Introduction to Ontology Matching
at

Méthodes et outils pour l'open data

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December 2014

Outline

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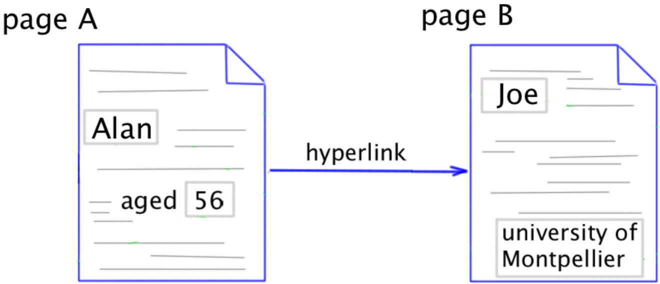
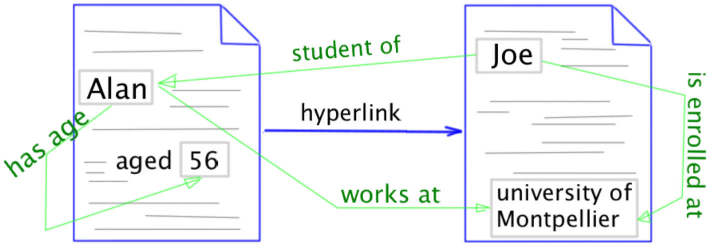
The web of documents

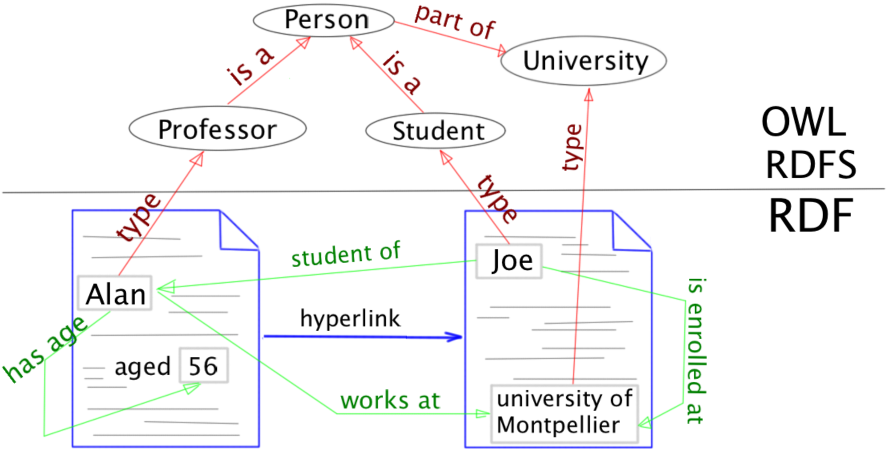


Linking Data



RDF

More semantics: the ontologies



Best practices on the Web of Data:

- Use terms from widely developed vocabularies to name things
  - Vocabularies describing common things (people, places, projects) have emerged on the WoD.
- **Align heterogeneous vocabularies**
  - State that terms in different vocabularies are equivalent, or related: ontology matching
  - –> Make data as self descriptive as possible

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  - State that terms in different vocabularies are equivalent, or related: ontology matching
  - –> Make data as self descriptive as possible

Definition (Ontological Elements)

- C a finite set of concepts
- $is\_a \subseteq C \times C$ a partial order on concepts
- R a set of relations on C
- $\mathscr{I}$ a set of instances
- $g : C \rightarrow 2^{\mathscr{I}}$ a function that assigns subsets of instances from $\mathscr{I}$ to each concept in C
- $l_L : C \rightarrow 2^{\Sigma_L^*}$ a function that assigns to each concept a set of labels from a set of labels Σ_L^* coming from some alphabet Σ_L specific for a language L

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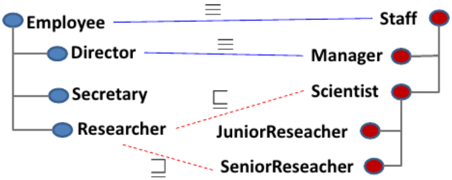
Ontology – an example

