Making Use of Existing Lexical Resources to Build a Verbnet like Classification of French Verbs

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Explore ways of building a syntactic semantic classification of French verbs where groups of verbs are associated with:

- syntactic information (subcategorisation frames)
- semantic information (thematic role sets)

Using existing lexical resources for French and English.
More specifically

- we explore ways of building a **syntactic classification**
- using the classification methods
  - Formal Concept Analysis (FCA) – **symbolic**
  - Incremental Growing Neural Gas with Feature maximisation (IGNGF) – neural clustering
- two-fold evaluation
  1. on verb groups
  2. on associations of verbs with syntactic frames and thematic role sets
Contributions

- automatic acquisition of a syntactic-semantic classification
- two classification techniques not yet used for verb classification
- novel translation approach to build a semantic classification
French syntactic lexicon  English syntactic-semantic verb classes (Verbnet)

Syntactic classification  Translation

Syntactic classification  <verbs, SCFs>

Semantic classification  <verbs, thematic role sets>

Syntactic classification with semantic labels  <verbs, SCFs, thematic role sets>
Overview

System Overview

Lexical Resources
- French Lexical Resources
- English Lexical Resource

Clustering Methods
- Formal Concept Analysis (FCA)
- Incremental Growing Neural Gas with Feature Maximisation (IGNGF)

Evaluation and Comparison
- Evaluating Semantic Verb Classes wrt. Existing Reference
- Evaluating Syntactic-Semantic Verb Classes wrt. Corpus Annotations
- Summary

Conclusion
Outline

3 Lexical Resources
- French Lexical Resources
- English Lexical Resource
Lexical resources

French existing lexical resources: Dicovalence, Ladl tables, TreeLex
  ▶ merged into unique syntactic lexicon
  ▶ provide additional syntactic and semantic features
  ▶ both used for classification

English Verbnet classes
  ▶ translated to French
  ▶ provide associations with thematic role sets
Merged syntactic lexicon

- 5918 verbs, 345 subcategorisation frames, 20443 verb, frame pairs.

<table>
<thead>
<tr>
<th>Verb: expédier</th>
<th>Source info</th>
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</thead>
<tbody>
<tr>
<td>SCF</td>
<td></td>
</tr>
<tr>
<td>SUJ:NP,DUMMY:REFL</td>
<td>DV:41640,41650</td>
</tr>
<tr>
<td>SUJ:NP,OBJ:NP</td>
<td>DV:41640,41650;TL</td>
</tr>
<tr>
<td>SUJ:NP,OBJ:NP,AOBJ:PP</td>
<td>TL</td>
</tr>
<tr>
<td>SUJ:NP,OBJ:NP,POBJ:PP</td>
<td>DV:41640</td>
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<tr>
<td>SUJ:NP,OBJ:NP,POBJ:PP,POBJ:PP</td>
<td>LA:38L</td>
</tr>
<tr>
<td>SUJ:NP,OBJ:NP,POBJ:VPinf</td>
<td>LA:3</td>
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<tr>
<td>SUJ:NP,POBJ:PP,DUMMY:REFL</td>
<td>DV:41640</td>
</tr>
</tbody>
</table>

DV: Dicovalence, LA: LADL tables, TL: Treelex
Other features extracted from the lexicons

<table>
<thead>
<tr>
<th>Mostly syntactic</th>
<th>Feature</th>
<th>Description</th>
<th>related VN class</th>
</tr>
</thead>
<tbody>
<tr>
<td>ArgNbr</td>
<td>4 or more arguments</td>
<td>get-13.5.1, send-11.1</td>
<td></td>
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<tr>
<td>Event</td>
<td>arguments realised as clauses</td>
<td>correspond-36.1, characterize-29.2, say-37.7, ...</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Mostly semantic</th>
<th>Feature</th>
<th>Description</th>
<th>related VN class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loc</td>
<td>location role</td>
<td>put-9.1, remove-10.1, ...</td>
<td></td>
</tr>
<tr>
<td>Nhum</td>
<td>concrete object, non human role</td>
<td>hit-18.1 (eg. Instrument role), other_cos-45.4, ...</td>
<td></td>
</tr>
</tbody>
</table>

...
English lexical resource – Verbnet

English Verbnet [Schuler, 2006]

- large scale syntactic semantic classification of English verbs
- verbs with similar syntactic and semantic behaviour manually grouped together
- Obtain associations of French verbs with Verbnet classes
**English Verbnet**

