Schema-Guided Query Induction

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Ph.D. Defense
September 10, 2010

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XML:
- Standard language for storing and exchanging semi-structured data
- Widespread in database, Web and document communities

Schemas: meta-description of XML documents

XML queries:
- Select data in XML documents
- Basis for XML transformations
How to Design Queries?

- Experts manually define queries by:
  - Writing Perl, Python or shell scripts
  - Using W3C standards (XPath)
  - Generating wrappers with tools like Lixto [Baumgartner et al., 2001]

- Average users need help:
  - Generic approach
  - No prior skills required
  - Use of graphical user interfaces
Wrapper Induction for Web Information Extraction

- Automatic construction of wrappers (queries)
- Various machine learning techniques:
  - String-based [Kushmerick, 2002]
  - Tree-based:
    - Inductive logic programming [Cohen et al., 2002]
    - Tree automata inference [Kosala, 2003]
    - Conditional random fields [Kristjansson et al., 2004]
    - Classification [Marty et al., 2006]
Wrapper Induction for Web Information Extraction

- Automatic construction of wrappers (queries)
- Various machine learning techniques:
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  - Tree-based:
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    - **Tree automata inference**
    - Conditional random fields [Kristjansson et al., 2004]
    - Classification [Marty et al., 2006]
Motivations for Schema-Guided Query Induction

- Add schema information into existing learning algorithms
  - Learn queries consistent with the schema
  - Define more accurate pruning strategies
- Formal characterization of heuristics
  - Learnability results
  - Classification of queries: what makes it hard to learn?
- Beyond HTML:
  - XML data have a richer semantics thanks to schemas
  - Nodes in XML trees associated to graphical objects
Contributions

- How to use schema knowledge in algorithms
  - Infer schema-consistent queries
    - Efficient inclusion checking
    - New learnability result
  - Schema-guided pruning
- Class of queries that are learnable w.r.t. pruning
  - Formal characterization by stable queries
  - New learnability result
- Relevance of stable queries in practice
  - New experiments with XML datasets
  - Best pruning strategies: schema-guided and related to stability
Contributions

- How to use schema knowledge in algorithms
  - Infer schema-consistent queries
    - Efficient inclusion checking
    - New learnability result
  - **Schema-guided pruning**
- Class of queries that are learnable w.r.t. pruning
  - Formal characterization by **stable queries**
  - **New learnability result**
- Relevance of stable queries in practice
  - **New experiments** with XML datasets
  - Best pruning strategies: schema-guided and related to stability
Outline

1. XML, Schemas and Queries
2. Tree Automata
3. Schema-Guided Pruning
4. Stable Queries
5. Learnability Results
6. Experiments
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Example: representation of geographical data

```xml
<country>
  <name>France</name>
  <city>Paris</city>
  <region>
    <name>Nord–Pas de Calais</name>
    <population>3 996 588</population>
    <city>Lille</city>
  </region>
  <region>
    <name>Vallée du Rhône</name>
    <city>Lyon</city>
    <city>Valence</city>
  </region>
</country>
```
Tree Representation

- Standard abstraction
- Example:

```
<table>
<thead>
<tr>
<th>country</th>
<th>region</th>
<th>region</th>
</tr>
</thead>
<tbody>
<tr>
<td>name</td>
<td>city</td>
<td>name</td>
</tr>
<tr>
<td>FR</td>
<td>Paris</td>
<td>population</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3 996 588</td>
</tr>
<tr>
<td>region</td>
<td>city</td>
<td>name</td>
</tr>
<tr>
<td>NPDC</td>
<td>Lille</td>
<td>city</td>
</tr>
<tr>
<td></td>
<td></td>
<td>VdR</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Lyon</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valence</td>
</tr>
</tbody>
</table>
```
Tree Representation

- Standard abstraction
- Example:

```
country
  name  city
  region
    name  population  city
   region
      name  city
      city
```

- We consider finite, ordered, unranked trees, over some alphabet $\Sigma$
- Text values (and attributes) are omitted
Schema Restrictions

- Schemas are used to describe sets of valid trees
- Available in most XML applications
- Standard languages: DTD, W3C XML Schema, Relax NG, ... 
- Example of DTD over $\Sigma$:

  
  $\mathit{country} \rightarrow \mathit{name} \cdot \mathit{city} \cdot \mathit{region}^*$

  $\mathit{region} \rightarrow \mathit{name} \cdot (\mathit{population} + \epsilon) \cdot \mathit{city}^*$

  $\mathit{name} \rightarrow \epsilon$

  $\mathit{city} \rightarrow \epsilon$

  $\mathit{population} \rightarrow \epsilon$
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  $\text{region} \rightarrow \text{name} \cdot (\text{population} + \epsilon) \cdot \text{city}^*$
  $\text{name} \rightarrow \epsilon$
  $\text{city} \rightarrow \epsilon$
  $\text{population} \rightarrow \epsilon$

Invalid tree

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We restrict ourselves to *monadic* node-selecting queries, i.e., functions that selects sets of nodes in trees: $Q(t) \subseteq \text{nod}(t)$.

**XPath:**
- Standard language for node-selecting queries over XML trees
- Used by other XML standards
- Expressiveness: first-order logic over unranked trees [Marx, 2005]
- Example: `//region[population]/name`

**Richer formalisms:**
- Monadic Datalog [Gottlob & Koch, 2004]
- Tree automata [Comon et al., 2007]
- Expressiveness: monadic second-order logic
What are the regions whose population is known?
Supervised Query Induction

Select one example region

- Nord-Pas de Calais (3 996 588)
- Bretagne (3 120 288)
- Aquitaine (3 150 890)
- Alsace-Moselle
- Strasbourg
- Paris
- Lyon
- Valence
- Corse (294 118)
Supervised Query Induction

Select one other example region

Nord-Pas de Calais
(3 996 588)

Bretagne
(3 120 288)

Aquitaine
(3 150 890)

Corse
(294 118)
The system will automatically infer the query.

Supervised Query Induction
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Finite state machines for dealing with sets of trees

Models:
- Ranked tree automata over binary encodings of unranked trees
- Hedge automata [Brüggemann-Klein et al., 2001]
- Deterministic stepwise tree automata [Carme et al., 2004]
  - Bottom-up deterministic tree automata over Curryfied encodings
  - Best-suited for schema-guided query induction
- Can express schemas: non-trivial conversion
Deterministic DTDs

country \rightarrow name \cdot city \cdot region^*
region \rightarrow name \cdot (population + \epsilon) \cdot city^*
name \rightarrow \epsilon
city \rightarrow \epsilon
population \rightarrow \epsilon

DTD $D$
Deterministic DTDs

country → name · city · region*
region → name · (population + ε) · city*
name → ε
city → ε
population → ε

country → q^0_c name → q^1_c city → q^2_c region → q^3_c

Glushkov automata: \(O(|\Sigma| \times |D|)\)
Deterministic DTDs

country → name · city · region*
region → name · (population + ε) · city*
name → ε
city → ε
population → ε

country → q_c^0 name → q_c^1 city → q_c^2 region → q_c^3
region → q_r^0 name → q_r^1 pop. → q_r^2 city → q_r^3

glushkov automata: $O(|Σ| \times |D|)$
Deterministic DTDs

country → name · city · region*
region → name · (population + ϵ) · city*
name → ϵ
city → ϵ
population → ϵ

country → q_c^0 name → q_c^1 city → q_c^2 region → q_c^3
name → q_name

region → q_r^0 name → q_r^1 pop. → q_r^2 city → q_r^3 city

Glushkov automata: $O(|Σ| \times |D|)$
Deterministic DTDs

country \rightarrow \text{name} \cdot \text{city} \cdot \text{region}^*
region \rightarrow \text{name} \cdot (\text{population} + \epsilon) \cdot \text{city}^*
name \rightarrow \epsilon
city \rightarrow \epsilon
population \rightarrow \epsilon

Glushkov automata: $O(|\Sigma| \times |D|)$
Deterministic DTDs

country → name · city · region
region → name · (population + \(\epsilon\) · city
name → \(\epsilon\)
city → \(\epsilon\)
population → \(\epsilon\)

