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A Statistical and Schema Independent Approach to Identify Equivalent Properties on Linked Data

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iSemantics 2013, Graz, Austria

Why we need property alignment and it is so important?

Firefox | Sig.ma EE- Semantic Information Mashup... | Google

SIG.MA SEMANTIC INFORMATION MASHUP | Version: 2.0.8 | Help | About | Support

Tim Berners-Lee | Add More Info | Start New | Order | Options | Use It

Tim Berners-Lee

picture:

before: First recipient [11]

is before of: Shuji Nakamura [11]

birth place: London, England [11]

birthday: 1955-06-08 [3,4,9,10,11,12,13,14]

8 [11]

er scientist, MIT professor and the inventor of the World Wide Web. He made a young student at CERN, he implemented the first successful communication The Web Science Research Initiative (WSRI), and a member of the advisory board of the MIT Center for Collective Intelligence. In 2004, Berners-Lee was knighted by Queen Elizabeth II for his pioneering work. In April 2009, he was elected a foreign associate of the United States National Academy of Sciences. [11]

Sir Timothy John "Tim" Berners-Lee, OM, KBE, FRS, FREng, FRSA (born 8 June 1955), also known as "TimBL" is an English computer scientist, MIT professor and the inventor of the World Wide Web. He made a proposal for an information management system in March 1989 and on 25 December 1990, with ti between a Hypertext Transfer Protocol (HTTP) client and server via the Internet. [11]

is creator of: Weaving the Web: The Original Design and Ultimate Destiny of the World Wide Web by its inventor [11]

Libwww [11]

Line Mode Browser [11]

Tabulator [11]

alma mater: http://dbpedia.org/resource/The_Queen's_College,_Oxford [11]

alternative name: Timothy John Berners-Lee [11]

after: Shuji Nakamura [11]

birth year: 1955-01-01T00:00:00+02:00 [11]

before: First recipient [11]

is before of: Shuji Nakamura [11]

birth place: London, England [11]

birthday: 1955-06-08 [11]

8 [11]

caption: Berners-Lee, Tim

is child of: Mary Lee Woods [11]

Conway Berners-Lee [11]

is children of: Mary Lee Woods [11]

Conway Berners-Lee [11]

category: Unitarian Universalism [3,4,9,10,12,13,14]

British [3,4,9,10,12,13,14]

is developer of: WorldWideWeb [11]

domain: www.linkedin.com [11]

en.wikipedia.org [3,4,10,12,13,14]

identi.ca [8]

encyclopedia.vbxml.net [9]

occupation: http://dbpedia.org/resource/Tim_Berners-Lee 1 [11]

Computer scientist [11]

place of birth: London, England [11]

photo collection: http://www4.wiwiw.fu-berlin.de/flickrwrapp/photos/Tim_Berners-Lee [11]

Sources (20) | Approved (0) | Rejected (0)

Pending

- 1 Tim Berners-Lee - Linked... 10 facts | 2010-07-06
<http://www.linkedin.com/in/timbl>
- 2 About: Berners-Lee 5 facts | 2010-05-11
<http://dbpedia.org/page/Berners-Lee>
- 3 Tim Berners-Lee - Wikiped... 12 facts | 2011-05-19
http://en.wikipedia.org/wiki/Tim_Berners-...
- 4 Tim Berners-Lee - Wikiped... 13 facts | 2011-01-17
http://en.wikipedia.org/wiki/Tim_Bernes-L...
- 5 Tim Berners-Lee CP 5 facts | 2013-08-29
<http://rdf.basekb.com/ns/m.05t49z5>
- 6 Untitled document 3 facts | 2013-08-29
<http://www.bbc.co.uk/programmes/people/ti...>
- 7 Tim Berners-Lee 6 facts | 2013-08-29
<http://www.qac.culture.gov.uk/images/stan...>
- 8 Tim Berners-Lee (timbl) ... 13 facts | 2011-05-19

13 Tim Berners-Lee - Wikiped... 12 facts | 2010-10-02
http://en.wikipedia.org/wiki/Tim_Berners_...

14 Tim Berners-Lee - Wikiped... 13 facts | 2011-01-17
http://en.wikipedia.org/wiki/Tim_Bernes_L...

↑ reject all | ↑ approve all

<http://example.loc/document.rdf> | + add source url

Same information in different names.
 Therefore, data integration for better presentation is required.

