Leveraging Data and Structure in Ontology Integration
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Ontologies

a quest for meaning

- A very common problem in IT is data modeling
  - Critical in the field of Information Systems
  - A good data model enables good data usage

- Tools used to describe concepts cannot express the implicit interpretation of data

- Semantic knowledge is lost after the modeling process

Example

<musician name="F. Mercury" sings-for="Queen" />
<musician name="B. May" plays-for="Queen" />

- How can we find all of Queen’s members?
Ontologies

a formal model

Ontology

An ontology is a *formal representation of*

- **concepts** within a *domain* (Song, Performer, Composer...)
- **relations** between those concepts (plays-for, member-of, written-by...)
- individual **instances** (queen, f.mercury, b.may...)

- *Well-defined constructs* to enrich descriptions with semantics
- Formal models to enable *automatic reasoning* *(DL, FOL)*
  
  \[ \text{member}(Y,Z) \rightarrow \text{sings-for}(Y,Z) \land \text{plays-for}(Y,Z) \]

- **OWL** is the W3C standard for an *ontology language*
Brief Introduction to Ontologies

What is an Ontology

OWL

A simple example
Motivating Scenario

The AAA principle

*Anyone can say Anything about Any topic*

- The same thing might be described in different ways
- There is a strong need to *integrate heterogeneous schemas*
  - Not only in a web scenario

Example

- DB schemas
- XML schemas
- Ontology schemas
An Integration Problem
Integration Techniques

Structure Based Matching
Uses schema *meta-data* (e.g. informations about tables or concepts models) to discover mapping elements among them, both on a structural and element level.

Instance Based Matching
Uses informations about *data instances* (e.g. contents of a table or individuals of an ontology) to discover mappings among entities representing them.
Motivations and State of the Art

Bringing data together

Ontology Integration

- **Ontologies offer further ways** to uncover aligning relations between entities
- **Explicit theoretic model semantics** can be leveraged to improve integration quality

**Example**

- Assume that *composed-by* is a functional property
- “Requiem K626” and “Requiem in D minor” are the same
- If we have:
  - composed-by(‘Requiem K626’, ‘Mozart’).
  - composed-by(‘Requiem in D minor’, ‘W.A. Mozart’).
- Then we might say that aligning “W.A. Mozart” and “Mozart” is a good choice
FCA-Merge and COMA++

**FCA-Merge (human-aided tool to merge ontologies)**
- Collects domain related natural language documents
- Searches those documents for ontologies’ concepts occurrences
- Derives an alignment that *has to be* validated by an operator

**COMA++ (framework with multiple match strategies)**
- Fragment based matching
- Reuse of previous matching results
- Comprehensive GUI for results evaluation
What’s missing

- Both COMA++ and FCA-Merge use only structure level matching.
- Moreover none of them makes use of the semantic potential offered by ontologies.
- There exist other solutions using reasoning support, however ...
  - it is used only for an a-posteriori consistency check of the result.
- An interesting improvement might be to leverage it for the actual matching process.
- That’s where ILIADS kicks in!
ILIADS
Integrated Learning In Alignment of Data and Schema

- Takes **two OWL Lite ontologies** as *input*
- *Combines* "traditional" schema matching approaches with a *logical inference algorithm*
  - Inference results are *used to influence confidence* in a presumed mapping
- Makes use of both schema (structure) and data (individuals)
- *Outputs* a set of axioms (the **alignment**) that tights the input ontologies together
Algorithm Overview

**INPUT:** Consistent Ontologies $O_1$ and $O_2$

**OUTPUT:** Alignment $A^*$

01: Initialize algorithm’s structures ($O$ is $O_1 \cup O_2$)
02: repeat:
03: Compute similarity scores between clusters
04: Heuristically select a type of clusters
05: for each couple $(c, c')$ of that type do
06: Determine a candidate relationship $a_{(c, c')}$
07: Perform incremental inference
08: Update similarity score
09: Select the best couple, update $O$ and $A^*$
10: until there are clusters with similarity $> \lambda_t$
11: return $A^*$
The Algorithm

Step by step

01: Initialize algorithm’s structures ($O$ is $O_1 \cup O_2$)
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Structures initialization

- The algorithms groups equivalent entities in **clusters**
- Clusters are classified by the type of their entities
  - Clusters of *Classes*
  - Clusters of *Properties*
  - Clusters of *Individuals*
- A new alignment can result in
  - **Merging** of clusters
  - A new **subsumption** relationship between clusters
- At the beginning a cluster is created for each entity
The Algorithm
Step by step

01: Initialize algorithm’s structures (\( O \) is \( O_1 \cup O_2 \))
02: \textbf{repeat}:
03: Compute similarity scores between clusters
04: Heuristically select a type of clusters
05: \textbf{for} each couple \((c, c')\) of that type \textbf{do}
06: Determine a candidate relationship \( a_{(c,c')} \)
07: Perform incremental inference
08: Update similarity score
09: Select the best couple, update \( O \) and \( A^* \)
10: \textbf{until} there are clusters with similarity > \( \lambda_t \)
11: \textbf{return} \( A^* \)
The Algorithm

Similarity Computation

Entities similarity score

\[ \text{sim}(e, e') = \lambda_x \cdot \text{sim}_{\text{lex}}(e, e') + \lambda_s \cdot \text{sim}_{\text{struct}}(e, e') + \lambda_e \cdot \text{sim}_{\text{ext}}(e, e') \]

- **lexical**: Jaro-Winkler (similar to edit distance) and thesauri
- **structural**: Jaccard for *neighborhoods* \( \text{Jac}_d(S_1, S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|} \)
- **extensional**: Jaccard on *extensions*

The set of parameters \( \{\lambda_x, \lambda_s, \lambda_e\} \) is *different for each entity type*