**Verbnet example class** *hit-18.1*:

<table>
<thead>
<tr>
<th>Verbs</th>
<th>batter, beat, bump, butt, drum, hammer, hit, jab, kick, knock, lash, pound, rap, slap, smack, smash, strike, tap</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thematic roles (semantics)</td>
<td>Agent, Instrument, Patient</td>
</tr>
<tr>
<td>Frames (syntax)</td>
<td>SUJ:NP,P-OBJ:PP</td>
</tr>
<tr>
<td></td>
<td>SUJ:NP,P-OBJ:PP,P-OBJ:PP</td>
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<tr>
<td></td>
<td>SUJ:NP,OBJ:NP</td>
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<td></td>
<td>SUJ:NP,OBJ:NP,P-OBJ:PP</td>
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<td></td>
<td>Agent V Patient</td>
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<td></td>
<td>Agent V Patient Instrument</td>
</tr>
<tr>
<td></td>
<td>Agent V Patient</td>
</tr>
<tr>
<td></td>
<td>Instrument V Patient</td>
</tr>
</tbody>
</table>

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Translating English Verbnet classes

- using dictionaries
- noisy because of polysemy

Filter using two approaches:

1. Based on translation frequencies
   - Only keep most frequent translations
2. Machine Learning with Support Vector Machines
   - train classifier
   - for \( \langle \text{French verb } v_{fr}, \text{English Verbnet class } C_{VN} \rangle \)
   - has \( v_{fr} \) thematic roles of \( C_{VN} \)?

**SVM classification performed best:** Distribution of verbs

- most similar to English Verbnet
- most similar to FCA classification
Derived **French** lexical resources

- merged syntactic lexicon – **French**
- syntactic and semantic features – **French**
- translated Verbnet classes – **English**

used to

1. extract features for classification
2. provide thematic role set to French verb classes
Extracted features

- from merged syntactic lexicon: subcategorisation frames
- from Dicovalence and Ladl resources: syntactic and semantic features other than subcategorisation frames
- from translated Verbnet classes: thematic role sets (grids)
French syntactic lexicon  English syntactic-semantic verb classes (Verbnet)

Syntactic classification  Semantic classification
<verbs, SCFs>  <verbs, thematic role sets>

Syntactic classification with semantic labels
<verbs, SCFs, thematic role sets>
Aligning French verb groups with translated Verbnet classes

- using F-measure between recall (R) and precision (P)
- verb cluster $C_{cluster}$, translated Verbnet class $C_{VN}$

\[
R(C_{cluster}, C_{VN}) = \frac{|\text{verbs} \in C_{VN} \cap C_{cluster}|}{|\text{verbs} \in C_{VN}|}
\]

\[
P(C_{cluster}, C_{VN}) = \frac{|\text{verbs} \in C_{VN} \cap C_{cluster}|}{|\text{verbs} \in C_{cluster}|}
\]

\[
F(C_{cluster}, C_{VN}) = \frac{2RP}{R + P}
\]
Associating French verb groups with thematic role sets

- $C_{\text{cluster}}$ aligned with translated class $C_{\text{VN}}$
- $C_{\text{cluster}}$ is assigned thematic role set of $C_{\text{VN}}$
- Verbnet classes identified with their thematic role set
- Verbnet roles grouped:
  - \textbf{AgExp}: Agent, Experiencer
  - \textbf{Start}: Source, Material
  - \textbf{End}: Product, Destination, Recipient
Outline

4 Clustering Methods

- Formal Concept Analysis (FCA)
- Incremental Growing Neural Gas with Feature Maximisation (IGNGF)
Formal Concept Analysis (FCA) [Ganter and Wille, 1999]

- symbolic method for deriving conceptual structures – concepts – out of data
- FCA organises concepts into a hierarchy – concept lattice
- Concepts determined by:
  - extent: set of objects shared by attributes in intent
  - intent: set of attributes shared by objects in extent
The data

Objects: 2091 verbs

Attributes:
- 238 frames from merged syntactic lexicon
- additional syntactic and semantic features from Dicovalence and Ladl

Example

<table>
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<tbody>
<tr>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>
The concept lattice

12,802 concepts
  ▶ need to filter

How to select the most relevant concepts?
Concept selection indices

- introduced in [Klimushkin et al., 2010]
- select relevant concepts
- in concept lattices built on noisy data

**Stability**
- How much does a concept depend on individual members in extent/intent?

**Separation**
- How well does a concept sort out verb and frames it covers from other verb and frames.

**Probability**
- What is the probability of a concept intent/extent to be a concept intent/extent by chance?
Which indices to select the best classes?