Glushkov automata: \(O(|\Sigma| \times |D|)\)
Deterministic DTDs

country → name · city · region*
region → name · (population + ε) · city*
name → ε
city → ε
population → ε

country → name · city · region*
region → name · (population + ε) · city*
name → ε
city → ε
population → ε

Stepwise tree automaton: $O(|\Sigma| \times |D|^2)$
Deterministic DTDs

country → name · city · region*
region → name · (population + $\epsilon$) · city*
name → $\epsilon$
city → $\epsilon$
population → $\epsilon$

Factorized tree automaton: $O(|\Sigma| \times |D|)$
Theorem

Let $A$ be a tree automaton for unranked trees (stepwise, first-child next-sibling, or hedge), and $D$ a deterministic DTD, both over $\Sigma$. Inclusion $L(A) \subseteq L(D)$ can be checked in time $O(|A| \times |\Sigma| \times |D|)$.

- Non-trivial algorithm:
  - Avoid complement automaton computation
  - Detect inclusion failure on the product automaton
  - Only accessible part is materialized

- Optimizations:
  - Early detection of inclusion failure
  - Incremental w.r.t. adding $\epsilon$-rules to $A$ (stepwise)
Monadic Queries

- Regular languages of annotated trees, i.e., over $\Sigma \times \{0, 1\}$
  - Functional: no contradictory annotations
  - Non-null: at least one positive annotation
- Node-selecting tree transducers (NSTTs) [Carme et al., 2007]:
  - Stepwise tree automata for monadic node-selecting queries
  - Functionality and non-nullity checked in polynomial time
  - Query answering done in combined linear time
Regular Query Induction

- Supervised learning problem
- Based on tree automata inference (RPNI-like algorithm)
- Variant of Gold’s identification in the limit model [Gold, 1978; de la Higuera, 1997]
- Regular monadic queries represented by NSTTs are identifiable from completely annotated examples [Carme et al., 2007]
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Why Pruning?

- Practical constraint: learn from partially annotated examples
- State-of-the-art systems use pruning in order to success [Carme et al., 2007; Raeymaekers, 2008]
- Basic idea: try to keep useful parts of tree examples that justify node selection, while removing irrelevant parts
- What can be learned depends on the fixed pruning strategy
Pruning Strategy

- Replace whole subtrees by symbols in some alphabet $\Gamma$
- Function $P$ from trees over $\Sigma \times \{0, 1\}$ to trees over $(\Sigma \times \{0, 1\}) \cup \Gamma$
  - Preserve at least selected nodes and their path from the root
  - Do not change label and annotation of preserved nodes
  - Expressible by some monadic query
- Schema-guided: let $\Gamma = sta(D)$
Path-Only Pruning

Annotated tree \( t \ast \beta \)
Path-Only Pruning

Annotated tree $t \ast \beta$
Path-Only Pruning

\[ \mathcal{P}_{\text{only}}^D(t \times \beta) \]

\textbf{Schema } D
Path-Only Pruning

\[ \mathcal{U} \text{-pruned tree } \mathcal{P}^\mathcal{U}_{\text{only}}(t * \beta) \]

\[ (\text{country}, 0) \]
\[ (\text{name}, 1) \]
\[ (\text{region}, 0) \]

\[ \text{Schema } \mathcal{U} \]
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Simple Queries?

Select all names:

```
country
  └── name
  └── city
    └── region
        └── region
            └── name
                └── city
                └── city
                └── city
```
Simple Queries?

Select all regions’ names whose population is known:

country

name city region

name population city

name city city
Select country’s name if all regions have no population:
Simple Queries?

Select country’s name if all regions have no population:

Conclusion: the larger is the dependency, the more difficult it is.
Annotated tree $t \ast Q(t)$
Insights

Relevant information for $Q$
Insights

\[ \mathcal{U}\text{-path-only pruning } \mathcal{P}_{\text{only}}^\mathcal{U}(t \ast Q(t)) \]
Insights

\[ U \text{-completion } t' \]
Annotated tree $t' \ast \mathcal{Q}(t')$
**Insights**

\[ D\text{-path-only pruning } \mathcal{P}_\text{only}^D \left( t \ast \mathcal{Q}(t) \right) \]
Insights

- country
  - name
  - city
  - region
  - region
    - name
    - population
    - city
    - name

