Leveraging Data and Structure in Ontology Integration

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Outline

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

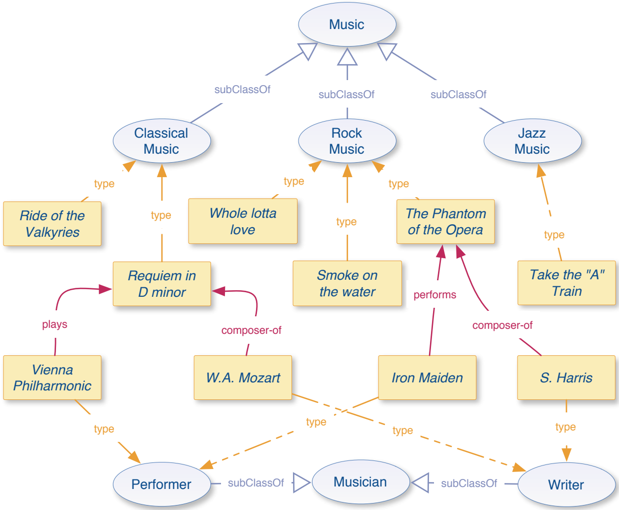
- **concepts** within a *domain* (Song, Performer, Composer...)
- **relations** between those concepts (plays-for, member-of, written-by...)
- individual **instances** (queen, f.mercury, b.may...)

- *Well-defined constructs* to enrich descriptions with semantics
- Formal models to enable *automatic reasoning* (**DL**, **FOL**)
  (member(Y,Z) :- sings-for(Y,Z) ; plays-for(Y,Z))

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

OWL

A simple example



Motivating Scenario

The AAA principle

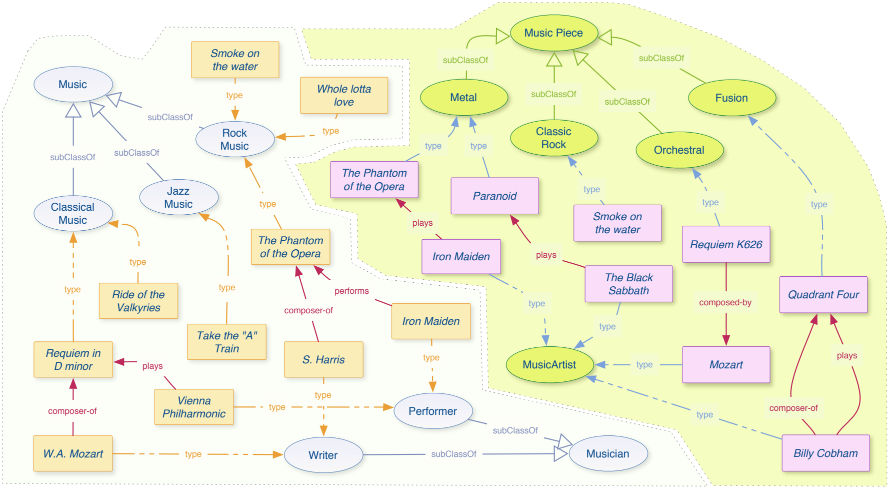
Anyone *can say* ***Anything*** *about* ***Any topic***

- 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

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^*

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

The Algorithm

Step by step

Initialize algorithm's structures (O is $O_1 \cup O_2$)
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The Algorithm

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

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The Algorithm

Similarity Computation

Entities similarity score

$$sim(e, e') = \lambda_x \cdot sim_{lex}(e, e') + \lambda_s \cdot sim_{struct}(e, e') + \lambda_e \cdot sim_{ext}(e, e')$$