Method:
Using fixed combination of indices

- select $N, (N \in \{1500, 1000, 500\})$ concepts from concept lattice with highest index combination
- align classes translated from Verbnet with these concepts
- select FCA concepts with associated Verbnet class
- compare obtained $\langle$verb, Verbnet class$\rangle$ associations with a reference

Best combination of indices:
- $\langle$verb, VN class$\rangle$ associations are closest to reference
- concepts associated to VN classes cover large proportion of verbs
Best combination of concept selection indices

stability + separation

- $F_2 = 25.16$
- close to upper bound (no selection)
- coverage 98.04%
Final classification method

1) use FCA to build classes grouping French verbs and SCFs
2) select 1500 concepts where stability + separation is highest
3) align translated Verbnet classes with selected concepts
4) keep FCA concepts aligned with a translated Verbnet class
5) associate these FCA concepts with the Verbnet class thematic role sets

Effectively we obtain a classification associating:

- groups of French verbs
- groups of subcategorisation frames
- sets of thematic roles
Resulting classification: sample concept

Concept 5312 – verbs of movement

verbs: bouger, déplacer, emporter, passer, promener, envoyer, expédier, jeter, porter, transmettre, transporter

syntactic frames: SUJ:NP,OBJ:NP,POBJ:PP,POBJ:PP

thematic roles: AgExp (Agent or Experiencer), Theme, Start, End
Incremental Growing Neural Gas with Feature Maximisation, [Lamirel et al., 2011b]

Growing neural gas clustering method
- based on Hebbian learning
- incremental
- *winning* clusters determined through distance function

IGNGF
- uses feature maximisation to determine *winning* cluster
- supports cluster labeling with distinguishing features
Incremental Growing Neural Gas with Feature Maximisation, [Lamirel et al., 2011b]

- crisp, non-overlapping
- flat, non-hierarchical structure
- features can be weighted:
  weight of feature $f$ for verb $v$ $\mapsto W_v^f$
- choose number of classes
Feature maximisation

Used for
- guiding the clustering
- cluster labeling
  i.e. associating relevant features to clusters

Feature $f$ maximal for cluster $c$: $FF_c(f)$ higher for $c$ than other cluster.

$FF_c(f)$ Feature F-measure for cluster $c$

$FR_c(f) = \frac{\sum_{v \in c} W_v^f}{\sum_{c' \in C} \sum_{v \in c'} W_v^f}$

(f, verb) combinations in $c$ vs.
all (feature, verb) combinations in $c$

$FP_c(f) = \frac{\sum_{v \in c} W_v^f}{\sum_{f' \in F_c, v \in c} W_v^{f'}}$
IGNGF vs. FCA

Differences
- crisp, non-overlapping, no hierarchical structure
- features can be weighted (not only binary):
  \[ W^f_v \in [0, 1] \]

Analogy
[Lamirel, 2010]: A cluster \( c \) where for all maximal features \( f \):

\[ FP_c(f) = 1 \] and \[ FR_c(f) = 1 \]

\( \implies \) \( c \) is formal concept:
- extent: verbs in \( c \)
- intent: maximal features for \( c \)
IGNGF classification method

Objects:  ▶ verbs
Features: ▶ same as for FCA
          ▶ + grid (thematic role set) feature

▶ IGNGF produces verb clusters
▶ label clusters with
  ▶ syntactic frames
  ▶ thematic role sets
Acquiring a Verbnet like Classification for French.

Clustering Methods

Incremental Growing Neural Gas with Feature Maximisation (IGNGF)

Associations with syntactic frames and semantic grids

Syntactic frames

- \( F_{\text{max}} \): cluster maximising features
- \( F_{\text{pos}} \): feature f-measure is above a global threshold

Thematic role sets

- \( \theta \) features: feature f-measure is above a global threshold
- \( \theta \) trans: assigned by alignment with translated classes
Best configuration

best performance in task based evaluation (simplified SRL)

- syntactic frames: feature f-measure above global threshold
  - Fpos
- thematic role sets: alignment with translated Verbnet classes
  - $\theta$ trans
Example IGNGF Cluster

C6- 14(14) [197(197)]

Prevalent Label — = AgExp-Cause

0.341100  G-AgExp-Cause
0.274864  C-SUJ:Ssub,OBJ:NP
0.061313  C-SUJ:Ssub
0.042544  C-SUJ:NP,DEOBJ:Ssub

**********

**********

0.017787  C-SUJ:NP,DEOBJ:VPinf
0.008108  C-SUJ:VPinf,AOBJ:PP

... 