D-completion $t_1$
Annotated tree $t_1 \ast Q(t_1)$
Stable Queries

Insights

Diagram:

- country
  - name
  - city
  - region
    - name
    - population
    - city
    - name
    - population
    - city

$D$-completion $t_3$
(country, 0)
(name, 0)  (city, 0)  (region, 0)  (region, 0)
(name, 1)(population, 0)  (city, 0)  (name, 1)(population, 0)  (city, 0)

Annotated tree $t_3 \ast Q(t_3)$
Stability

Definition

A query \( Q \) is stable by a \( D \)-pruning \( P \) (or \( P \)-stable) if and only if for all \( t_0 \in \mathcal{L}(D) \), let \( t' = P(t_0 \ast Q(t_0)) \):

\[
\forall t_1 \in \text{compl}_D(t'), \forall \nu(t'(\nu) \in \Sigma \times \{0, 1\}), (\nu \in Q(t_1) \iff \nu \in Q(t_0))
\]

Informally stated: for every \( D \)-completion of a \( D \)-pruned tree, a \( P \)-stable query \( Q \) selects exactly the same nodes on the non-pruned part as on the original tree.
Classification of Pruning Strategies

Definition

Let $P_1$ be a $D_1$-pruning and $P_2$ be a $D_2$-pruning, $P_1$ is more preserving than $P_2$ if $\text{compl}_{D_1}(P_1(s)) \subseteq \text{compl}_{D_2}(P_2(s))$ for all annotated trees $s$.

Proposition

Let $Q$ be a query and $P_1, P_2$ be two pruning strategies. If $P_1$ is more preserving than $P_2$ and $Q$ is $P_2$-stable then $Q$ is $P_1$-stable.
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Tree Automata for Pruned Trees

- **$D$-functionality**: no contradictory annotations for $D$-pruned trees that share a $D$-completion
- Monadic queries: regular languages of $D$-pruned trees
  - $D$-functional
  - Non-null
- **$D$-NSTT{s}**
  - $D$-functionality and non-nullity checked in polynomial time
  - Query answering done in combined linear time
**Lemma**

Let $Q$ be a monadic query, $P$ be a $D$-pruning, and $L$ the language of $D$-pruned trees such that

$$L = \{ P(t \ast Q(t)) \mid t \in \mathcal{L}(D) \}.$$ 

If $Q$ is $P$-stable then $L$ is $D$-functional.
Learnability Results

Learning Algorithm

\[ t_{RPNI}^P_D(S) \]

// parameters: \( D \), a schema; \( P \), a \( D \)-pruning strategy
// input: \( S \), a sample of \( D, P \)-pruned trees
// output: \( A \), a \( D \)-NSTT

\( A \leftarrow \text{init}(S) \) // maximal deterministic automaton recognizing \( S \)

\( \text{while} \ (p_1, p_2) \leftarrow \text{pick\_two\_states}(A) \ \text{do} \) // states properly ordered
\( \quad A' \leftarrow \text{deterministically\_merge}(A, p_1, p_2) \)
\( \quad \text{if} \ A' \text{ is a } D\text{-NSTT then} \) // check \( D\)-functional, non-null
\( \quad \quad A \leftarrow A' \)

\text{return} \ A
Main Result

Theorem

Let $D$ be a deterministic schema over $\Sigma$ and $\mathcal{P}$ a $D$-pruning strategy. The class of $\mathcal{P}$-stable queries represented by deterministic $D$-NSTTs over $\Sigma$ is learnable from $D$-pruned examples by $t_{\text{RPNI}}^\mathcal{P}_D$ in the following sense:

1. given a sample $S$ of $D$, $\mathcal{P}$-pruned trees, $t_{\text{RPNI}}^\mathcal{P}_D(S)$ returns a $D$-NSTTs in time polynomial in $|S|$;
2. for all $D$-NSTTs $A$ representing a $\mathcal{P}$-stable query, there exists a characteristic set $\mathcal{CS}$ of $D$, $\mathcal{P}$-pruned trees of cardinality polynomial in $|A|$ for which, given $S \supseteq \mathcal{CS}$ consistent with $A$, $t_{\text{RPNI}}^\mathcal{P}_D(S)$ returns a $D$-NSTTs equivalent to $A$. 
Proof Sketch

- Reduction onto learnability of regular monadic queries ($t_{RPNI}$)
- Based on the relation between $\mathcal{P}$-stable queries and $D$-functionality
- Characteristic set obtained by $D$-completion
- Bisimulation of $t_{RPNI}$ and $t_{RPNI}^D$
Learnability Results

Learnability of Schema-Consistent Queries

**Corollary**

Let $D$ be a deterministic schema. The class of $D$-consistent queries represented by NSTTs can be learned from completely annotated examples.