- **lexical**: Jaro-Winkler (similar to edit distance) and thesauri
- **structural**: Jaccard for *neighborhoods* ($Jac_d(S_1, S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|}$)
- **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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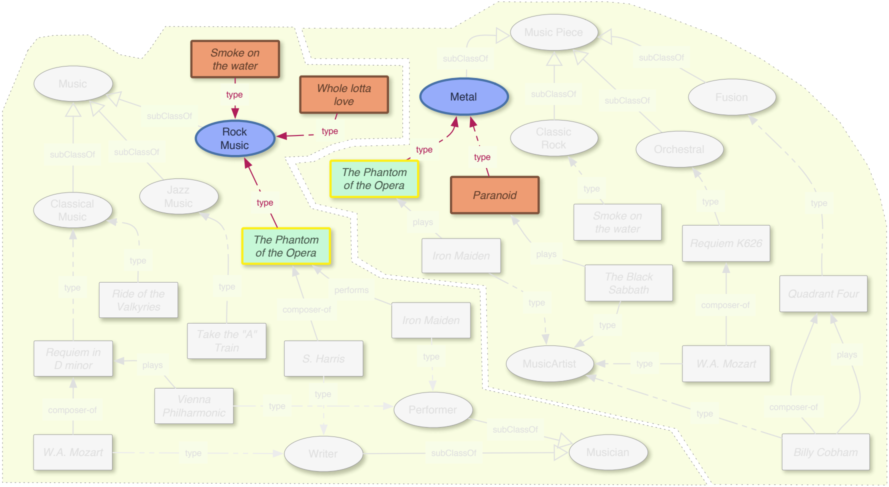
The Algorithm

Selecting a relationship

- Iterates over each couple (c, c') such that $sim(c, c')$ is above a **threshold** λ_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

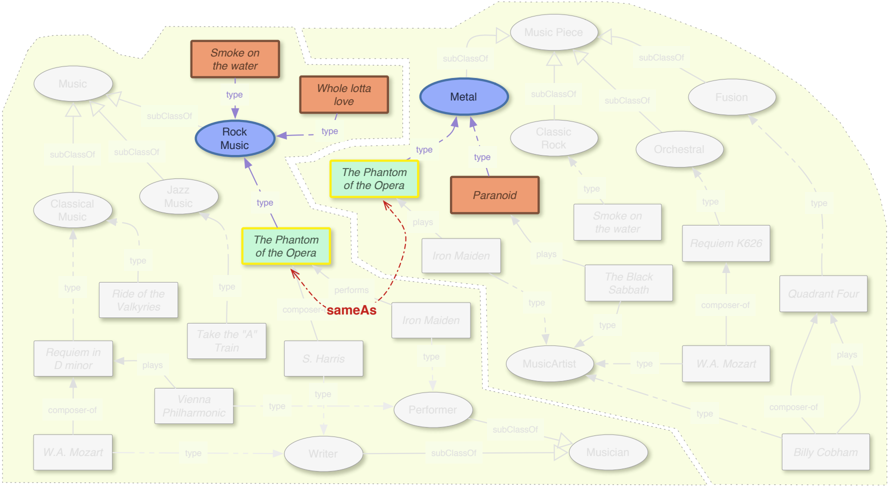
The Algorithm

Selecting a relationship - Example (1)



