ne disposait pas de données de développement permettant d'ajuster les paramètres du système (même dans le cas du same, pour lequel il existe maintenant des données importantes, notamment le corpus annoté syntaxiquement au format UD). Nous avons donc limité les expériences, notamment lors de la phase d'apprentissage, en considérant toutes les données disponibles une fois, sans arrêt anticipé, suivant Guo *et al.* 2016. D'autres stratégies seraient possibles (plusieurs itérations en faisant varier les phrases utilisées lors de l'apprentissage par exemple), mais le gain observé sur les résultats est minime et souvent non significatif. Ce type d'approches pose en outre des problèmes de réplicabilité et nous l'avons donc laissé de côté. Enfin, il faut noter que, pour l'élaboration d'un modèle multilingue, les différentes sources de données sont de taille très déséquilibrée. Pour pallier ce problème, et suivant les travaux antérieurs de Guo *et al.* 2016, nous avons effectué vingt fois plus d'itérations pour les langues faiblement dotées que pour les autres langues.

Comparaison avec la tâche commune CoNLL 2017. Nous avons utilisé les mêmes conditions pour l'entraînement de notre système dans les expériences décrites ici que pour la tâche commune CoNLL. En particulier nous n'avons pas de corpus de développement (nous disposons juste de vingt phrases annotées pour le same et de

Équipe	Score LAS	Score UAS
C2L2 (Ithaca)	48,96	58,85
IMS (Stuttgart)	40,67	51,56
HIT-SCIR (Harbin)	38,91	52,51
Notre système	**28,39**	**42,72**

Table B.2: Meilleurs résultats (officiels) pour le same lors de la tâche commune CoNLL 2017 et résultat obtenu par le LATTICE lors de cette même évaluation

dix phrases annotées pour le komi pour la mise au point du système, comme dit plus haut).

Le tableau 2 présente les résultats obtenus par les trois meilleures équipes sur le same lors de la tâche commune CoNLL 2017, ainsi que les résultats de notre propre système. Il est évident, au vu de ces résultats, que notre système était alors loin d'être aussi performant que les meilleurs systèmes sur le same, à savoir ceux de Cornell (Shi et al., 2017b) , de Stuttgart (Björkelund et al., 2017b) ou de Harbin (Che et al., 2017b).

Lors de CoNLL 2017, C2L2 (Cornell Univ.) a obtenu les meilleures performances pour le same avec une approche par transfert délexicalisé (en utilisant un corpus de finnois pour l'entraînement et un corpus de développement de vingt phrases en same pour ajuster les paramètres du système, sans utilisation de traits lexicaux, c'est-à-dire en se fondant uniquement sur les étiquettes morphosyntaxiques et non sur les mots eux-mêmes). IMS (Stuttgart) a utilisé une approche similaire (approche par transfert délexicalisé) en utilisant pour l'entraînement quarante corpus différents encodés au format UD, et a ainsi obtenu le deuxième meilleur résultat.

Comparaison avec la tâche commune CoNLL 2018. Le same était à nouveau une langue de test lors de la campagne d'évaluation CoNLL 2018. Le meilleur système a obtenu les résultats suivants lors de la campagne 2018 : 69,87 LAS et 76,66 UAS. Ces résultats sont bien meilleurs que ceux rapportés pour l'évaluation CoNLL 2017 (tableau 2) ou même dans cet article (tableau 3), mais en 2018 des données d'entraînement importantes étaient fournies pour le same (il s'agissait essentiellement du corpus de same au format UD publié après la campagne d'évaluation 2017, comme indiqué dans l'introduction). Il est donc important de souligner que les résultats

obtenus sur le corpus CoNLL 2018 ne sont en rien comparables avec les résultats 2017, où seules vingt phrases étaient disponibles pour la mise au point des systèmes.