[**déprimer 0.934345 4(0)] [affliger 0.879122 3(0)] [éblouir 0.879122 3(0)] [choquer 0.879122 3(0)] [décevoir 0.879122 3(0)] [décontenancer 0.879122 3(0)] [décontracter 0.879122 3(0)] [désillusionner 0.879122 3(0)] [**ennuyer 0.879122 3(0)] [fasciner 0.879122 3(0)] [**heurter 0.879122 3(0)] ...
Outline

5 Evaluation and Comparison

- Evaluating Semantic Verb Classes wrt. Existing Reference
- Evaluating Syntactic-Semantic Verb Classes wrt. Corpus Annotations
- Summary
Evaluation

Goal: evaluate both FCA and IGNGF wrt.

- groups of verbs
- associations with syntactic frames – \langle \text{verb, frame} \rangle pairs
- associations with thematic grids – \langle \text{verb, thematic role set} \rangle pairs
- associations with both syntactic frames and thematic grids – \langle \text{verb, syntactic frame, thematic role set} \rangle triples

Other question:

- Which features work best for what classification technique?
Resources for evaluation

**V-gold by [Sun et al., 2010]**

- groups ≈ 160 verbs in 16 Levin classes

<table>
<thead>
<tr>
<th>VN class role set</th>
<th>French translations in gold</th>
</tr>
</thead>
</table>
| amalgamate-22.2 AgExp, PatientSym | incorporer; associer; réunir; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; mélanger; 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Evaluating verb groups – metrics

Modified Purity: How well can the clustering be embedded into gold?
Cluster $C \rightarrow \text{prev}(C) \in$ gold classification with maximal $|\text{prev}(C) \cap C|$

$$mPUR = \frac{\sum_{C \in \text{Clustering}, |\text{prev}(C)| > 1} |\text{prev}(C) \cap C|}{\sum_{C \in \text{Gold} \ \text{Verbs}_{\text{Clustering} \cap C}},}$$

Weighted Class Accuracy: How well can the gold be embedded into the clustering?
gold class $C \rightarrow \text{dom}(C) \in$ clustering with maximal $|\text{dom}(C) \cap C|$

$$ACC = \frac{\sum_{C \in \text{Gold}} |\text{dom}(C) \cap C|}{\sum_{C \in \text{Gold} \ \text{Verbs}_C}}$$
Evaluating verb groups – the classifications

- **Verbs**
  - in Verbnet classes from V-gold translated to French
  - 2100 verbs

- **Features**
  - scf: subcategorisation frames
  - sem/synt: additional syntactic and/or semantic features
  - grid: translated classes a verb is a member of (IGNGF only)
Evaluating verb groups – results

Classifying 2100 verbs:

<table>
<thead>
<tr>
<th></th>
<th>Purity</th>
<th>Accuracy</th>
<th>F-measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCA</td>
<td>32.30</td>
<td>95.61</td>
<td>48.29</td>
</tr>
<tr>
<td>IGNGF</td>
<td>86.00</td>
<td>59.00</td>
<td>70.00</td>
</tr>
</tbody>
</table>

[Sun et al., 2010], corpus based features, slightly different gold

55-65.4

Discussion

- IGNGF outperforms FCA wrt. F-measure
- IGNGF: better results than related work by [Sun et al., 2010]
- IGNGF: higher purity, verb groupings more similar to gold
- FCA: higher accuracy, gold groups can be embedded in FCA groupings more easily.
Evaluating association with thematic role sets

FCA and IGNGF provide associations of clusters with thematic role sets.