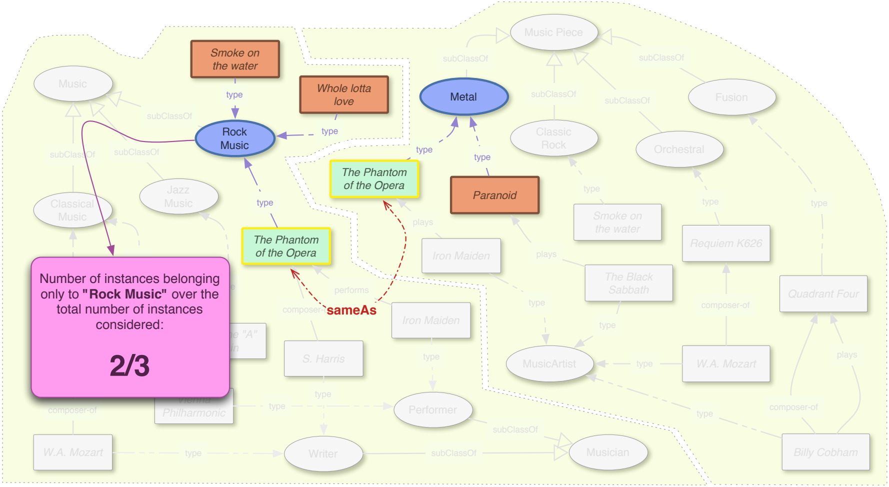
The Algorithm

Selecting a relationship - Example (2)



The Algorithm

Selecting a relationship - Example (3)

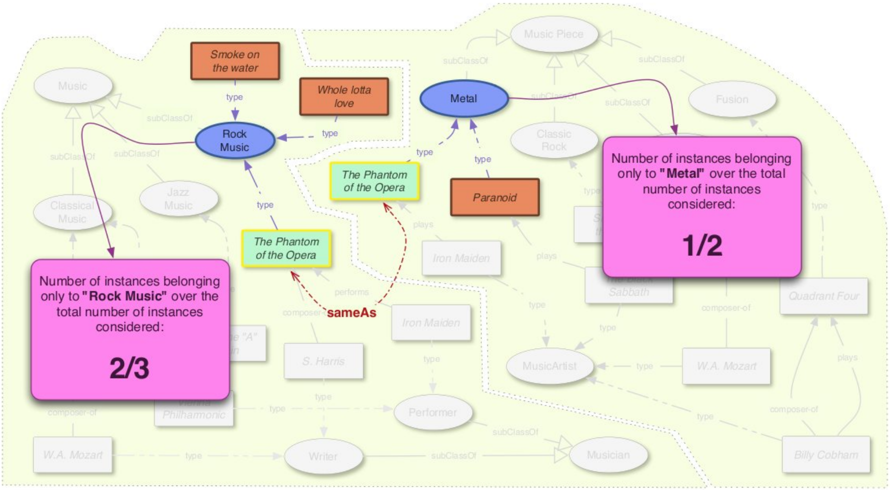


Number of instances belonging only to **"Rock Music"** over the total number of instances considered:

2/3

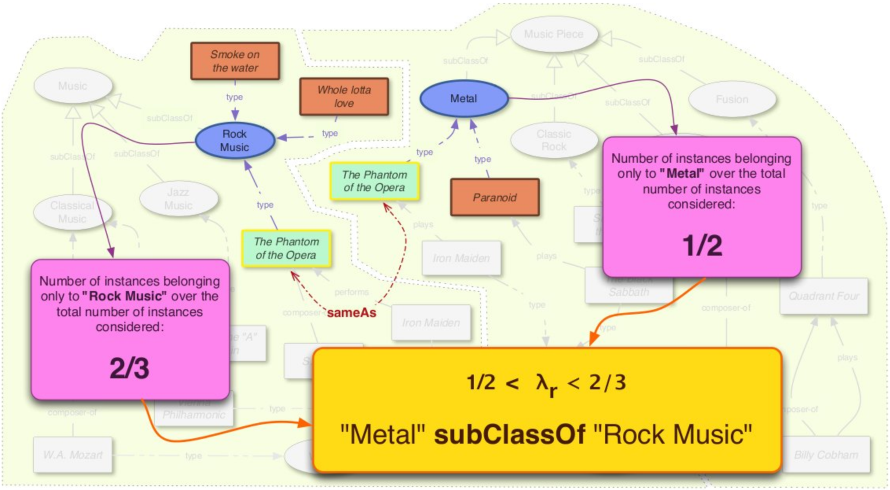
The Algorithm

Selecting a relationship - Example (4)



The Algorithm

Selecting a relationship - Example (5)