Les résultats du meilleur système lors de la campagne d'évaluation CoNLL 2018 (69,87 LAS et 76,66 UAS) donnent malgré tout une idée de l'état de l'art pour une langue à morphologie riche, comme le same, quand on dispose d'un corpus d'entraînement moyennement volumineux. Ils permettent aussi d'avoir une idée de l'écart de performance entre une langue pour laquelle on dispose de données annotées et une langue pour laquelle on ne dispose pas de telles ressources (entre 10 et 15 points de différence environ), et aussi une idée de l'écart par rapport à l'anglais (là aussi, entre 10 et 15 points de différence – ces chiffres sont évidemment à prendre avec précaution car il faudrait faire d'autres expériences, avec d'autres langues et des conditions expérimentales plus directement comparables pour obtenir des résultats vraiment fiables). On confirme là, par l'observation, des résultats très évidents : une langue synthétique à morphologie riche est plus complexe à analyser qu'une langue analytique avec une complexité morphologique moindre, et un corpus d'entraînement de grande taille est aussi un facteur majeur d'amélioration des performances. Pour le reste, redisons-le : les résultats CoNLL 2018 ne sont en rien comparables aux résultats 2017 du fait des conditions expérimentales radicalement différentes pour le same lors de ces deux campagnes.

B.6 Résultats et analyse

Les résultats pour le same du nord sont donnés dans le tableau 3, et les résultats pour le komi-zyriène dans le tableau 4. Les résultats du tableau 3 diffèrent de ceux du tableau 2 car les expériences faites après la campagne CoNLL 2017 ont permis de mieux utiliser les vingt phrases fournies pour la mise au point du système et surtout de tester différentes combinaisons de langues afin d'identifier le modèle le plus performant pour la tâche. On voit que le système de base est ainsi plus performant que le système officiel ayant participé à CoNLL 2017, même sans ressources extérieures ni modèle multilingue.

	Corpus utilisés	**Score LAS**	**Score UAS**
1	sme (20)	32,96	46,85
2	eng (12 217)	32,72	50,44
3	fin (12 543)	40,74	54,24
4	sme (20) + eng (12 217)	46,54	61,61
5	**sme (20) + fin (12 543)**	**51,54**	**63,06**

Table B.3: Évaluation de l'analyse du same du nord (sme) : scores LAS (labeled attachment scores*) et UAS (*unlabeled attachment scores*), c'est-à-dire scores calculés en prenant en compte l'étiquette de la relation (score LAS, colonne de gauche), et sans elle (score UAS, colonne de droite). La première ligne sme (20) réfère à l'expérience utilisant uniquement sur les vingt phrases annotées de same disponibles pour l'entraînement. Les autres lignes montrent les résultats avec différentes combinaisons de corpus annotés : anglais (eng) et finnois (fin). Pour chaque corpus, le nombre de phrases utilisées est indiqué entre parenthèses.*

Globalement, les expériences que nous avons menées en utilisant le finnois comme source de connaissances (en particulier pour élaborer des plongements de mots bilingues) ont permis d'obtenir de meilleurs résultats qu'avec d'autres langues (on obtient de meilleurs résultats avec le finnois qu'avec l'anglais pour l'analyse syntaxique du same du nord, cf. tableau 3, et on obtient également de meilleurs résultats avec le finnois qu'avec l'anglais pour l'analyse du komi, cf. tableau 4 – le russe est toutefois plus performant pour analyser le komi que le finnois). Ceci semble indiquer d'une part qu'il est possible d'inférer des connaissances linguistiques utiles pour l'analyse à partir d'une langue tierce et, d'autre part, que la typologie et la situation linguistique jouent un rôle (on obtient de meilleurs résultats sur le same ou le komi à partir du finnois ou éventuellement du russe qu'à partir de l'anglais, même si les données utilisées pour l'anglais sont largement plus volumineuses).

La stratégie de transfert de connaissances d'une langue vers l'autre a bien fonctionné pour le finnois vis-à-vis du same, ce qui peut sembler logique car le finnois et le same sont supposés relativement proches génétiquement parlant (mais n'importe quel locuteur pourra aussi dire à quel point ces langues sont éloignées : il n'y a pas d'intercompréhension, même limitée, et même le vocabulaire de base est très différent). Le transfert fonctionne bien aussi pour le komi, alors que le komi est supposé plus éloigné du finnois d'un point de vue génétique.