Compare resulting \( \langle \text{verb, thematic role set} \rangle \) pairs with those given by gold using Recall (R), Precision (P) and their F-measure (F):

\[
R = \frac{|\text{pairs in gold} \cap \text{pairs in classes}|}{|\text{pairs in gold}|}
\]
\[
P = \frac{|\text{pairs in gold} \cap \text{pairs in classes}|}{|\text{pairs in classes}|}
\]
Evaluating association with thematic role sets II

Results

<table>
<thead>
<tr>
<th></th>
<th>Precision</th>
<th>Recall</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCA</td>
<td>24.09</td>
<td>75.00</td>
<td>36.47</td>
</tr>
<tr>
<td>IGNGF</td>
<td>27.16</td>
<td>26.67</td>
<td>27.16</td>
</tr>
</tbody>
</table>

Discussion

- FCA outperforms IGNGF wrt. \{verb, thematic role set\} associations.
- FCA better represents polysemy – overlapping classification
What are the best features?

FCA - \langle \text{verb, thematic role set} \rangle \text{ evaluation}

<table>
<thead>
<tr>
<th>Features</th>
<th>cov.</th>
<th>prec</th>
<th>rec</th>
<th>f</th>
</tr>
</thead>
<tbody>
<tr>
<td>scf &amp; sem.</td>
<td>96.17</td>
<td>24.09</td>
<td>75.00</td>
<td><strong>36.47</strong></td>
</tr>
<tr>
<td>scf &amp; synt. &amp; sem.</td>
<td>96.05</td>
<td>23.95</td>
<td>75.00</td>
<td>36.31</td>
</tr>
<tr>
<td>scf (frames only)</td>
<td>95.37</td>
<td>23.48</td>
<td>73.80</td>
<td>35.63</td>
</tr>
<tr>
<td>scf &amp; synt.</td>
<td>96.34</td>
<td>21.51</td>
<td>74.40</td>
<td>33.38</td>
</tr>
</tbody>
</table>

IGNGF - Evaluating groups of verbs

<table>
<thead>
<tr>
<th>Features</th>
<th>mPUR</th>
<th>ACC</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>grid &amp; scf &amp; sem</td>
<td>86.00</td>
<td>59.00</td>
<td><strong>70.00</strong></td>
</tr>
<tr>
<td>grid &amp; scf &amp; sem &amp; synt</td>
<td>99.00</td>
<td>52.00</td>
<td>69.00</td>
</tr>
<tr>
<td>grid &amp; scf</td>
<td>94.00</td>
<td>54.00</td>
<td>68.00</td>
</tr>
<tr>
<td>scf &amp; sem</td>
<td>83.00</td>
<td>55.00</td>
<td>66.00</td>
</tr>
<tr>
<td>scf</td>
<td>93.00</td>
<td>48.00</td>
<td>64.00</td>
</tr>
<tr>
<td>grid &amp; scf &amp; synt</td>
<td>87.00</td>
<td>50.00</td>
<td>63.00</td>
</tr>
<tr>
<td>scf &amp; synt</td>
<td>91.00</td>
<td>45.00</td>
<td>61.00</td>
</tr>
<tr>
<td>scf &amp; sem &amp; synt</td>
<td>89.00</td>
<td>47.00</td>
<td>61.00</td>
</tr>
</tbody>
</table>
For both IGNGF and FCA

- semantic features *improve* classification
- syntactic features *degrade* classification

Possible reason for *syntactic feature* behaviour:

- information missing from lexicons
Evaluating syntactic-semantic verb classes

- Goal: evaluate associations
  - \langle \text{verb, syntactic frame} \rangle
  - \langle \text{verb, syntactic frame, thematic role set} \rangle
- V-gold does not provide associations with French syntactic frames
- Create SRL-gold reference providing \langle \text{verb, syntactic frame, thematic role set} \rangle associations.
- Evaluate
  - recall for \langle \text{verb, syntactic frame} \rangle, \langle \text{verb, thematic role set} \rangle
  - task based: simplified Semantic Role Labeling
The SRL-gold reference

- sentences from Paris 7 Dependency Treebank [Candito et al., 2009]
- annotate ⟨verb, syntactic argument⟩ instances with Verbenet thematic roles.