- ❑ Background
- ❑ Statistical Equivalence of properties
- ❑ Evaluation
- ❑ Discussion, interesting facts, and future directions
- ❑ Conclusion

- ❑ Existing techniques for property alignment fall into three categories.
 - I. Syntactic/dictionary based
 - Uses string manipulation techniques, external dictionaries and lexical databases like WordNet.
 - II. Schema dependent
 - Uses schema information such as, domain and range, definitions.
 - III. Schema independent
 - Uses instance level information for the alignment.

- ❑ Our approach falls under schema independent.

- ❑ Properties capture meaning of triples and hence they are complex in nature.
- ❑ Syntactic or dictionary based approaches analyze property names for equivalence. But in LOD, name heterogeneities exist.
- ❑ Therefore, syntactic or dictionary based approaches have limited coverage in property alignment.
- ❑ Schema dependent approaches including processing domain and range, class level tags do not capture semantics of properties well.

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- ❑ Statistical Equivalence is based on analyzing owl:equivalentProperty.
- ❑ owl:equivalentProperty - properties that have same property extensions.

Example 1:

Property P is defined by the triples, $\{ a P b, c P d, e P f \}$

Property Q is defined by the triples, $\{ a Q b, c Q d, e Q f \}$

P and Q are owl:equivalentProperty, because they have the **same extension**,
 $\{ \{a,b\}, \{c,d\}, \{e,f\} \}$

Example 2:

Property P is defined by the triples, $\{ a P b, c P d, e P f \}$

Property Q is defined by the triples, $\{ a Q b, c Q d, e Q h \}$

Then, P and Q are not owl:equivalentProperty, because their extensions are not the same. But they provide **statistical evidence** in support of equivalence.

Intuition

- ❑ Higher rate of subject-object matches in extensions leads to equivalent properties. In practice, it is hard to have exact same extensions for matching properties. Because,
 - Datasets are incomplete.
 - Same instance may be modelled differently in different datasets.
- ❑ Therefore, we analyze the property extensions to identify equivalent properties between datasets.
- ❑ We define the following notions. Let the statement below be true for all the definitions.
 $S_1P_1O_1$ and $S_2P_2O_2$ be two triples in Dataset D_1 and D_2 respectively.

Definition 1: Candidate Match

The two properties P_1 and P_2 are a *candidate match* iff $S_1 \xleftrightarrow{ECR^*} S_2$ and $O_1 \xleftrightarrow{ECR^*} O_2$.

We say two instances are connected by an ECR^* link if there is a link path between the instances using ECR links (* is the *Kleene star notation*). ECR links are Entity Co-reference Relationships such as those formalized using *owl:sameAs* and *skos:exactMatch*.

Example

The two datasets *DBpedia(d)* and *Freebase(f)*

<i>d:Arthur Purdy Stout</i>	<i>d:place of birth</i>	<i>d:New York City</i>
<i>f:Arthur Purdy Stout</i>	<i>f:place of death</i>	<i>f:New York City</i>

- ❑ The above is a *candidate match*, but not equivalent, because intensions are different (*coincidental match*).
- ❑ We need further analysis to decide on equivalence.