The Algorithm

Step by step

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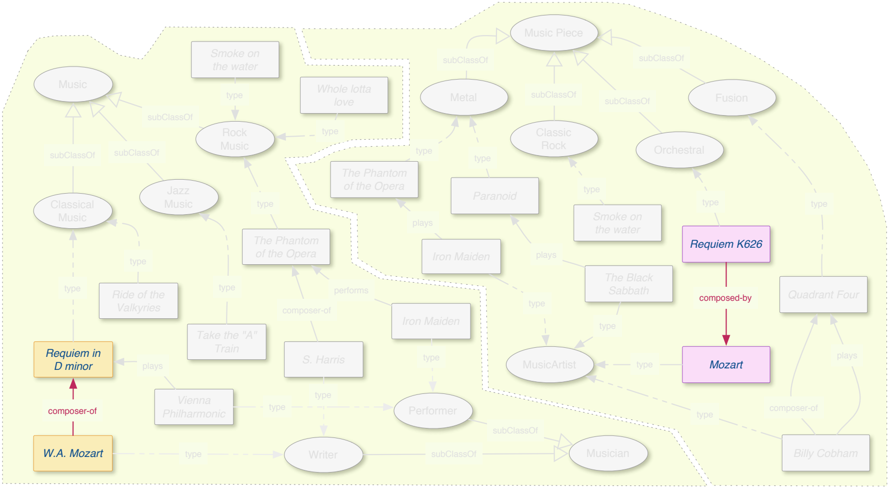
The Algorithm

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 EXPTIME in OWL Lite)
  - Only a *small number of steps* is actually performed
  - However this may cause inconsistencies not to be found

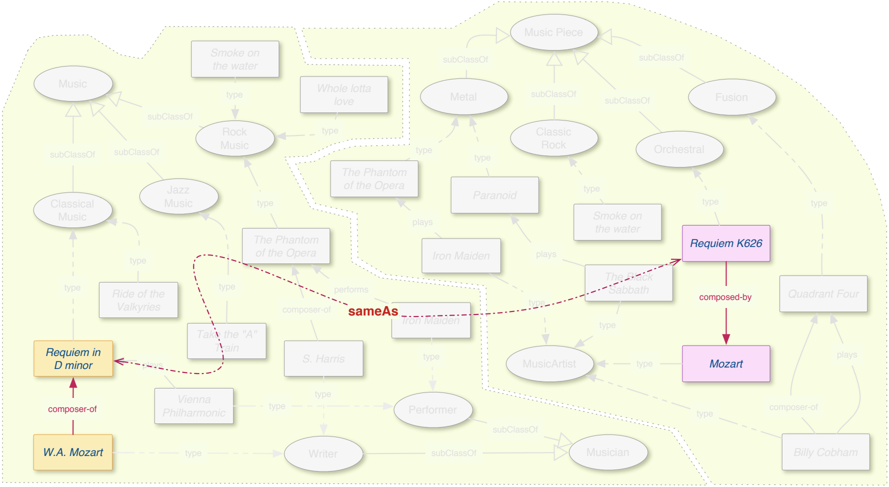
The Algorithm

Incremental Logical Inference - Example (1)