	Corpus utilisés	**Score LAS**	**Score UAS**
1	kpv (10)	22,33	51,78
2	eng (12 217)	44,47	59,29
3	rus (3 850)	53,85	71,29
4	fin (12 543)	48,22	66,98
5	kpv (10) + eng (12 217)	50,47	66,23
6	kpv (10) + rus (3 850)	53,10	69,98
7	kpv (10) + fin (3 850)	53,66	71,29
8	kpv (10) + fin (12 543)	55,16	**73,73**
9	kpv (10) + eng (12 217) + fin (12,543)	52,50	68,57
10	**kpv (10) + rus (3 850) + fin (12 543)**	**56,66**	71,86

Table B.4: Évaluation de l'analyse syntaxique du komi. La première ligne kpv (10) réfère à l'expérience utilisant uniquement les dix phrases annotées de komi disponibles pour l'entraînement. Les autres lignes montrent les résultats avec différentes combinaisons de corpus annotés : anglais (eng), russe (rus), et finnois (fin). Pour chaque corpus, le nombre de phrases utilisées est indiqué entre parenthèses.

Concernant le komi, une des hypothèses que nous avions faites *a priori* était qu'un modèle élaboré à partir du russe pourrait aboutir à de meilleurs résultats qu'un modèle acquis à partir du finnois, car le russe a beaucoup « contaminé » le komi depuis plusieurs décennies (du fait de la situation linguistique et du bilinguisme de tous les locuteurs komis). Les résultats pour le russe sont, de fait, étonnants (ligne 3 du tableau 4). On obtient ainsi d'excellents résultats, qui surpassent même les résultats obtenus en ajoutant les dix phrases annotées de komi lors de l'apprentissage (ligne 6). Ceci est en fait sans doute dû à la proximité du russe et du komi, à la présence de cognats et surtout, aux conditions dans lesquelles sont faites ces expériences. L'apprentissage d'analyseurs avec si peu de données est donc possible, mais il faut garder à l'esprit que les résultats sont alors relativement instables (ceci pose d'ailleurs la question de la validité des résultats obtenus à partir d'échantillons aussi petits). Il est probable que, dans d'autres conditions expérimentales, les résultats obtenus avec le corpus russe seul seraient moins bons.

Si l'on fait abstraction des performances obtenues pour le komi à partir du corpus russe seul, nos résultats montrent que l'ajout de phrases annotées de la langue à analyser, même en petite quantité, peut améliorer significativement les résultats obtenus (lignes 5 à 10 ; on l'avait déjà vu lors de notre participation officielle à la

tâche commune CoNLL 2017, où l'usage des vingt phrases fournies par défaut, et le fait d'en réserver une partie ou non comme corpus de développement, pouvaient avoir un effet très positif sur les résultats finaux). La taille des corpus bruts utilisés pour l'obtention des plongements de mots, et les ressources annexes utilisées pour l'acquisition de connaissances linguistiques jouent aussi un rôle important (on comparera ainsi les lignes 7 et 8, où le modèle est à chaque fois conçu à partir du finnois, mais avec deux corpus de tailles différentes). C'est logiquement le corpus le plus grand qui permet d'obtenir le modèle le plus performant. On peut aussi comparer les performances relatives obtenues avec des modèles élaborés à partir du russe, du finnois et de l'anglais : l'anglais, même avec un ensemble de phrases annotées très supérieur, n'est pas vraiment compétitif sur le komi. Comme on l'a dit, ces résultats sont toutefois fragiles et sont validés sur un corpus très petit. Il faut donc souhaiter davantage d'études sur des langues variées, afin d'obtenir une meilleure vue des types de résultats possibles en fonction des langues, des ressources et des algorithmes utilisés.

Finalement, c'est le modèle élaboré à partir du finnois et du russe qui permet d'obtenir les meilleurs résultats (et non celui élaboré à partir de l'anglais, même si on dispose de plus de données pour l'anglais). Il semble bien que les langues choisies pour l'apprentissage jouent un rôle, et il est important de choisir celles-ci en fonction de critères linguistiques et typologiques.