Match Count $\mu(P_1, P_2)$ – Number of triple pairs for P_1 and P_2 that participate in candidate matches.

$$\mu(P_1, P_2) = | \left\{ S_1 P_1 O_1 \in D_1 \mid \exists S_2 P_2 O_2 \in D_2 \wedge S_1 \xrightarrow{ECR^*} S_2 \wedge O_1 \xrightarrow{ECR^*} O_2 \right\} |$$

Co-appearance Count $\lambda(P_1, P_2)$ – Number of triple pairs for P_1 and P_2 that have matching subjects.

$$\lambda(P_1, P_2) = | \left\{ S_1 P_1 O_1 \in D_1 \mid \exists S_2 P_2 O_2 \in D_2 \wedge S_1 \xrightarrow{ECR^*} S_2 \right\} |$$

Definition 2: Statistically Equivalent Properties

The pair of properties P_1 and P_2 are *statistically equivalent* to degree (α, k) iff,

$$F = \frac{\mu(P_1, P_2)}{\lambda(P_1, P_2)} \geq \alpha,$$

Where, $\mu(P_1, P_2) \geq k$, and $0 < \alpha \leq 1$, $k > 1$

Candidate Matching Algorithm Process

Algorithm 1 GenerateCandidateMatches(X , $namespace$)

Input: X , $namespace$

Output: λ , μ for each property pair

```

1: for  $i = 1 \rightarrow \text{Size}(X)$  do
2:    $subject\ S1 \leftarrow X[i]$ 
3:    $subject\ S2 \leftarrow \text{GetCorsEntity}(subjectS1, namespace)$ 
4:    $map\ l1 \leftarrow \text{ExtractPO}(S1)$ 
5:    $map\ l2 \leftarrow \text{ExtractPO}(S2)$ 
6:   for each property  $p \in l1$  do
7:      $object\ o1 \leftarrow l1(p)$ 
8:      $Set\ o1\_ecr \leftarrow \text{GetECRLinks}(o1)$ 
9:     for each property  $q \in l2$  do
10:      if  $p\ exactmatch\ q$  then
11:         $p\ matches\ q$ 
12:      else
13:        update  $\lambda(p, q)$ 
14:         $object\ o2 \leftarrow l2(q)$ 
15:         $Set\ o2\_ecr \leftarrow \text{GetECRLinks}(o2)$ 
16:         $isMatch \leftarrow \text{Match}(o1\_ecr, o2\_ecr)$ 
17:        if  $isMatch$  then
18:          update  $\mu(p, q)$ 
19:        end if
20:      end if
21:    end for
22:  end for
23: end for

```

Complexity:

If the average number of properties for an entity is x and for each property, average number of objects is j . For n subjects, it requires $n*j^2*x^2+2n$ comparisons. Since $n > j$, $n > x$, and x and j are independent of n , **$O(n)$** .

Example:

Same instances are shown using dotted arrows between the two datasets.

Generated Candidate Matching Property Lists – Matches selected are in Boldface

[D1:doctoralStudent] [**[D2:academic.advises, 2:2]** , [D2:influenced, 1:2]] ← matching list for doctoralStudent

[D1:birth_place] [**[D2:place_of_birth, 2:3]** , [D2:place_of_death, 1:1]] ← matching list for birth_place

Property Pair (matched)	MatchCount	Co-appearanceCount
[D1:doctoralStudent, D2:academic.advises]	2	2
[D1:birth_place, D2:place_of_birth]	2	3

Selection using $\alpha = 0.5$ and $k = 2$

Parallel computation (Map-Reduce implementation)

- ❑ Generating candidate matches can be done for each instance independently. Hence, we implemented the algorithm in Hadoop 1.0.3 framework.
- ❑ Generating candidate matches for instances is distributed among mappers and each mapper outputs μ and λ to the reducer for property pairs.
 - Map Phase
 - Let the number of subject instances in dataset D_1 be X and namespace of dataset D_2 be ns . For each subject $i \in X$, start a mapper job for `GenerateCandidateMatches( $i, ns$ )`.
 - Each mapper outputs (key,value) pairs as $(p:q, \mu(p,q):\lambda(p,q))$. $p \in D_1$ and $q \in D_2$.
- ❑ The reducer collects all μ and λ values and aggregate them for final analysis.
 - Reduce phase
 - Collects output from mappers and aggregates $\mu(p,q)$ and $\lambda(p,q)$ for each key $p:q$.
- ❑ The map reduce version on a 14 node cluster was able to achieve a speed up of 833% compared to the desktop version.