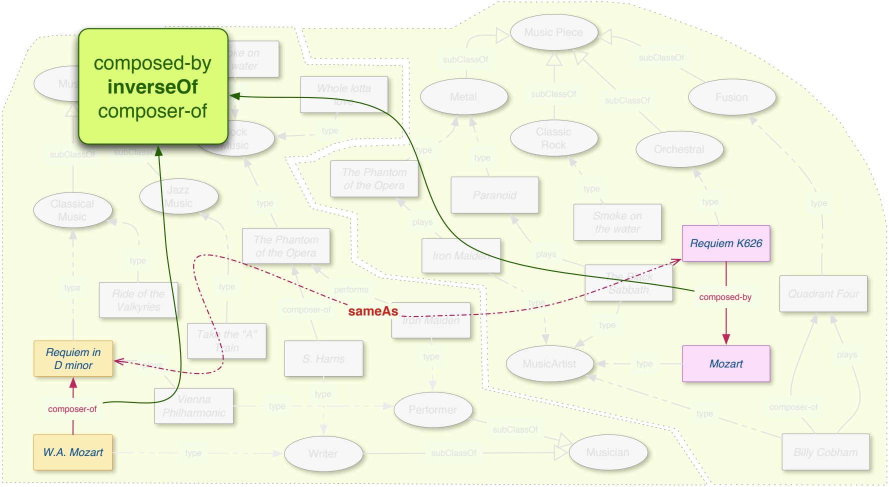
The Algorithm

Incremental Logical Inference - Example (2)



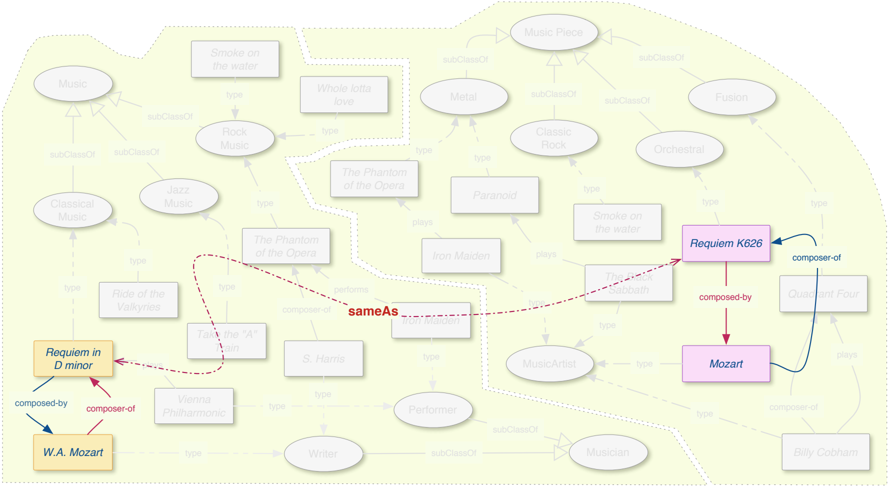
The Algorithm

Incremental Logical Inference - Example (3)



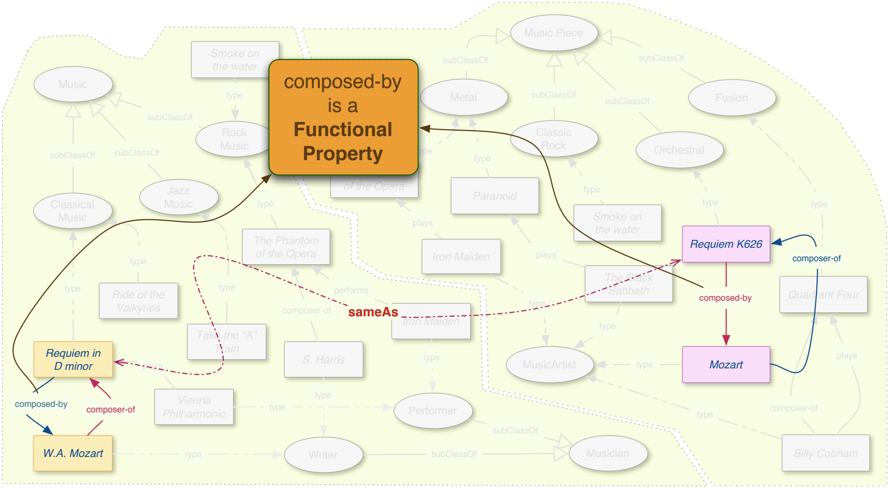
The Algorithm

Incremental Logical Inference - Example (4)