Sentences chosen as follows:
- for 116 verbs in V-gold and P7
- randomly choose up to 25 sentences containing verb

Results in:
- 1600 verb instances associated with thematic grid,
- 3605 ⟨verb, syntactic argument⟩ instances associated with thematic roles.
Larger classifications

Verbs
- all verbs in syntactic lexicon – 4200

Features/Attributes
- scf: subcategorisation frames
- sem: additional semantic features
- grid: derived from translated classes (IGNGF only)
Associations with frames and thematic role sets

<table>
<thead>
<tr>
<th>SCFs (types)</th>
<th>SRL gold</th>
<th>SRL gold &amp; classif</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>IGNGF</td>
<td>316</td>
<td>163</td>
<td>59.59</td>
</tr>
<tr>
<td>FCA</td>
<td>316</td>
<td>243</td>
<td>88.69</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Grids (types)</th>
<th>SRL gold</th>
<th>SRL gold &amp; classif</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>IGNGF</td>
<td>318</td>
<td>153</td>
<td>48.11</td>
</tr>
<tr>
<td>FCA</td>
<td>318</td>
<td>280</td>
<td>88.05</td>
</tr>
</tbody>
</table>

FCA better reflects associations with frames and grids
Linking

- How good are the induced \( \langle \text{verb, synt. arg., sem. role} \rangle \) associations?
  - Adapt SRL method by [Swier and Stevenson, 2004]

- [Swier and Stevenson, 2004]:
  - Associate \( \langle \text{verb, syntactic argument} \rangle \) instances in English corpus with Verbnet thematic roles
  - By aligning syntactic frames from corpus parses with Verbnet thematic grids

- Our adaptation:
  - Associate \( \langle \text{verb, syntactic argument} \rangle \) instances in French P7 corpus with Verbnet thematic roles
  - By aligning syntactic frames from classification with Verbnet thematic grids
### Evaluating Syntactic-Semantic Verb Classes wrt. Corpus Annotations

**Semantic role labeling example**

\[
\langle \text{voler, SUJ:NP,OBJ:NP,DEOBJ:PP} \rangle
\]

<table>
<thead>
<tr>
<th>FCA class role set</th>
<th>theta-grids for voler</th>
<th>syntactic construction</th>
<th>%(\theta)</th>
<th>%SCF</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>6583</td>
<td>Agent-Theme</td>
<td>Agent</td>
<td>100</td>
<td>67</td>
<td>167</td>
</tr>
<tr>
<td></td>
<td>Agent-Theme-Start</td>
<td>Agent</td>
<td>100</td>
<td>100</td>
<td>200</td>
</tr>
<tr>
<td></td>
<td>Agent-Theme-Benef</td>
<td>Agent</td>
<td>100</td>
<td>100</td>
<td>200</td>
</tr>
<tr>
<td></td>
<td>Agent-Theme-Start-Benef</td>
<td>Agent</td>
<td>75</td>
<td>100</td>
<td>175</td>
</tr>
<tr>
<td>Agent, Benef</td>
<td></td>
<td>Agent</td>
<td>100</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Start, Theme</td>
<td></td>
<td>Theme</td>
<td>100</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(steal-10.5)</td>
<td></td>
<td>Start</td>
<td>100</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Benef</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Start/Benef</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**FCA concept 6583:**

- **Verbs:** acheter, assurer, attendre, ..., voler
- **Thematic roles:** Agent, Beneficiary, Start, Theme
Semantic role labeling example

\[ \langle \text{voler, SUJ:NP,OBJ:NP,DEOBJ:PP} \rangle \]

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<tr>
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<th>%SCF</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>6583 Agent, Benef Start, Theme</td>
<td>Agent-Theme</td>
<td>Agent Theme Start</td>
<td>100</td>
<td>67</td>
<td>167</td>
</tr>
<tr>
<td>6583 Agent-Theme-Start</td>
<td>Agent-Theme-Start</td>
<td>Agent Theme</td>
<td>100</td>
<td>100</td>
<td>200</td>
</tr>
<tr>
<td>6583 Agent-Theme-Benef</td>
<td>Agent-Theme-Benef</td>
<td>Agent Theme Benef</td>
<td>100</td>
<td>100</td>
<td>200</td>
</tr>
<tr>
<td>6583 Agent-Theme-Start-Benef</td>
<td>Agent-Theme-Start-Benef</td>
<td>Agent Theme Start/Benef</td>
<td>75</td>
<td>100</td>
<td>175</td>
</tr>
</tbody>
</table>

FCA concept 6583:

Verbs: \textit{acheter, assurer, attendre, \ldots, voler}

Thematic roles: Agent, Beneficiary, Start, Theme

Frames:

- SUJ:NP
- SUJ:NP,OBJ:NP
- SUJ:NP,OBJ:NP,AOBJ:PP
- SUJ:NP,OBJ:NP,DEOBJ:PP
Semantic role labeling example

\[ \langle \text{voller}, \text{SUJ:NP,OBJ:NP,DEOBJ:PP} \rangle \]