On observe enfin que les scores UAS (c'est-à-dire sans tenir compte des étiquettes de relations syntaxiques) varient légèrement plus que les scores LAS (scores avec les étiquettes des relations syntaxiques), autrement dit les relations de base ont été trouvées et la racine correctement identifiée dans un certain nombre de cas, même quand les étiquettes des relations n'ont pas été attribuées correctement. Il est intéressant de noter que le modèle qui obtient le meilleur score UAS est le couple komi-finnois, même si d'autres combinaisons (avec l'ajout du russe notamment) permettent d'obtenir les meilleurs scores LAS.

B.7 Conclusion

Dans cet article, nous avons présenté une approche fondée sur l'utilisation de modèles multilingues, afin de fournir une analyse syntaxique pour des langues disposant de peu de ressources, et en particulier ne disposant pas de données annotées (à part quelques phrases utilisées comme amorçage, dix à vingt phrases dans les expériences menées ici et lors de la campagne CoNLL 2017). Nous avons montré que l'approche suivie était efficace dans le cas du same et du komi, même si les performances restent évidemment bien en deçà de ce que l'on peut obtenir avec un corpus d'entraînement de grande taille, comme en témoignent nos résultats pour le same lors de la campagne d'évaluation CoNLL 2018 (avec un corpus d'entraînement au format UD). Il s'agit toutefois, à notre avis, d'un cadre intéressant pour aider à produire des corpus annotés pour des langues peu dotées. Le cas du komi est à cet égard un cas d'étude intéressant, dans la mesure où il s'agit d'une langue avec peu de ressources, mais avec des locuteurs intéressés et demandeurs d'outils d'analyse automatique. Ce cadre pose toutefois un problème d'évaluation, en l'absence de données de référence (*gold standard*).

Nous avons observé que les modèles multilingues permettent généralement d'améliorer les performances par rapport à des modèles monolingues. Les langues génétiquement liées semblent être la meilleure source de connaissances (le finnois est ainsi efficace pour l'analyse du same comme du komi), mais la prise en compte de langues de contact semble aussi pertinente (ainsi le russe pour l'analyse du komi), de même que des langues pour lesquelles on dispose tout simplement de gros corpus (comme l'anglais). Une meilleure compréhension de l'apport réel de chaque langue au processus global serait intéressante pour permettre de définir une stratégie plus générale, et surtout reproductible, concernant le développement et l'utilisation de modèles multilingues pour l'analyse syntaxique.

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Annexe : contribution à l'élaboration d'un corpus arboré pour le komi

Afin de permettre l'évaluation de l'analyseur décrit dans cet article, un ensemble de phrases en komi ont été annotées au format UD. Ce corpus comprend actuellement environ trois cents phrases, et devrait en contenir mille prochainement. Une première version de ce corpus a été incluse dans la distribution officielle Universal Dependencies d'avril 2018[9]. Au-delà de la réalisation d'un nouveau corpus arboré, plusieurs points peuvent être soulignés, qui nous semblent relativement typiques du cas des langues de terrain et des langues minoritaires.

Les données disponibles sont de deux types très différents. On a d'un côté des sources écrites, parfois anciennes, écrites dans une langue relativement élaborée et littéraire, parfois très éloignée de la langue quotidienne. De l'autre, on dispose de corpus beaucoup plus modestes (en taille) correspondant à des enquêtes de terrain faites par des linguistes. Ce matériau est précieux, car directement issu de travaux linguistiques, il rend compte de la langue réellement utilisée par les locuteurs au quotidien, mais il pose plusieurs difficultés. Des difficultés matérielles d'abord, dans la mesure où ces données sont souvent encodées dans des formats particuliers, qui ne conviennent pas directement à un traitement automatique ; des difficultés liées à la taille des corpus

[9]Voir le site officiel de l'initiative Universal Dependencies : `http://universaldependencies.org`.

existants, qui rendent difficile l'utilisation de techniques d'apprentissage artificiel par exemple. Enfin, ces corpus sont représentatifs de l'oral : ils posent donc des problèmes particuliers et les outils mis au point pour l'écrit ne sont pas très performants sur ce type de données.

