A Machine Learning Approach to Multilingual and Cross-lingual Ontology Matching

Dennis Spohr, Philipp Cimiano and Laura Hollink

CITEC, University of Bielefeld

Delft University of Technology

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Outline

Motivation

Background and definitions

Machine learning approach

Evaluation and findings

Conclusion

Open research questions in ontology matching

- Impact of machine translation in cross-lingual scenarios
- Impact of structural information
- Multilingual vs. cross-lingual ontology matching
- "Real" multilingual ontology matching understudied

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  - *"High-quality MT is prerequisite for good matching"* (Fu et al., 2009)
  - Can this be mitigated by translating to several languages?
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  - Aggregation of similarity scores within a single language and across multiple languages?

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⇒ **Ideal use case for multilingual and cross-lingual ontology matching**

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- **XEBR uses the *eXtensible Business Reporting language (XBRL)***
- **The work presented here is based on an RDF conversion of XBRL**

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Multi-lingual and cross-lingual ontology matching

Monolingual matching

…is the process of matching entities in S and T by comparing the labels in $S(l)$ and $T(l)$ in **a single language** $l \in L_S \cap L_T$.

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Cross-lingual matching

…is the process of matching entities in S and T either

a. by **translating the labels in** $S(l)$ **to at least one language** $l' \in L_T$ and comparing the labels in $S(l')$ with those in $T(l')$, or

b. by **translating the labels in** $T(l)$ **to at least one language** $l' \in L_S$ and comparing the labels in $S(l')$ with those in $T(l')$, or

c. by **translating the labels** $S(l)$ **and the labels** $T(l')$ **to at least one language** $l'' \notin L_S \cup L_T$ comparing the labels in $S(l'')$ with those in $T(l'')$.

Intralingual and interlingual aggregation

Intralingual aggregation

…concerns the **aggregation of similarity scores** for all labels $a_i \in S(l) \cup T(l)$ **in a language** *l*

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Interlingual aggregation

…concerns the **aggregation of intralingual scores across all languages** l_i **shared by** S **and** T

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Machine learning approach

- Ranking SVMs
- Feature set definition
- Learning a ranking function with SVM^{rank}

Evaluation and findings

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Ranking SVMs

- **SVMs for learning ranking functions**
- **Originally developed to improve search engine quality**
  by analysing clickthrough logs (Joachims, 2002)
- **Input not classes (e.g. *1 or -1*), but pairwise preference constraints**

Ranking SVMs

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  by analysing clickthrough logs (Joachims, 2002)
- **Input not classes (e.g. *1 or -1*), but pairwise preference constraints**
- Given 10 query results and knowing the user clicked on results 1, 3 and 5, the **input to the ranking SVM** is:

$$result_3 <_{r*} result_2 \qquad result_5 <_{r*} result_4$$
$$result_5 <_{r*} result_2$$

where $r*$ is the ranking preferred by the user

Applying ranking SVMs to ontology matching

Applied to ontology matching, this means:

We want to **learn a ranking function** which

- ranks ***matching concepts*** **higher than** ***non-matching concepts***
- ranks ***exact matches*** **higher than** ***close matches***

Feature set definition

- **Definition of 20 different string-based features**
  - Five different measures (e.g. Levenshtein, Cosine)
  - Four different intralingual and interlingual aggregations (see next slide)

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  - Concept type (e.g. monetary vs. abstract)
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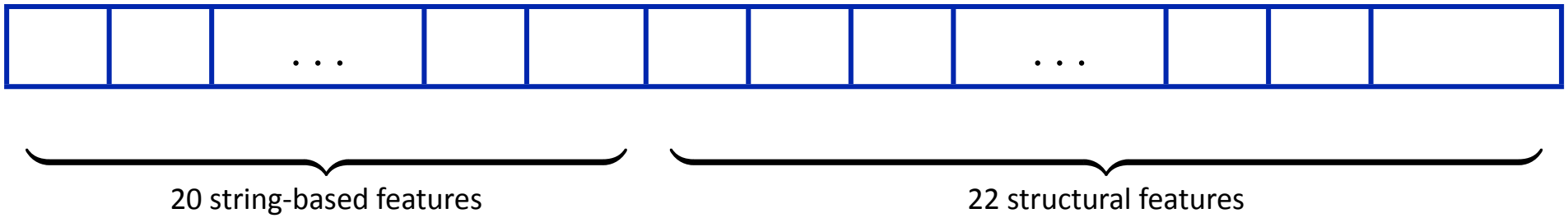
- **Construction of similarity vector for each pair $C_T \times C_S$**