- A set of concepts: EMPLOYEE, DIRECTOR, SECRETARY, RESEARCHER
- A set of labels: *"employee"*, *"director"*, *"secretary"*, *"researcher"*
- A subsumption relation (is_a) on the set of concepts

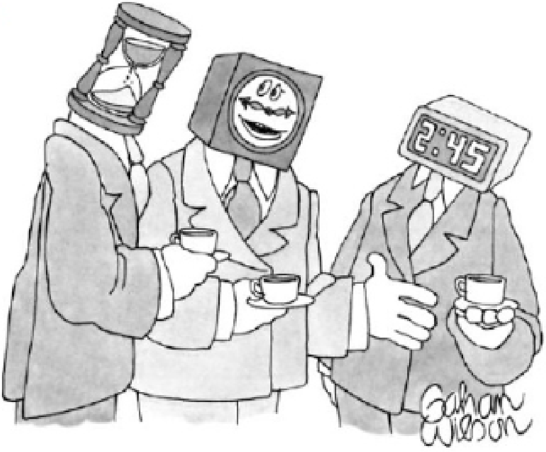
Note: often a set of labels is assigned to a single concept (e.g., a set of synonyms, translations).

Ontologies are created in a **decentralized**, strongly **human biased** manner.

Ontologies describing the same domain of interest => ontology heterogeneity.



=> **Ontology Matching:** detect the semantic correspondences between the elements of two ontologies.



"Basically, we're all trying to say the same thing."

Borrowed by a tutorial by S. Staab and A. Hotho.

Outline

Heterogeneity Types

- Syntactic

  about the formal expression of ontologies

  example: OWL vs. F-logic

- Terminological

  about the choice of labels

  example: "director" vs. "manager"

- Structural / Conceptual

  about the relations between elements

  example: " is_a(director, person)" vs. " is_a(director, employee)"

  - granularity
  - coverage
  - scope

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Ontology Alignment

The process of ontology matching results in an alignment.

An alignment:
a set of correspondances between the elements of two heterogeneous ontologies, derived by *resolving the different heterogeneities* that they manifest.

Similarity measures on element level or global level are applied for every heterogeneity type (e.g., terminological measures, etc.).

A function $\sigma : o \times o \rightarrow \mathbb{R}$ with some properties:

$$\forall x, y \in o, \quad \sigma(x,y) \geq 0$$
$$\forall x, y, z \in o, \quad \sigma(x,x) \geq \sigma(y,z)$$
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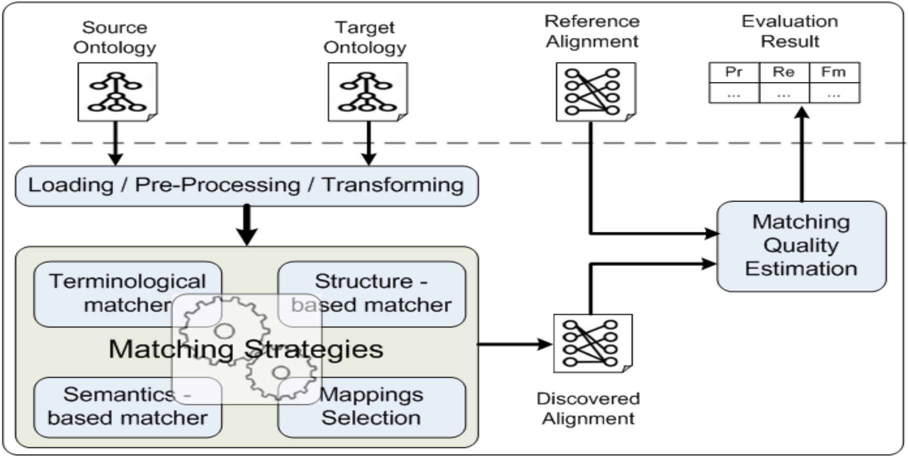


Figure : Ontology Matching: System Architecture and Evaluation Scenario

Outline

1. Ontologies and the Semantic Web
2. Heterogeneities and Alignments
3. **Techniques**
   - Terminological Methods
   - Structural Methods
   - Instance-based Methods
   - Combination of Measures
4. An Ontology Matching System
5. Some Current Topics in OM