Notre travail se situe dans le cadre d'un effort en cours en vue de fournir des données annotées pour un certain nombre de langues finno-ougriennes. Des corpus arborés sont déjà disponibles pour le finnois, l'estonien et le hongrois. L'année 2017 a vu l'émergence d'un corpus arboré important pour le same du nord (produit en grande partie automatiquement à partir des outils d'analyse mis au point à l'université de Tromsø et non entièrement vérifié manuellement). Un corpus arboré est actuellement en préparation pour l'erzya (langue mordve), ce qui permettra de couvrir à terme une partie non négligeable des langues finno-ougriennes, même si des efforts seront encore nécessaires pour les autres langues. Une tendance similaire est observée pour ce qui concerne la réalisation de corpus arborés à partir du résultat d'enquêtes de terrain. À notre connaissance, des projets existent par exemple pour le dargwa (langue du Caucase), le pnar (langue austro-asiatique) et le shipibo-konibo (langue du Pérou).

En pratique...

La plupart des travaux sur la langue komie sont actuellement menés à Syktyvkar, Russie (capitale de la République komie). Le FU-Lab, dirigé par Marina Fedina, a en particulier numérisé un nombre important de livres komis (datant du début du XX^{e} siècle jusqu'à aujourd'hui), ceux libres de droits étant directement mis à disposition en ligne. Ce corpus brut compte actuellement quarante millions de mots et l'objectif à long terme est de numériser tous les livres publiés en komi-zyriène. Le nombre total des publications est estimé à environ quatre mille cing cents livres, auxquels il faut ajouter des dizaines de milliers de pages issues de journaux et de revues. Pour la constitution de notre corpus, nous avons évidemment veillé à n'utiliser que des textes libres de droits, afin d'en assurer une distribution aussi large et simple que possible. Il est possible qu'à un stade ultérieur des matériaux moins standard puissent être inclus dans la base de données, par exemple des textes issus de blogs et

de discussions en ligne, mais cela pose immédiatement des problèmes de droits et de diffusion.

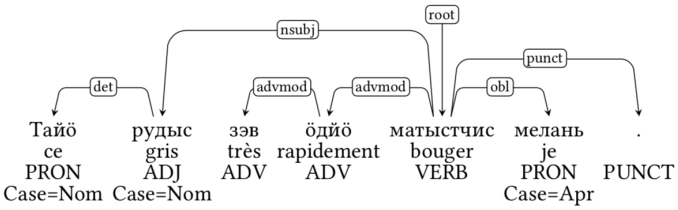
En dehors du projet mené à Syktyvkar, un des plus grands projets de recherche sur le komi parlé a été un projet de documentation dirigé par Rogier Blokland (université de Uppsala) en 2014-2016. Ce projet a abouti à un grand corpus en langue parlée transcrite. Ces données sont précieuses, pour les raisons que nous avons données *supra*, mais elles sont aussi problématiques car elles ne peuvent généralement pas être diffusées directement dans le domaine public. Le corpus contient aussi des formes dialectales, et comme le komi-zyriène écrit ne suit pas les principes utilisés pour les transcriptions, il semble problématique de mélanger ce matériau avec les données issues de sources écrites. Le corpus oral contient enfin de nombreuses phrases où le komi est mêlé à du vocabulaire russe, les locuteurs pratiquant le code switching en permanence. Cette langue est donc non standard, mais elle est par ailleurs scientifiquement intéressante et pertinente.

À partir de ce point de départ, il a été décidé de créer deux corpus différents, le premier avec les matériaux écrits et le deuxième avec les données orales issues d'enquêtes de terrain.

Annotation syntaxique du corpus komi-zyriène au format UD

Pour l'annotation du corpus komi-zyriène, nous nous sommes inspirés de corpus arborés existants et des consignes d'annotation liées, notamment celles ayant été constituées pour le finnois, le same du nord et l'erzya, ainsi que pour le russe. Il s'agit de langues proches du komi (langues de la même famille, à l'exception du russe), et il nous semblait naturel d'aller voir du côté de ces langues en priorité. De fait, les consignes d'annotation ont facilement pu être transposées au komi et quasiment toutes les configurations observées correspondaient à des cas de figure observés (*mutatis mutandis*) dans au moins une de ces langues.