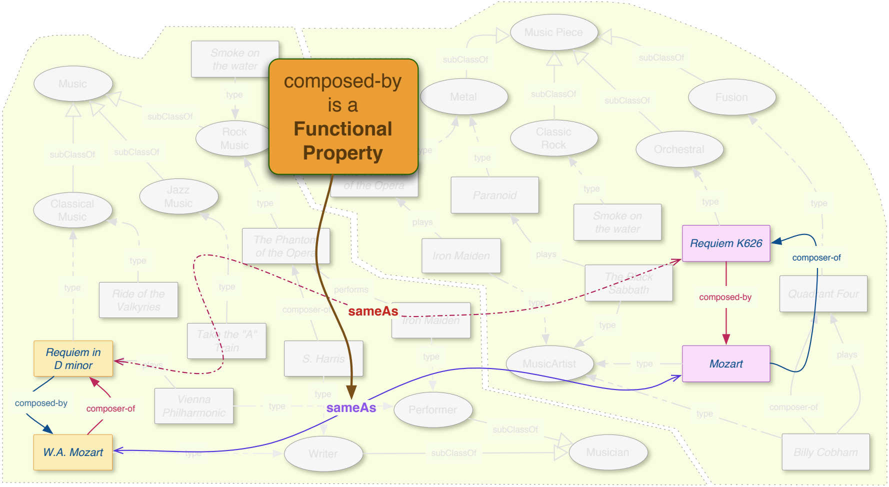
The Algorithm

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

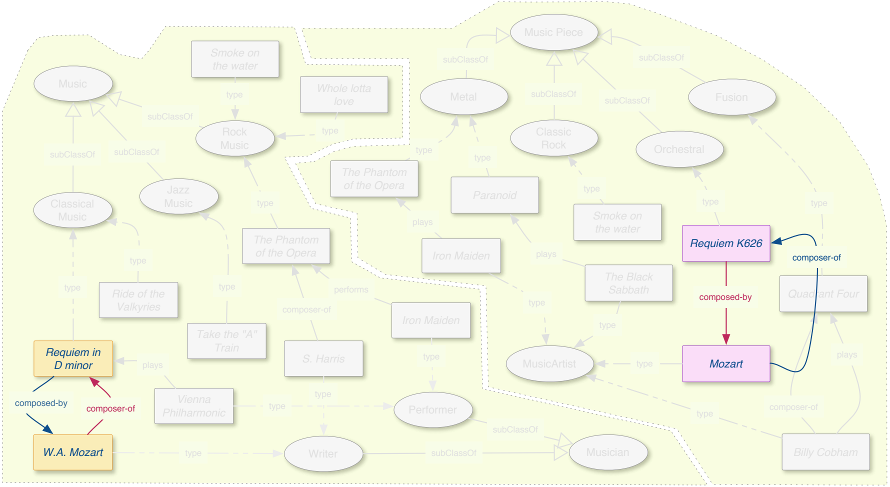
$$f = \prod_{(e_1, e_2) \in Q} \frac{sim(e_1, e_2)}{1 - sim(e_1, e_2)}$$

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
  - $sim_{inf}(c, c') = min(f \cdot sim(c, c'), 1)$

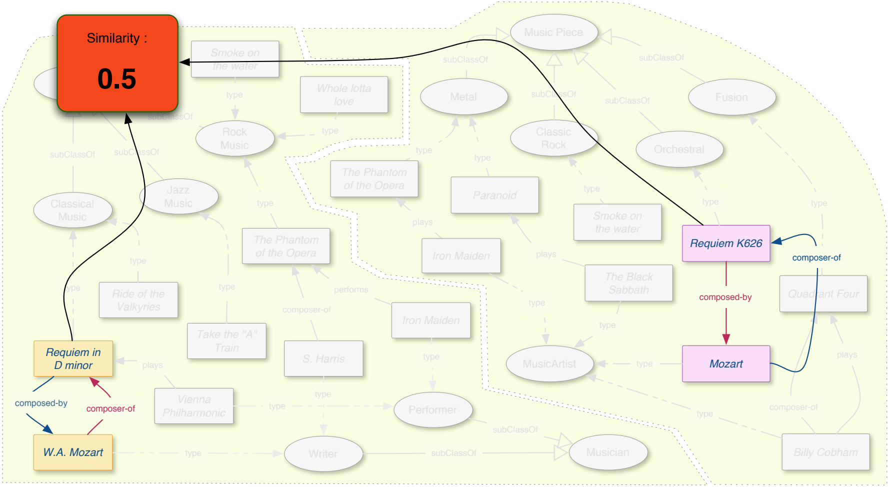
The Algorithm

Update similarity score - Example (1)



