

UNIVERSITÀ DEGLI STUDI DI TRENTO

## S-Match: an Algorithm and an Implementation of Semantic Matching

**Fausto Giunchiglia** 

work in collaboration with Pavel Shvaiko and Mikalai Yatskevich



## Outline

- Semantic Matching
- •The S-Match Algorithm
- Element Level Semantic Matching
- The S-Match System
- A Comparative Evaluation
- •Future Work







## **Semantic Matching**





## Matching

Matching: given two graph-like structures (e.g., concept hierarchies or ontologies), produce a mapping between the nodes of the graphs that semantically correspond to each other







# Concept of a Label *Europe Pictures Wine and Cheese*

### • The idea:

 Labels in classification hierarchies are used to define the set of documents one would like to classify under the node holding the label

Austria

 A label has an intended meaning, which is what this label means in the world

# **Concept of a label** is the set of documents that are about what the label means in the world



Italy



## **Concept of a Node**

### Observations:

- the semantics of a label are the real world semantics
- the semantics of the concept of a label are in the space of documents
- the relation being that the documents in the extension of the concept of a label are about what the label means in the real world



Concept of a node is the set of documents that we would classify under this node, given it has a certain label and it is positioned in a certain place in the tree





## **Semantic Matching**

Mapping element is a 4-tuple  $< ID_{ij}$ ,  $n_{1j}$ ,  $n_{2j}$ , R >, where

- *ID<sub>ij</sub>* is a unique identifier of the given mapping element;
- *n*<sub>*i*</sub> is the *i*-th node of the first graph;
- *n*<sub>2</sub> is the *j*-th node of the second graph;
- *R* specifies a semantic relation between the concepts at the given nodes

**Computed** *R*'s, listed in the decreasing binding strength order:

```
equivalence { = };
more general/specific { ⊒, ⊑};
mismatch { ⊥ };
overlapping { □ }.
```

Semantic Matching: Given two graphs G1 and G2, for any node  $n_i \in G1$ , find the strongest semantic relation R'holding with node  $n_i \in G2$ 





### **Example**



Step 4



## **The S-Match Algorithm**





## **Four Macro Steps**

**Given two labeled trees T1 and T2, do:** 

- 1. For all labels in T1 and T2 compute *concepts at labels*
- 2. For all nodes in T1 and T2 compute *concepts at nodes*
- 3. For all pairs of labels in T1 and T2 compute relations between concepts at labels
- 4. For all pairs of nodes in T1 and T2 compute relations between concepts at nodes

Steps 1 and 2 constitute the preprocessing phase, and are executed once and each time after the schema/ontology is changed (OFF- LINE part)

Steps 3 and 4 constitute the matching phase, and are executed every time the two schemas/ontologies are to be matched (ON - LINE part)





## Step 1: compute concepts at labels

- The idea:
  - Translate natural language expressions into internal formal language
  - Compute concepts based on possible senses of words in a label and their interrelations

### • Preprocessing:

- Tokenization. Labels (according to punctuation, spaces, etc.) are parsed into tokens. E.g., Wine and Cheese → <Wine, and, Cheese>;
- Lemmatization. Tokens are morphologically analyzed in order to find all their possible basic forms. E.g., Images  $\rightarrow$  Image;
- Building atomic concepts. An oracle (WordNet) is used to extract senses of lemmatized tokens. E.g., Image has 8 senses, 7 as a noun and 1 as a verb;
- Building complex concepts. Prepositions, conjunctions, etc. are translated into logical connectives and used to build complex concepts out of the atomic concepts

E.g.,  $C_{Wine and Cheese} = \langle Wine, U(WN_{Wine}) \rangle [] \langle Cheese, U(WN_{Cheese}) \rangle$ , where U is a union of the senses that WordNet attaches to lemmatized tokens





### Step 2: compute concepts at nodes

- The idea: extend concepts at labels by capturing the knowledge residing in a structure of a graph in order to define a context in which the given concept at a label occurs
- Computation: Concept at a node for some node n is computed as an intersection of concepts at labels located above the given node, including the node itself







### Step 3: compute relations between concepts at labels

• The idea: Exploit a priori knowledge, e.g., lexical, domain knowledge with the help of element level semantic matchers



### • Results of step 3:

T1 T2	C <sub>Europe</sub>	C <sub>Pictures</sub>	C <sub>Wine</sub>	C <sub>Cheese</sub>	C <sub>Italy</sub>	<b>C</b> <sub>Austria</sub>
C <sub>Images</sub>		=				
C <sub>Europe</sub>	=					
C <sub>Austria</sub>					Ţ	=
C <sub>Italy</sub>					=	Ţ





