Leveraging Data and Structure in Ontology Integration
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Outline

1. Brief Introduction to Ontologies
   - What is an Ontology

2. Motivations and State of the Art
   - Bringing data together
   - Existing Solutions

3. ILIADS
   - Overview
   - The Algorithm
   - Experimental Results
   - Conclusions and Future Developments

4. Demo
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" />
```
Ontologies
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**Example**

```xml
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- 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*)
  
  \[(\text{member}(Y,Z) \iff \text{sings-for}(Y,Z) \lor \text{plays-for}(Y,Z))\]

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

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Brief Introduction to Ontologies

What is an Ontology

OWL

A simple example

![Diagram showing relationships between musical genres, composers, and performers.](image-url)
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
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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.
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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
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Motivations and State of the Art

Bringing data together

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# 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

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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.
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- 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
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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

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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
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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
The Algorithm
Similarity Computation

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The Algorithm

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
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The Algorithm

Selecting a relationship - Example
The Algorithm
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The Algorithm

Selecting a relationship - Example

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

2/3
The Algorithm
Selecting a relationship - Example

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

2/3

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

1/2
The Algorithm

Selecting a relationship - Example

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:

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

\[ \frac{1}{2} < \lambda_r < \frac{2}{3} \]

"Metal" subClassOf "Rock Music"
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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 EXPTIME in OWL Lite)
  - Only a *small number of steps* is actually performed
  - However this may cause inconsistencies not to be found
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Incremental Logical Inference - Example

MusicArtist

The Black Sabbath

Mozart

Music Piece

Requiem K626

Smoke on the water

subClassOf
type

Classic Rock

subClassOf

Metal

subClassOf

Fusion

Orchestral

Quadrant Four

Whole lotta love

Paranoid

Orchestral

subClassOf
type

plays

S. Harris

Requiem in D minor

W.A. Mozart

composer-of

Vienna Philharmonic

Take the "A" train

The Phantom of the Opera

Ride of the Valkyries

W.A. Mozart

composer-of

Requiem in D minor

composer-of

Vienna Philharmonic

sameAs

Requiem in D minor

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composed-by

is a Functional Property
The Algorithm

Incremental Logical Inference - Example
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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
  - $\text{sim}_{\text{inf}}(c, c') = \min(f \cdot \text{sim}(c, c'), 1)$
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The Algorithm

Update similarity score - Example
**The Algorithm**

Update similarity score - Example

![Diagram of the algorithm showing relationships between music artists, pieces, and genres with a similarity score of 0.5 between Smoke on the Water and Requiem K626.](image)
The Algorithm

Update similarity score - Example
The Algorithm
Update similarity score - Example

Similarity : 0.5

f = 0.6 / (1 - 0.6) = 1.5
The Algorithm
Update similarity score - Example

Similarity: 0.75

\[ f = \frac{0.6}{1 - 0.6} = 1.5 \]
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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 $a^{*}_{(c,c')} \in A^{*}$ 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
Building the alignment

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- 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

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: return \( A^* \)
The Algorithm

The End(ing)

- The algorithm halts when there are *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 *guaranteed to terminate* because
  - Previously used cluster pairs are not re-used unless their score changes
  - The merging process decreases the number of clusters
The Algorithm

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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
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Summary

- **Explicit semantics** provided by ontologies can improve the quality of data integration
- **Instance data** exploitation could significantly enhance traditional matching techniques
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Future developments

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

Group 15

A. Sorbini   E. Savioli   A. Reale
For Further Reading I

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

  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.*