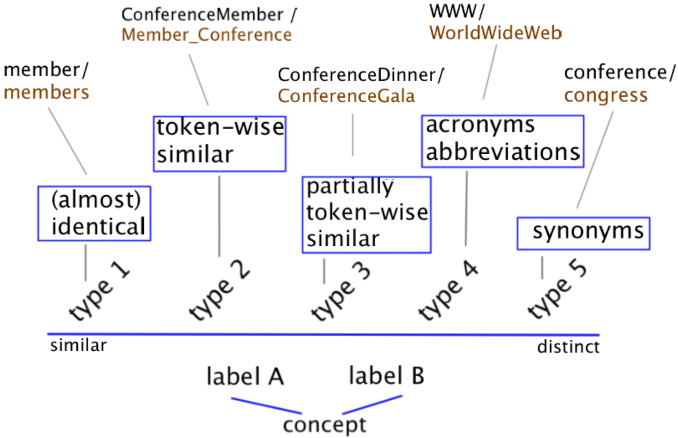
Outline

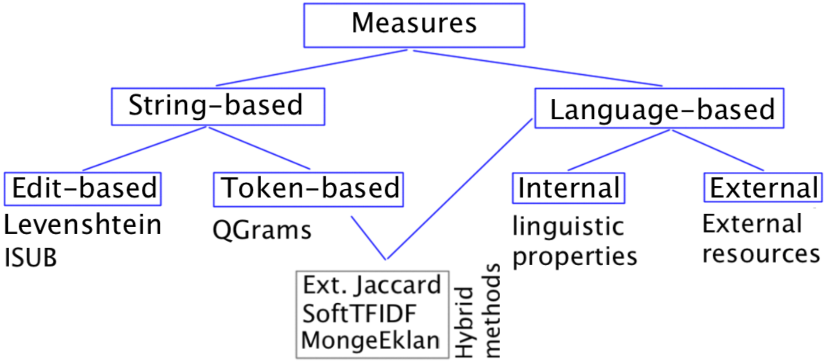
Terminological Heterogeneity

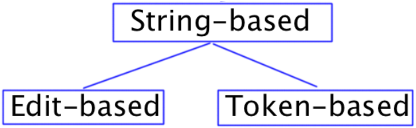
A Typology

Hypothesis: A concept = meaning of its label(s). –>

Terminological Heterogeneity: Any difference in *spelling* between two labels which are assumed to refer to the same concept [4].



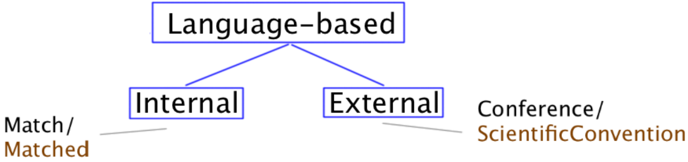

Measures
String–based
Language–based
Edit–based
Levenshtein
ISUB
Token–based
QGrams
Internal
linguistic
properties
External
External
resources
Ext. Jaccard
SoftTFIDF
MongeEklan
Hybrid
methods



- Token-based
  - can handle compound labels
  - are less sensitive to word-swaps ("ConferenceMember" vs. "MemberConference")
  - sometimes need external resources to assign weights to the composing tokens (large corpus)
- Edit-based
  - can handle one-token labels with tiny variations in spelling
  - often used inside of a token-based measure

Terminological Heterogeneity

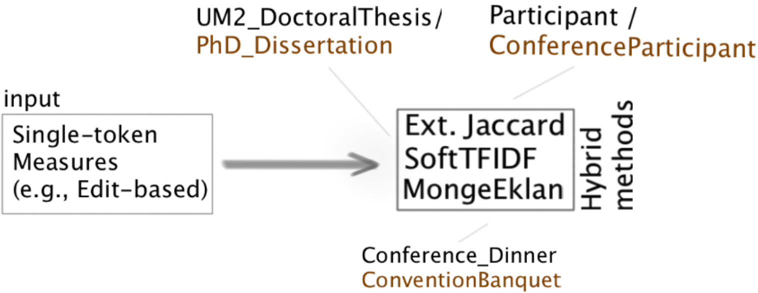
Discussion II



Sources of external information: dictionaries, thesauri, lexical databases (WordNet).