## Step 4: compute relations between concepts at nodes

The idea: Reduce the matching problem to a validity problem

- We take the relations between concepts at labels computed in step 3 as axioms (Context) for reasoning about relations between concepts at nodes. rel = { =, ⊇, ⊑, ⊥, □}.
- Construct the propositional formula (C1<sub>i</sub> in Tree1 and C2<sub>j</sub> in Tree2)
  - $C1_i = C2_j$  is translated into  $C1_i \leftrightarrow C2_j$
  - $C1_i \subseteq C2_j$  is translated into  $C1_i \rightarrow C2_j$  (analogously for  $\supseteq$ )
  - $C1_i \perp C2_j$  is translated into  $\neg (C1_i \land C2_j)$

 $Context \rightarrow rel \, (C1_i, \, C2_j)$ 

• A propositional formula is valid iff its negation is unsatisfiable

SAT deciders are sound and complete...







## Step 4: cont'd (1)

- 1. i, j, N1, N2: *int*;
- 2. context, goal: *wff*;
- 3. n1, n2: *node*;
- 4. T1, T2: tree of (node);
- 5. *relation* = {=,⊑,⊒,⊥};
- 6. ClabMatrix(N1, N2), CnodMatrix(N1, N2), relation: *relation*
- 7. function mkCnodMatrix(T1, T2, ClabMatrix) {
- 8. for (i = 0; i < N1; i++) do
- 9. for (j = 0; j < N2; j++) do
- 10. CnodMatrix(i, j):=NodeMatch(T1(i),T2(j), ClabMatrix)}
- 11. function NodeMatch(n1, n2, ClabMatrix) {
- 12. context:=mkcontext(n1, n2, ClabMatrix, context);
- 13. foreach (relation in  $\langle =, \subseteq, \supseteq, \bot \rangle$ ) do {
- 14. goal:= w2r(mkwff(relation, GetCnod(n1), GetCnod(n2));
  - if VALID(mkwff( $\rightarrow$ , context, goal))
    - return relation;}

return 🗆 ;}

15.

16.

17.



### Step 4: cont'd (2)

### • Example. Suppose we want to check if $C1_2 = C2_2$

$$(C1_{Images} \leftrightarrow C2_{Pictures}) \land (C1_{Europe} \leftrightarrow C2_{Europe}) \rightarrow (C1_{2} \leftrightarrow C2_{2})$$

Context

Goal

T1 T2	<i>C2</i> <sub>1</sub>	<i>C2</i> <sub>2</sub>	<i>C2</i> <sub>3</sub>	<i>C2</i> <sub>4</sub>	<i>C2</i> <sub>5</sub>
C1 <sub>1</sub>	П		П		
<i>C1</i> <sub>2</sub>		=	П		П
<i>C1</i> <sub>3</sub>			П	$\bot$	
Cl <sub>4</sub>			П	=	L





### Step 4: cont'd (2)





## **Element Level Semantic Matching**





## **Element level Semantic Matchers**

- String based matchers have two labels as input and produce semantic relations exploiting string comparison techniques.
- Sense based matchers have two WordNet senses in input and produce semantic relations exploiting structural properties of WordNet hierarchies.
- Gloss based matchers have two WordNet senses as input and produce relations exploiting gloss comparison techniques.





## **Element level Semantic Matchers: Overview**

Matcher name	Execution Order	Approximation level	Matcher type	Schema info
Prefix	2	2		
Suffix	3	2		Labels
Edit distance	4	2	String based	
Ngram	5	2		
Text Corpus	13	3		Labels + Corpus
WordNet	1	1	Samea basad	WordNat sansas
Hierarchy distance	6	3	Sense based	wordiver senses
WordNet Gloss	7	3		
Extended WordNet Gloss	8	3	Gloss based WordNet set	We all the second
Gloss Comparison	9	3		
Extended Gloss Comparison	10	3		wordinet senses
Semantic Gloss Comparison	11	3		
Extended semantic gloss comparison	12	3		





## **String based matchers: Prefix**

**Prefix:** checks whether one input label starts with the other. It returns an equivalence relation in this case, and *Idk* otherwise.

Source label	Target label	Relation	Time, ms
net	network	=	0.00006
hot	hotel	=	0.00006
cat	core	Idk	0.00005

**Prefix** is efficient in matching cognate words and similar acronyms (e.g., **RDF** and **RDFS**) but often syntactic similarity does not imply semantic relatedness.

The matcher returns equality for *hot* and *hotel* which is wrong but it recognizes the right relations in the case of the pairs *net*, *network* and *cat*, *core*.