Proof: $t\mathcal{RPNI}_D^P$ with $\mathcal{P} = \mathcal{P}_{id}$ and $D$-inclusion checking.
Some Practical Questions

- XML data rather than HTML data
- Does schema’s semantics help?
- Are stable queries relevant?
- Given a query that is stable by several pruning strategies, which one is the most appropriate?
- New learning system in OCaml
- Learning algorithm implemented parameters:
  - Prunings: $\mathcal{P}^u\text{only}$, $\mathcal{P}^u\text{ext}$, $\mathcal{P}^d\text{only}$, $\mathcal{P}^d\text{ext}$.
  - Dynamic/static inclusion checking, “horizontal” typing heuristic
- Several combinations are not theoretically complete
Protocol

- Simulation of the user behaviour when defining a new query
- Interactions between the user and the system:
  - The user provides annotated examples to the system
  - The system infers a new query, which in turn the user evaluates
  - More examples while not satisfied
- Weak interactions:
  - Annotations “per document” instead of “per node”
  - Sufficient for evaluating the system
- Cross-validation by repeated random sub-sampling
- Compute F-measure w.r.t. number of examples
XPath Queries

- **XMark-A1:**
  `/site/closed_auctions/closed_auction/annotation/description/text/keyword`

- **XMark-02:**
  `/site/open_auctions/open_auction/bidder[1]/increase`

- **XMark-21:**
  `/site/open_auctions/open_auction[count(bidder) ≥ 3]/itemref`

- **XMark-A6:**
  `/site/people/person[profile/gender and profile/age]/name`
## Datasets

<table>
<thead>
<tr>
<th>Query id.</th>
<th># doc.</th>
<th>( \mathcal{P}^U_{\text{only}} )</th>
<th>( \mathcal{P}^U_{\text{ext.}} )</th>
<th>( \mathcal{P}^D_{\text{only}} )</th>
<th>( \mathcal{P}^D_{\text{ext.}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>XMark-A1</td>
<td>50</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>XMark-02</td>
<td>100</td>
<td>no</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>XMark-21</td>
<td>50</td>
<td>no</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>XMark-A6</td>
<td>250</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>yes</td>
</tr>
</tbody>
</table>
Pruning Alone

XMark-A1

XMark-21

# of examples

# of examples
Combination of Heuristics

Experiments

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Facts

- Confirmation: pruning is essential for XML query induction
- Contextual information brought by the schema are very useful
- The most appropriate pruning is one for which the query is stable, and which makes use of the schema
- Combining dynamic inclusion checking with schema-guided pruning enables to learn “difficult” queries
## Summary

### Main contributions

- Complete learning algorithms
  - Stable queries
  - Schema-consistent queries
- Classification of pruning strategies w.r.t. stability
- Experiments on XML datasets
- Efficient inclusion checking (Information and Computation, 2009)
  - Both practical and theoretical interest
  - Factorized tree automata for DTDs
Summary

Main contributions

- Complete learning algorithms
  - Stable queries
  - Schema-consistent queries
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Some lessons we can drawn...

- Using schema information improves XML query induction
  - Theoretical fundations
  - Practical justification
- Difficulty scale of target queries can be addressed through stability
Perspectives

- How perform other learning approaches on stable queries?
- Interactive learning:
  - Start with the less preserving pruning (i.e., $\mathcal{P}^D_{\text{only}}$)
  - Evolve towards more preserving prunings
- $n$-ary queries:
  - How should we prune?
  - Same definition of stable queries?
- Text values: schemas may contain type information
- Extension to XML transformations: notion of stability?