Intra- and interlingual score aggregation

Intralingual aggregation

For example ***average intralingual similarity***

- $sim^{l}_{intra\sim}(C_S(l), C_T(l)) = \frac{1}{n * m} \sum_{i=1}^{n} \sum_{j=1}^{m} sim_{lev}(lab^{i}_{C_S}, lab^{j}_{C_T})$

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Interlingual aggregation

For example ***average of average intralingual similarity***

- $sim_{inter\sim/\sim}(C_S, C_T) = \frac{1}{n} \sum_{i=1}^{n} sim^{i}_{intra\sim}(C_S(i), C_T(i))$

Learning the matching function

- **Calculate similarity vectors** for all combinations of source and target concepts
- Use **exact and close matches** from XEBR to **determine rank** of a vector
- **Generate training file for SVM**^{rank}

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```
3 qid:1 1:0.5155 2:0.6491 3:0.5757 ...  # C_Si × C_Tm
2 qid:1 1:0.4012 2:0.5660 3:0.4401 ...  # C_Si × C_T1
1 qid:1 1:0.2613 2:0.3333 3:0.2884 ...  # C_Si × C_T2
1 qid:1 1:0.2972 2:0.3492 3:0.0913 ...  # C_Si × C_T3
  ...
3 qid:2 1:0.2903 2:0.3548 3:0.5303 ...  # C_Sj × C_Tn
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- **Construction of training set:**

  Use XEBR mappings to derive mappings between national standards

C_{XEBR} *exactMatch* C_S	C_{XEBR} *exactMatch* C_S
C_{XEBR} *exactMatch* C_T	C_{XEBR} *closeMatch* C_T
———	———
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  $\Rightarrow$ **Mappings between XEBR, German "Handelsgesetzbuch" (HGB) and Italian "Codice Civile" (ITCC)**

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  $\Rightarrow$ **Mappings between XEBR, German "Handelsgesetzbuch" (HGB) and Italian "Codice Civile" (ITCC)**

- **Languages:**
  - XEBR: English
  - HGB: English, German
  - ITCC: English, French, German, Italian

Evaluation settings

- **Different scenarios**
  - **Monolingual:** English
  - **Multilingual:** English, German (for HGB × ITCC)
  - **Cross-lingual:** English × Italian, English × German, Italian × English
    - First translate ontology, then apply monolingual matching (cf. Fu et al., 2009)
    - Additional: *translate to several languages and apply multilingual matching*
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- **Evaluation**
  - Precision: how often is exact match at rank 1
  - Further measure how often it is among top 5 and top 10

Evaluation results

Scenario	Setting	XEBR / ITCC			ITCC / HGB		
		1	5	10	1	5	10
Monolingual	$Struct_1$	**51.67**	**76.67**	**81.67**	**44.83**	**65.52**	**68.97**
	$NoStruct_1$	46.67	66.67	76.67	41.38	55.17	58.62
Multilingual	$Struct_n$	--	--	--	**51.72**	**68.97**	**68.97**
	$NoStruct_n$	--	--	--	51.72	55.17	65.52
Cross-lingual, *S* translated to one language	$Struct_1^S$	**35.00**	**56.67**	**63.33**	34.48	**65.52**	**68.97**
	$NoStruct_1^S$	28.33	53.33	53.33	**41.38**	51.72	55.17
Cross-lingual, *S* translated to several langs	$Struct_n^S$	**56.67**	**78.33**	**86.67**	44.83	**65.52**	**72.41**
	$NoStruct_n^S$	46.67	70.00	81.67	**48.28**	58.62	65.52
Cross-lingual, transfer	$Struct_n^{S_{tr}}$	**45.67**	**76.67**	**85.00**	**41.38**	**62.07**	**75.86**
	$NoStruct_n^{S_{tr}}$	23.33	60.00	73.33	31.03	58.62	65.52

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  - 25 out of 27 values are significantly better
- **Multilingual outperforms monolingual**
  - **Even in cross-lingual scenario!**
  - For XEBR × ITCC, cross-lingual produced best results
- **Transfer learning produces good results as well**

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- **"Real" multilingual ontology matching understudied**
  - We have given precise definitions of *intralingual* and *interlingual* aggregation

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Thank you very much for your attention!

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