- Two common problems (for both internal and external measures)

- dealing with single words and not compound ones ("PhDThesis" is not found in WN, although "PhD" and "Thesis" are)
- typos or non-conventional abbreviations prevent from finding the words in dictionaries

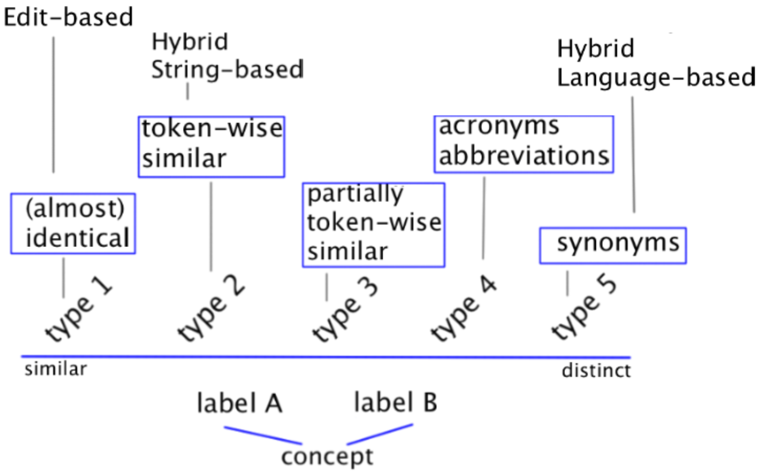


- Limitations

- require large corpus for weight computation
- MongeElkan and softTFIDF are asymmetric

Terminological Heterogeneity

Measures and Heterogeneity Types

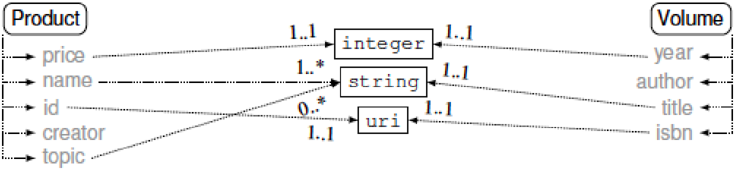


Outline

Compute similarity based on the internal structure of elements (e.g., classes)

- their properties
- range
- cardinalities, etc

Usually combined with terminological techniques



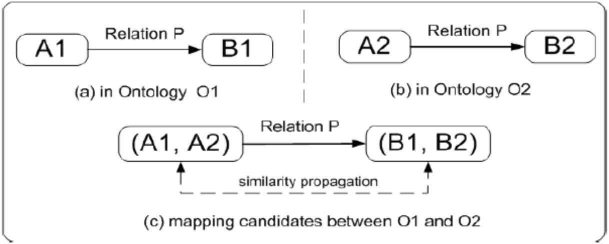
Taken from [1].

Structural Matchers

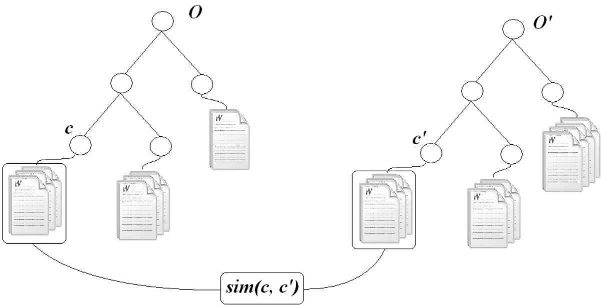
External (relational) methods

Consider the relations of concepts to other concepts. Rely on already discovered **terminological** similarities.

- Standard methods
  - exploring structural relations between entities:
    –> *descendants, ancestors, siblings, etc.*
- Similarity Propagation



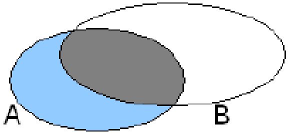
Outline



The similarity of two cross-ontology concepts is assessed by the help of the instances of these concepts

-> Many possible measures.