## **String based matchers: Edit distance**

Edit Distance: calculates the edit distance measure between two labels. The calculation includes counting the number of the simple editing operations (delete, insert and replace) needed to convert one label into another. If the value exceeds a given threshold the equivalence relation is returned, otherwise, *ldk* is produced.

Source label	Target label	Relation	Time, ms
street	street1	=	0.019
proper	propel	=	0.016
owe	woe	Idk	0.007





## Sense based matchers: WordNet

WordNet : return a relation which holds in WordNet between two input labels.

The relations provided by WordNet are converted to semantic relations according to the following rules:

- $A \subseteq B$  if A is a hyponym, meronym or troponym of B;
- $A \supseteq B$  if A is a hypernym or holonym of B;

 A = B if they are connected by synonymy relation or they belong to one synset;

•A ⊥ B if they are connected by antonymy relation or they are the siblings in the part of hierarchy

Source label	Target label	Relation	Time, ms
car	minivan	⊇	2,3
car	auto	=	0.6
tail	dog	⊆	0.2
red	pink	Idk	0.4





## **Sense based matchers: Hierarchy distance**

Hierarchy distance: returns the equivalence relation if the distance between two input senses in a WordNet hierarchy is less than a given threshold value and *Idk* otherwise.

Source label	Target label	Relation	Time, ms
red	pink	=	0.159
catalog	classification	Idk	0.203

There is no direct relation between *red* and *pink in WordNet*. However, the distance between these concepts is 2 (1 more general link and 1 less general). Thus, we can infer that *red* and *pink* are close in their meaning and return the equivalence relation.







## **Gloss based matchers: WordNet gloss**

WordNet gloss: compares the labels of the first input sense with the WordNet gloss of the second.

Source label	Target label	Relation	Time, ms
hound	dog	UI	0.031
hound	ear	UI	0.014
dog	cat	Idk	0.033

Hound is any of several breeds of dog used for hunting typically having large drooping ears. Hound is described through the specification of the more general concept dog.





## **Gloss based matchers: Gloss comparison**

Gloss comparison: The number of the same words occurring in the two input glosses increases the similarity value. The equivalence relation is returned if the resulting similarity value exceeds a given threshold.

Source label	Target label	Relation	Time, ms
Afghan hound	Maltese dog	=	0,074
dog	cat	Idk	0,019

- Maltese dog is a breed of toy dogs having a long straight silky white coat
- Afghan hound is a tall graceful breed of hound with a long silky coat; native to the Near East





## **The S-Match System**





## **S-Match: Logical Level**





**NOTE:** Current version of **S-Match** is a rationalized re-implementation of the **CTXmatch** system with a few added functionalities



## **A Comparative Evaluation**





## **Testing Methodology**

Matching systems

• S-Match vs. Cupid, COMA and SF as implemented in Rondo

### Measuring match quality

- Expert mappings are inherently subjective
- Two degrees of freedom
  - Directionality
  - Use of Oracles
- Indicators
  - Precision, [0,1]
  - Recall, [0,1]
  - Overall, [-1,1]
  - F-measure, [0,1]
  - Time, sec.







## **Preliminary Experimental Results**

- Three experiments, test cases from different domains
- Some characteristics of test cases: #nodes 4-39, depth 2-3



• PC: PIV 1,7Ghz; 256Mb. RAM; Win XP



#### **Average Results**





## **Future Work**

- Extend the semantic matching algorithm for computing mappings between graphs
- Develop iterative semantic matching
- Elaborate results filtering strategies according to the binding strength of the resulting mappings
- Efficient semantic matching
- Robust semantic matching
- Do throught testing of the system (small or big ontologies)





## References

- Project website ACCORD: <u>http://www.dit.unitn.it/~accord/</u>
- F. Giunchiglia, P.Shvaiko, M. Yatskevich: S-Match: an algorithm and an implementation of semantic matching. In Proceedings of *ESWS'04*.
- F. Giunchiglia, P.Shvaiko: Semantic matching. In The Knowledge Engineering Review journal, 18(3):265-280, 2004. Short versions in Proceedings of *SI* workshop at *ISWC'03* and *ODS* workshop at *IJCAI'03*.
- P. Bouquet, L. Serafini, S. Zanobini: Semantic coordination: a new approach and an application. In Proceedings of *ISWC'03*.
- F. Giunchiglia, I. Zaihrayeu: Making peer databases interact a vision for an architecture supporting data coordination. In Proceedings of CIA'02.
- C. Ghidini, F. Giunchiglia: Local models semantics, or contextual reasoning = locality + compatibility. Artificial Intelligence journal, 127(3):221-259, 2001.





# Thank you!