Le komi-zyriène présente malgré tout quelques particularités et différences qui le distinguent de ces langues proches. Il existe notamment deux cas spatiaux largement spécifiques au komi (en fait aux langues permiennes, branche des langues finno-



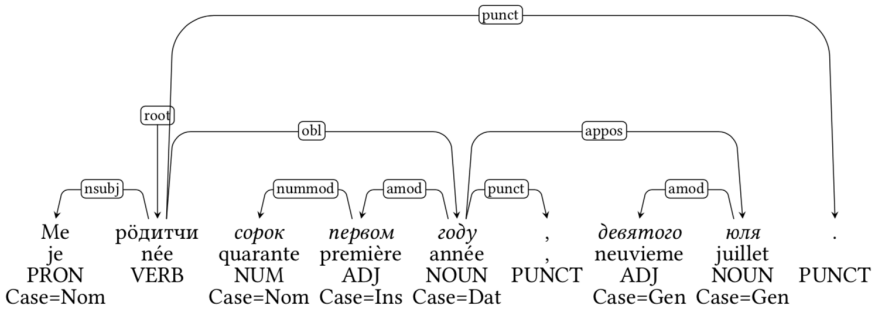
ID phrase: belyx-011.042
Traduction: Ce (nuage) gris est venu très rapidement vers moi.

ougriennes qui regroupe le komi et l'oudmourte) : l'égressif et l'approximatif. Ces deux cas expriment le mouvement depuis et vers une direction. Ils se distinguent de l'élatif et de l'illatif (deux cas bien répandus dans l'ensemble des langues finno-ougriennes) : l'élatif et l'illatif expriment aussi un mouvement depuis ou vers un lieu, mais ils insistent justement sur ce point de départ ou d'arrivée, alors que l'égressif et l'approximatif insistent davantage sur le mouvement, sans préciser le point de départ ou d'arrivée.

L'exemple ci-dessous illustre précisément l'utilisation du cas approximatif, sans aucun caractère égressif.

Il existe deux autres cas directionnels en komi, traditionnellement appelés prolatifs et transitifs, qui expriment le mouvement le long d'un chemin. Ceux-ci correspondent assez bien au cas appelé « perlatif » du guide d'annotation au format UD (Universal Dependencies), mais ce cas ne figure pas dans les exemples annotés jusqu'ici. Plus généralement, ceci pose la question de la terminologie employée et de la mise en rapport des cas (et plus généralement des notions linguistiques) à travers les langues : nous pensons que le prolatif et le translatif correspondent au perlatif, mais ceci mériterait sûrement une discussion approfondie. UD est en tout cas l'occasion de s'interroger sur la terminologie en cours, les notions manipulées et les correspondances entre langues. Il était à cet égard utile de garder un œil sur le russe lors de l'annotation, dans la mesure où le komi emprunte certaines constructions au russe. De plus, il semble souhaitable d'être, autant que faire se peut, cohérent et homogène au niveau des annotations.

Le premier exemple illustre une situation typique où la date est exprimée en russe, y compris au niveau du marquage morphologique et syntaxique.



ID phrase: kpv_izva20150403-2-b.014
Traduction: Je suis née (l'année) 1941, le 9 juillet.

Nous avons cherché ici à avoir une annotation comparable à celle de la structure correspondante en russe. Ce choix diffère de ce qui a été fait pour la plupart des autres langues, où les mots ou structures en langue étrangère sont généralement marqués en tant que tels, et donc globalement plutôt mis de côté. Vu le bilinguisme de tous les locuteurs komis qui se retrouve en partie dans les corpus, nous souhaitons avoir une annotation qui intègre pleinement les passages en russe (y compris à l'intérieur d'une même phrase en cas de code switching comme ici) et les considère comme faisant pleinement partie du corpus komi.

Il faut toutefois noter que ceci peut aussi entraîner différents problèmes. Par exemple, certaines structures (provenant du russe) auront un trait gender (exprimant le genre grammatical), alors qu'il s'agit d'un trait morphologique étranger au komi. Ceci est évidemment aussi un défi pour les outils de TAL et les analyseurs en général, qui doivent gérer des situations linguistiques plus complexes que ce que l'on trouve dans la plupart des grands corpus monolingues disponibles. C'est cette richesse qui fait l'intérêt de ces langues trop longtemps laissées de côté.