<table>
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<td>67</td>
<td>167</td>
</tr>
<tr>
<td></td>
<td>Agent-Theme-Start</td>
<td>Agent Theme Start</td>
<td>100</td>
<td>100</td>
<td>200</td>
</tr>
<tr>
<td></td>
<td>Agent-Theme-Benef</td>
<td>Agent Theme Benef</td>
<td>100</td>
<td>100</td>
<td>200</td>
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<tr>
<td></td>
<td>Agent-Theme-Start-Benef</td>
<td>Theme Start/Benef</td>
<td>75</td>
<td>100</td>
<td>175</td>
</tr>
<tr>
<td>6583 Start, Theme</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(steal-10.5)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Thematic role set **Agent, Beneficiary, Start, Theme**: English Verbnet class **steal-10.5**:

Verbs: *abduct, annex, cabbage, capture,* ..., *steal,* ...

Thematic roles: Agent, Beneficiary, Start, Theme

Frames:

- SUJ:NP,OBJ:NP
- SUJ:NP,OBJ:NP,P-OBJ:PP
- SUJ:NP,OBJ:NP,P-OBJ:PP,P-OBJ:PP

Agent V Theme
Agent V Theme Start
Agent V Theme Benef
Agent V Theme Start Benef
Semantic role labeling example

\[ \langle \text{voler}, \text{SUJ:NP,OBJ:NP,DEOBJ:PP} \rangle \]

<table>
<thead>
<tr>
<th>FCA class role set</th>
<th>theta-grids for voler</th>
<th>syntactic construction</th>
<th>(%\theta)</th>
<th>(%\text{SCF})</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>6583 Agent, Benef Start, Theme (steal-10.5)</td>
<td>Agent-Theme</td>
<td>Agent</td>
<td>100</td>
<td>67</td>
<td>167</td>
</tr>
<tr>
<td></td>
<td>Agent-Theme-Start</td>
<td>Theme</td>
<td>100</td>
<td>100</td>
<td>200</td>
</tr>
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<td>175</td>
</tr>
<tr>
<td>Agent-Theme-Start-Benef</td>
<td>Agent-Theme-Benef</td>
<td>Theme</td>
<td>100</td>
<td>100</td>
<td>200</td>
</tr>
</tbody>
</table>

resulting labeling: non-ambiguous associations

- \(\langle \text{voler}, \text{SUJ:NP} \rangle \rightarrow \text{Agent}\)
- \(\langle \text{voler}, \text{OBJ:NP} \rangle \rightarrow \text{Theme}\)
- \(\langle \text{voler}, \text{DEOBJ:PP} \rangle \) no label
## Results

Comparison with SRL gold:

<table>
<thead>
<tr>
<th></th>
<th>%total (R)</th>
<th>%labeled (P)</th>
<th>F</th>
<th>%not labeled</th>
</tr>
</thead>
<tbody>
<tr>
<td>baseline (default associations)</td>
<td>65.21</td>
<td>65.21</td>
<td>65.21</td>
<td>0.00</td>
</tr>
<tr>
<td>FCA</td>
<td>30.87</td>
<td>70.40</td>
<td>42.92</td>
<td>56.14</td>
</tr>
<tr>
<td>IGNGF</td>
<td>47.43</td>
<td>71.91</td>
<td><strong>57.39</strong></td>
<td>34.79</td>
</tr>
<tr>
<td>S&amp;S (English, baseline 74.00)</td>
<td></td>
<td></td>
<td>76.00</td>
<td>38.00</td>
</tr>
</tbody>
</table>

- IGNGF outperforms FCA
- IGNGF & FCA lower than baseline
- precision better than baseline
Evaluation Summary

<table>
<thead>
<tr>
<th>Reference</th>
<th>FCA</th>
<th>IGNGF</th>
<th>Related work</th>
</tr>
</thead>
<tbody>
<tr>
<td>V-gold (PUR/ACC F)</td>
<td>48.29</td>
<td><strong>70.00</strong></td>
<td>Sun et al. 55-65</td>
</tr>
<tr>
<td>V-gold (F)</td>
<td><strong>36.47</strong></td>
<td>27.16</td>
<td></td>
</tr>
<tr>
<td>SRL-gold (R)</td>
<td><strong>88.05</strong></td>
<td>48.11</td>
<td></td>
</tr>
<tr>
<td>SRL-gold (R)</td>
<td><strong>88.69</strong></td>
<td>59.59</td>
<td></td>
</tr>
<tr>
<td>SRL-gold (F)</td>
<td>42.92</td>
<td><strong>57.39</strong></td>
<td>S&amp;S 76</td>
</tr>
</tbody>
</table>