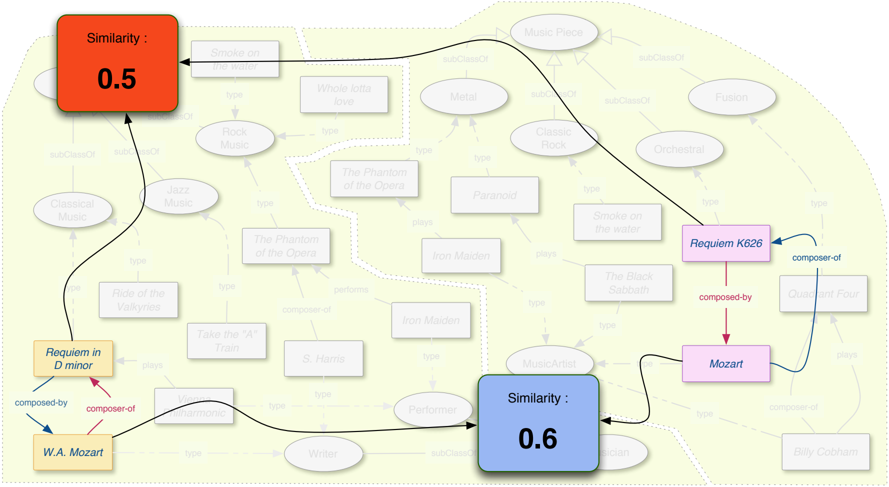
The Algorithm

Update similarity score - Example (2)



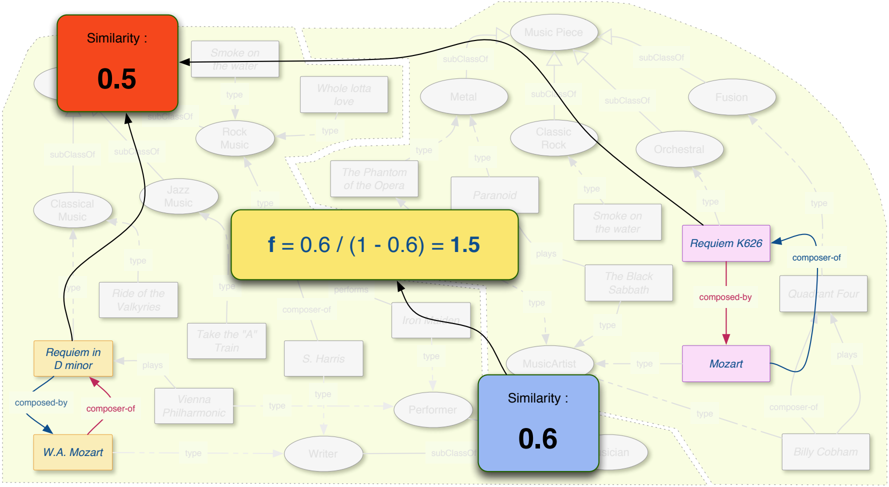
The Algorithm

Update similarity score - Example (3)