Intersection of class instance sets

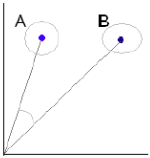


-> Same instances need to be found in both ontologies.

The cosine of the prototypes

$$sim(A,B) = s\left(\frac{1}{|A|}\sum_{j=1}^{|A|}\mathbf{i}_j^A, \frac{1}{|B|}\sum_{k=1}^{|B|}\mathbf{i}_k^B\right),$$

with $s(x,y)$ the cosine similarity of x and y.

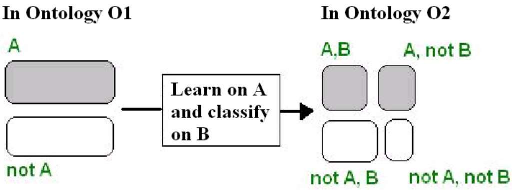


-> Flattening class structure

The Jaccard coefficient

$$Jacc(A,B) = Pr(A \cap B)/Pr(A \cup B).$$

Machine learning is used to estimate the joint probabilities.



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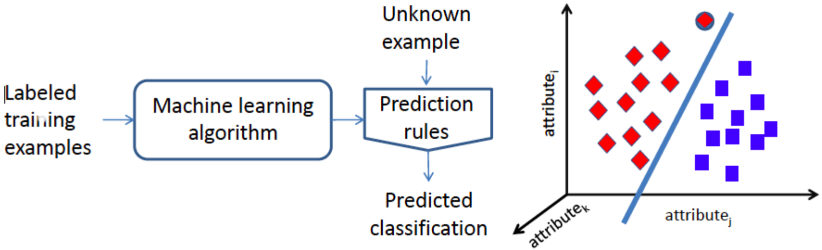
Machine Learning Approach

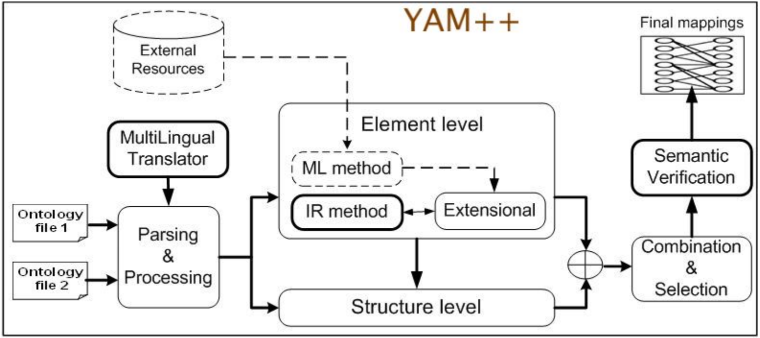


Ontology matching	Supervised binary classification
<source entity, target entity>	Example
Similarity measures	Attribute names
Similarity values	Attribute values
Confidence value	Predicted class

Outline

An OM System

YAM++ (not) Yet Another Matcher



[Ngo *et al.*, EKAW 2012], [http://oaei.ontologymatching.org]

Many matching systems are out there. Here are some of the pluses of YAM++:

- Automatic configuration: similarity measures selection, tuning, and combination
- A novel terminological measure based on Tversky's similarity
- Able to deal with large ontologies, multilingual

Among the best performing systems in the current state-of-the-art (cf. OAEI reports)

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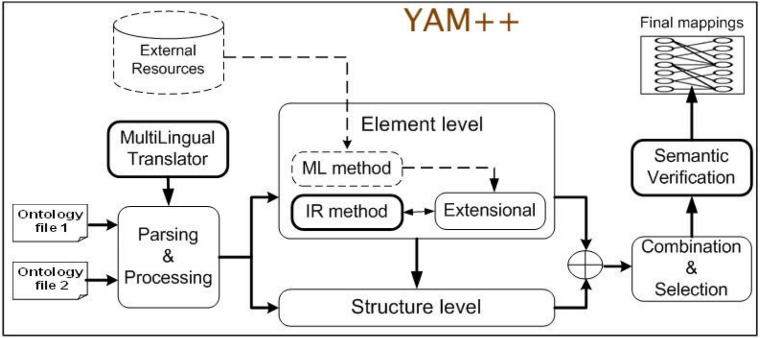