Similarity between clusters is computed combining the similarities of their entities
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Selecting a relationship

- Iterates over each couple \((c, c')\) such that \(\text{sim}(c, c')\) is above a threshold \(\lambda_t\)

- For each of those a candidate relationship is chosen between:
  - **Equivalence**
    (Two concepts are said to be equivalent if they denote the same concept)
  - **Subsumption**
    (A concept subsumes another concept if it always denotes a superset of the second)

- The selection is done by looking at the intersection of entities’ *extensions*:
  - The set of its instance individuals, for a class
  - The couples of individuals involved, for a property
The Algorithm

Selecting a relationship - Example (1)
The Algorithm

Selecting a relationship - Example (2)
The Algorithm

Selecting a relationship - Example (3)

Number of instances belonging only to "Rock Music" over the total number of instances considered:

2/3
The Algorithm

Selecting a relationship - Example (4)

Number of instances belonging only to "Rock Music" over the total number of instances considered:

\[ \frac{2}{3} \]

Number of instances belonging only to "Metal" over the total number of instances considered:

\[ \frac{1}{2} \]
The Algorithm

Selecting a relationship - Example (5)

Number of instances belonging only to "Rock Music" over the total number of instances considered: 2/3

1/2 < \( \lambda_r \) < 2/3

"Metal" subClassOf "Rock Music"
The Algorithm

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The Algorithm
Incremental Logical Inference

- The inference step is used to:
  - Look for inconsistencies of the candidate relationship
  - Infer logical consequences of the new axiom
  - Possibly enforce the confidence in it

- The inference is not complete (it would be \textsc{ExpTime} in OWL Lite)
  - Only a small number of steps is actually performed
  - However this may cause inconsistencies not to be found
The Algorithm
Incremental Logical Inference - Example (1)
The Algorithm

Incremental Logical Inference - Example (2)
The Algorithm

Incremental Logical Inference - Example (3)
The Algorithm
Incremental Logical Inference - Example (4)
The Algorithm
Incremental Logical Inference - Example (5)
The Algorithm
Incremental Logical Inference - Example (6)
The Algorithm

Step by step

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The Algorithm

Update similarity score

- This is the key point of the algorithm
  - A value $f$ - the influence factor of the inference - is computed

The “$f$” factor

$$f = \prod_{(e_1, e_2) \in Q} \frac{\text{sim}(e_1, e_2)}{1 - \text{sim}(e_1, e_2)}$$

$Q$: the set of entity pairs that became equivalent as a consequence of inference

- $f$ is used to update the similarity score for the current couple
  - $\text{sim}_{\text{inf}}(c, c') = \min(f \cdot \text{sim}(c, c'), 1)$
The Algorithm

Update similarity score - Example (1)
The Algorithm

Update similarity score - Example (2)
The Algorithm

Update similarity score - Example (3)
The Algorithm

Update similarity score - Example (4)

\[ f = \frac{0.6}{1 - 0.6} = 1.5 \]
The Algorithm

Update similarity score - Example (5)

Similarity :

\[ f = \frac{0.6}{1 - 0.6} = 1.5 \]
The Algorithm
Step by step

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The Algorithm

Building the alignment

- By now for each candidate pair of clusters of a given type
  - A possible relationship has been explored
  - A set of consequences has been inferred
  - An “inference-weighted” similarity has been computed

- Before restarting the loop:
  - The axiom $a^*_{(c,c')}$ with the highest similarity score is chosen
  - It is added to the output alignment $A^*$
  - If $a^*_{(c,c')}$ is an equivalence $c$ and $c'$ are merged
The Algorithm

Step by step

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The Algorithm

The End(ing)

- The algorithm halts when there are \textit{no more candidate clusters}
  - When there are no clusters having similarity greater than the threshold $\lambda_t$
  - Remaining clusters are not likely to share any relationship

- Intuitively ILIADS is \textbf{guaranteed to terminate} because
  - Previously used cluster pairs are not re-used unless their score changes
  - The merging process decreases the number of clusters
Comparative results
Precision, Recall and F-1
Tests Analysis

- The interplay between structure and instance integration delivers higher quality
  - Significant *improvement of recall*
  - Tests on ontologies without instance data showed comparable results with the other systems

- **Lambda-tuning** allows ILIADS to adapt itself better to particular pairs of ontologies

- Inconsistent alignments due to limited inference steps were found only in the .5% of tests
Summary

- **Explicit semantics** provided by ontologies can improve the quality of data integration
- **Instance data** exploitation could significantly enhance traditional matching techniques
- **ILIADS** leverages both these opportunities and shows promising results

Future developments

- Intra-ontology differentiated $\lambda$ parameters
- Alignment of ”distant” sections of the ontologies in parallel
And now an ultra-fancy demo
Thank you.

Group 15

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For Further Reading I

**W3C OWL resources.**
http://www.w3.org/2004/OWL/.

**D. Aumueller, H.H. Do, S. Massmann, and E. Rahm.**
Schema and ontology matching with COMA++.

**I. Horrocks, P.F. Patel-Schneider, and F. van Harmelen.**
From SHIQ and RDF to OWL: the making of a Web Ontology Language.
For Further Reading II

Y. Kalfoglou and M. Schorlemmer.
Ontology mapping: the state of the art.

E. Rahm and P.A. Bernstein.
A survey of approaches to automatic schema matching.

P. Shvaiko and J. Euzenat.
A survey of schema-based matching approaches.
For Further Reading III

G. Stumme and A. Maedche.  
FCA-MERGE: Bottom-Up Merging of Ontologies.  

O. Udrea, L. Getoor, and R.J. Miller.  
HOMER: Ontology alignment visualization and analysis.

F. Baader.  
*The description logic handbook: theory, implementation, and applications.*  