**semantic and syntactic features**

- similar effect on FCA and IGNGF classification
Major issues

Associations with syntactic frames:
- **FCA**: too general → classes associated to high frequency frames
- **IGNGF**: too specific → classes associated to low frequency frames

Associations with thematic role sets:
- Large heterogeneous classes aligned to small, very specific Verbnet classes
- How to better align translated classes with clusters/concepts?
Conclusion
Conclusion

Large scale syntactic-semantic classification of French verbs
- based on existing French and English lexical resources
- using the FCA and IGNGF clustering methods

Classification methods
- useful verb classes associated with syntactic frames and thematic role sets
- complementary
  - FCA: better associations with frames and thematic role sets
  - IGNGF: better support in SRL task.
- main shortcoming: association with syntactic frames

- classifications: http://talc.loria.fr/-Classifications-.html
Future Work

Improve classifications

- Better associations with syntactic frames:
  - FCA ▶ attribute (scf) based selection indices
  - exploit hierarchical structure
  - IGNGF ▶ cluster labeling depending on individual frames
  - towards creating overlapping classifications

- Better associations with thematic grids:
  - better methods of aligning clusters and translated Verbnet classes
  - explore other methods of associating verbs/frames with thematic role sets.

- Better evaluation method:
  - How significant is comparison with < 10% reference data?
  - Use unsupervised evaluation measures (eg. cumulated micro precision [Lamirel et al., 2011a]).
Future Work

Polysemy
- How to adequately represent it?
- How to evaluate?

Explore fully unsupervised approach
- using distributional data – eg. LexSchem
Publications


Associations with frames and thematic role sets (more detailed)

\langle \text{verb, frame} \rangle \text{ pairs in corpus: recall 59.59 for IGNGF, 88.69 for FCA.}

<table>
<thead>
<tr>
<th>SCFs</th>
<th>SRL gold</th>
<th>classif</th>
<th>SRL gold &amp; classif</th>
<th>SRL gold &amp; lex ¬ classif</th>
<th>SRL gold ¬ lex</th>
<th>Recall</th>
<th>Recall w/o missing in lex</th>
</tr>
</thead>
<tbody>
<tr>
<td>IGNGF</td>
<td>316</td>
<td>1149</td>
<td>163</td>
<td>111</td>
<td>42</td>
<td>51.58</td>
<td>59.59</td>
</tr>
<tr>
<td>FCA</td>
<td>316</td>
<td>16542</td>
<td>243</td>
<td>31</td>
<td>42</td>
<td>76.90</td>
<td>88.69</td>
</tr>
</tbody>
</table>

\langle \text{verb, thematic grid} \rangle \text{ pairs in corpus: recall 48.11 for IGNGF, 88.05 for FCA.}

<table>
<thead>
<tr>
<th>Grids</th>
<th>gold</th>
<th>gold &amp; classif</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
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</tr>
<tr>
<td>FCA</td>
<td>318</td>
<td>280</td>
<td>88.05</td>
</tr>
</tbody>
</table>

FCA better reflects associations with frames and grids in SRL gold.
IGNGF vs. FCA

Differences

- crisp, non-overlapping, no hierarchical structure
- features can be weighted (not only binary):

  \[ W_v^f \in [0, 1] \]

Analogy

[Lamirel, 2010]: A cluster \( c \) where for all maximal features \( f \):

\[ FP_c(f) = 1 \text{ and } FR_c(f) = 1 \]

\( \Rightarrow \) \( c \) is formal concept:

- extent: verbs in \( c \)
- intent: maximal features for \( c \)


J. C. Lamirel, P. Cuxac, and R. Mall.
A new efficient and unbiased approach for clustering quality evaluation.
In *QIMIE’11, PaKDD*, Shenzen, China, 2011.

J.-C. Lamirel, R. Mall, P. Cuxac, and G. Safi.
Variations to incremental growing neural gas algorithm based on label maximization.
In *Neural Networks (IJCNN), The 2011 International Joint Conference on*, pages 956–965, 2011.

Jean-Charles Lamirel.
A new multi-viewpoint and multi-level clustering paradigm for efficient data mining tasks.

Karin Kipper Schuler.