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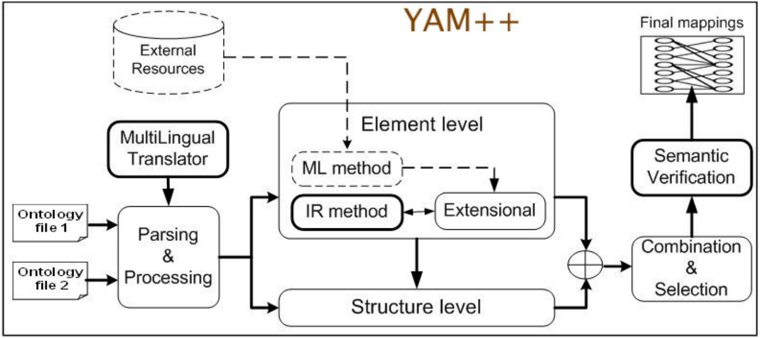

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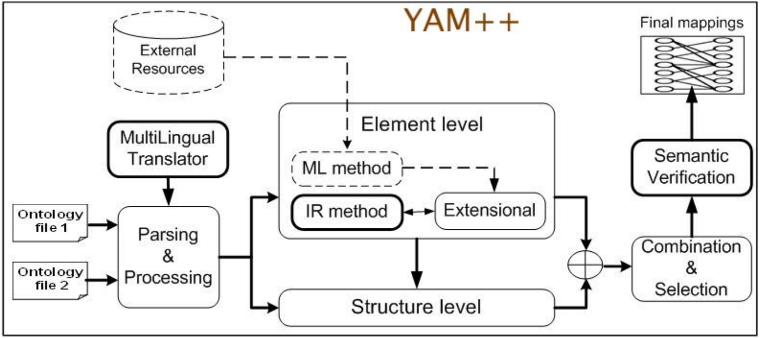

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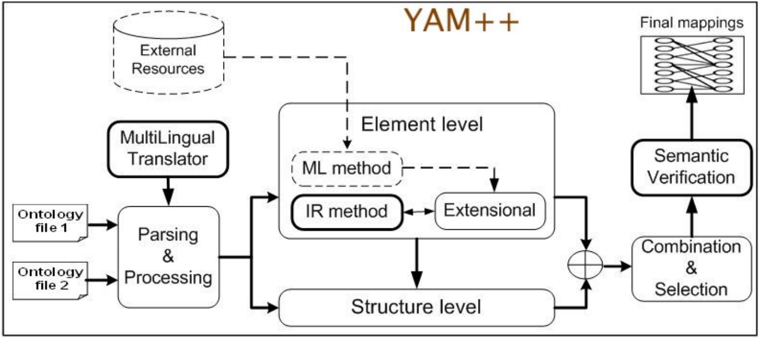

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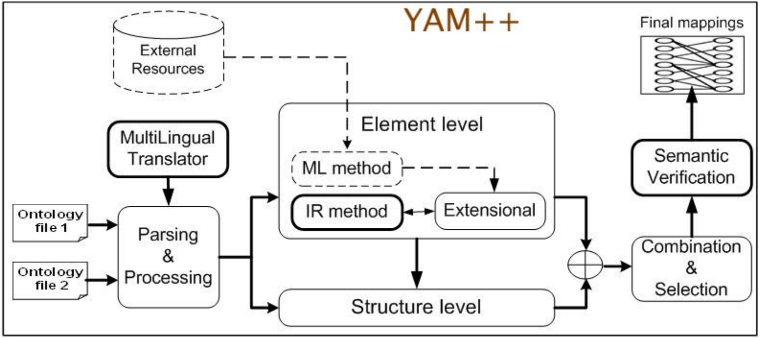

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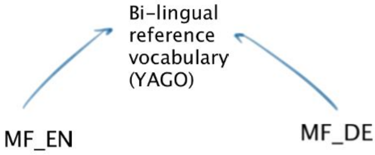
Background knowledge (BK) – any piece of external information that improves or enables the alignment [7].