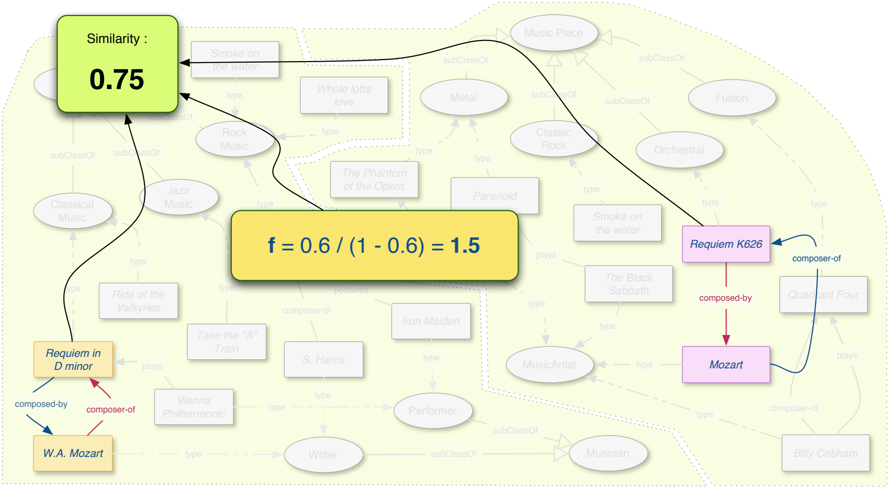
The Algorithm

Update similarity score - Example (4)



The Algorithm

Update similarity score - Example (5)



The Algorithm

Step by step

```
Initialize algorithm's structures (O is O_1 ∪ O_2)
repeat:
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  Select the best couple, update O and A*
until there are clusters with similarity > λ_t
return A*
```

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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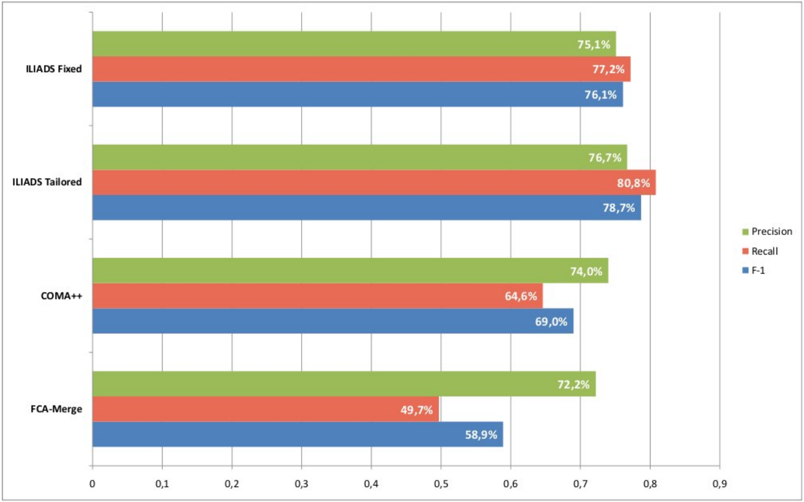
The Algorithm

The End(ing)

- The algorithm halts when there are *no more candidate clusters*
  - When there are no clusters having similarity greater than the threshold λ_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

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

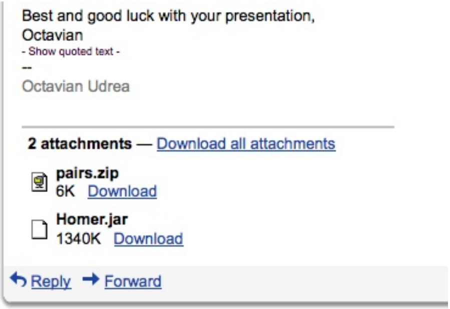
- **Explicit semantics** provided by ontologies can improve the quality of data integration
- **Instance data** exploitation could significantly enhance traditional matching techniques
- **ILIADS** leverages both these opportunities and shows promising results

Future developments

- Intra-ontology differentiated λ parameters
- Alignment of ”distant” sections of the ontologies in parallel

Demo

And now an **ultra-fancy demo**



Thank you.

Group 15

A. Sorbini E. Savioli A. Reale

For Further Reading I

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