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RÉSUMÉ

L'analyse en dépendances est une composante essentielle de nombreuses applications de TAL (Traitement Automatique des Langues), dans la mesure où il s'agit de fournir une analyse des relations entre les principaux éléments de la phrase. La plupart des systèmes d'analyse en dépendances sont issus de techniques d'apprentissage supervisées, à partir de grands corpus annotés. Ce type d'analyse est dès lors limité à quelques langues seulement, qui disposent des ressources adéquates. Pour les langues peu dotées, la production de données annotées est une tâche impossible le plus souvent, faute de moyens et d'annotateurs disponibles. Afin de résoudre ce problème, la thèse examine trois méthodes d'amorçage, à savoir (1) l'apprentissage par transfert multilingue, (2) les plongements vectoriels contextualisés profonds et (3) le co-entrainement. La première idée, l'apprentissage par transfert multilingue, permet de transférer des connaissances d'une langue pour laquelle on dispose de nombreuses ressources, et donc de traitements efficaces, vers une langue peu dotée. Les plongements vectoriels contextualisés profonds, quant à eux, permettent une représentation optimale du sens des mots en contexte, grâce à la notion de modèle de langage. Enfin, le co-entrainement est une méthode d'apprentissage semi-supervisée, qui permet d'améliorer les performances des systèmes en utilisant les grandes quantités de données non annotées souvent disponibles pour les différentes langues visées. Nos approches ne nécessitent qu'un petit dictionnaire bilingue ou des ressources non étiquetées faciles à obtenir (à partir de Wikipedia par exemple) pour améliorer la précision de l'analyse pour des langues où les ressources disponibles sont insuffisantes. Nous avons évalué notre analyseur syntaxique sur 57 langues à travers la participation aux campagnes d'évaluation proposées dans le cadre de la conférence CoNLL. Nous avons également mené des expériences sur d'autres langues, comme le komi, une langue finno-ougrienne parlée en Russie : le komi offre un scénario réaliste pour tester les idées mises en avant dans la thèse. Notre système a obtenu des résultats très compétitifs lors de campagnes d'évaluation officielles, notamment lors des campagnes CoNLL 2017 et 2018. Cette thèse offre donc des perspectives intéressantes pour le traitement automatique des langues peu dotées, un enjeu majeur pour le TAL dans les années à venir.

MOTS CLÉS

Analyse en dépendances; analyse en déTransfert de connaissancependances; représentations lexicales multilingues.

ABSTRACT

Dependency parsing is an essential component of several NLP applications owing its ability to capture complex relational information in a sentence. Due to the wider availability of dependency treebanks, most dependency parsing systems are built using supervised learning techniques. These systems require a significant amount of annotated data and are thus targeted toward specific languages for which this type of data are available. Unfortunately, producing sufficient annotated data for low-resource languages is time- and resource-consuming. To address the aforementioned issue, the present study investigates three bootstrapping methods, namely, (1) multi-lingual transfer learning, (2) deep contextualized embedding, and (3) Co-training. Multi-lingual transfer learning is a typical supervised learning approach that can transfer dependency knowledge using multi-lingual training data based on multi-lingual lexical representations. Deep contextualized embedding maximizes the use of lexical features during supervised learning based on enhanced sub-word representations and language model (LM). Lastly, co-training is a semi-supervised learning method that leverages parsing accuracies using unlabeled data. Our approaches have the advantage of requiring only a small bilingual dictionary or easily obtainable unlabeled resources (e.g., Wikipedia) to improve parsing accuracy in low-resource conditions. We evaluated our parser on 57 official CoNLL shared task languages as well as on Komi, which is a language we developed as a training and evaluation corpora for low-resource scenarios. The evaluation results demonstrated outstanding performances of our approaches in both low- and high-resource dependency parsing in the 2017 and 2018 CoNLL shared tasks. A survey of both model transfer learning and semi-supervised methods for low-resource dependency parsing was conducted, where the effect of each method under different conditions was extensively investigated.

KEYWORDS

Dependency Parsing; transfer learning; multilingual word representation.