- Dictionaries, thesaurus, previous alignments, ontologies, the web...
- Domain specific sources of knowledge
  - domain specific corpora (of schemas and mappings);
  - domain specific ontologies, e.g., in the field of anatomy, upper-level ontologies, or all the ontologies available on the semantic web;
- The web and specifically linked data, Wikipedia (DBPedia, YAGO) [7];
- The use of BK results in a transformation of the input ontologies

Motivation

- No one-to-one correspondence between the majority of terms across different languages
- Machine translation still tolerates low precision levels
- No large training corpora with OM data

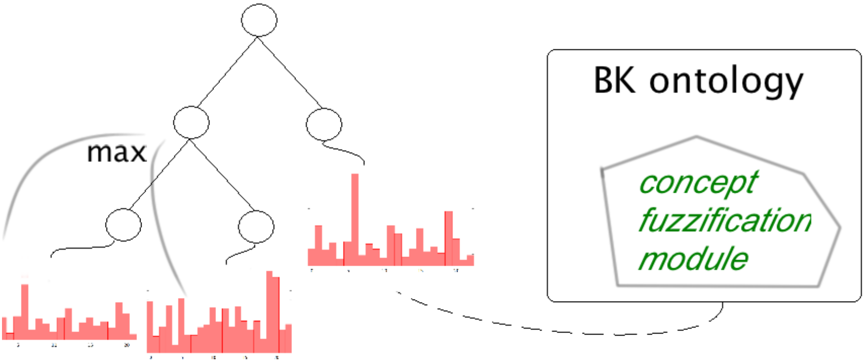
Use of background knowledge [6]



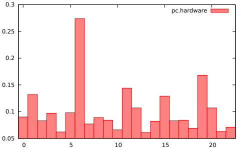
- Implicit alignment of cross-lingual ontologies (mediated by a YAGO/Wordnet taxonomy with multilingual labels)
- No use of automatic translation
- Allows to capture various aspects of the similarity of concepts given in different languages

Fuzzy Matching with BK

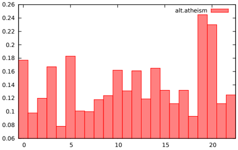
Hierarchical Fuzzification of an Ontology



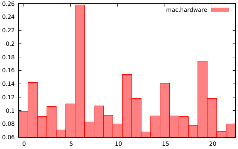
Example of Fuzzy Membership functions



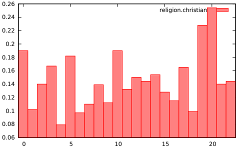
(a) *pc.hardware*



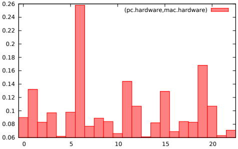
(b) *alt.atheism*



(c) *mac.hardware*



(d) *religion.christian*



(e) *(pc.hardw.,mac.hardw.)*

(a)–(d) single fuzzy concepts; (e) the fuzzy concept of the match of two concepts.

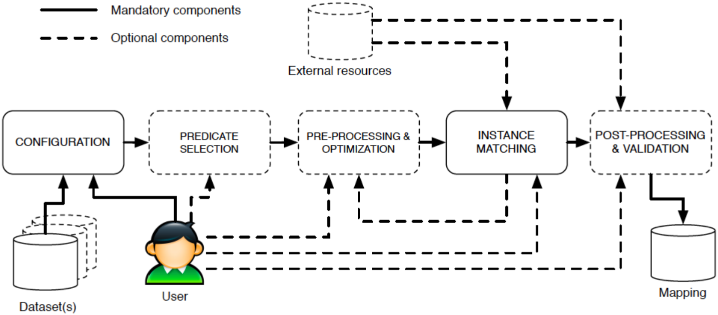
Current Topics in OM

...and also

- User Involvement: include the user in the matching process
- Large-scale matching (large ontologies or multiple ontologies)
- Many-to-many type alignment
- Matcher evaluation
- Imprecision and uncertainty in the matching process

OM for Data Linking

Many OM techniques are used in the data linking process (instance matching [2]).



Thank you for listening.

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