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- ❑ Objectives of the evaluation
 - Show the effectiveness of the approach in linked datasets
 - Compare with existing aligning techniques
- ❑ We selected 5000 instance samples from DBpedia, Freebase, LinkedMDB, DBLP L3S , and DBLP RKB Explorer datasets.
- ❑ These datasets have,
 - Complete data for instances in different viewpoints
 - Many inter-links
 - Complex properties

Experiment details

- $\alpha = 0.5$ for all experiments (works for LOD) except DBpedia and Freebase movie alignment where it was 0.7.

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— 0.8 fo

DBpedia-Freebase(Person)

DBpedia-Freebase(Film)

DBLP RKB-DBLP L3S (Article)

DBpedia-Freebase (Software)

DBpedia-LinkedMDB (Film)

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Alignment results

	Measure type	DBpedia – Freebase (Person)	DBpedia – Freebase (Film)	DBpedia – Freebase (Software)	DBpedia – LinkedMDB (Film)	DBLP_RKB – DBLP_L3S (Article)	Average
Extension Based Algorithm	Precision	0.8758	0.9737	0.6478	0.7560	1.0000	0.8427
	Recall	0.8089*	0.5138	0.4339	0.8157	1.0000	0.7145
	F measure	0.8410*	0.6727	0.5197	0.7848	1.0000	0.7656
WordNet Similarity	Precision	0.5200	0.8620	0.7619	0.8823	1.0000	0.8052
	Recall	0.4140*	0.3472	0.3018	0.3947	0.3333	0.3582
	F measure	0.4609*	0.4950	0.4324	0.5454	0.5000	0.4867
Dice Similarity	Precision	0.8064	0.9666	0.7659	1.0000	0.0000	0.7078
	Recall	0.4777*	0.4027	0.3396	0.3421	0.0000	0.3124
	F measure	0.6000*	0.5686	0.4705	0.5098	0.0000	0.4298
Jaro Similarity	Precision	0.6774	0.8809	0.7755	0.9411	0.0000	0.6550
	Recall	0.5350*	0.5138	0.3584	0.4210	0.0000	0.3656
	F measure	0.5978*	0.6491	0.4903	0.5818	0.0000	0.4638

* Marks estimated values for experiment 1 because of very large comparisons to check manually. Boldface marks highest result for each experiment.

Example identifications

Property pair types	Dataset 1 (DBpedia)	Dataset 2 (Freebase)
Simple string similarity matches	db:nationality	fb:nationality
	db:religion	fb:religion
Synonymous matches	db:occupation	fb:profession
	db:battles	fb:participated_in_conflicts
Complex matches	db:screenplay	fb:written_by
	db:doctoralStudent	fb:advisees

WordNet similarity failed to identify any of these

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- ❑ Our experiment covered multi-domain to multi-domain, multi-domain to specific domain and specific-domain to specific-domain dataset property alignment.
- ❑ In every experiment, the extension based algorithm outperformed others (F measure). F measure gain is in the range of **57% to 78%**.
- ❑ Some properties that are identified are intentionally different, e.g., *db:distributor* vs *fb:production_companies*.
 - This is because many companies produce and also distribute their films.
- ❑ Some identified pairs are incorrect due to errors in data modeling.
 - For example, *db:issue* and *fb:children*.
- ❑ *owl:sameAs* linking issues in LOD (not linking exact same thing), e.g., linking London and Greater London.
 - We believe few misused links won't affect the algorithm as it decides on a match after analyzing many matches for a pair.

- ❑ Less number of interlinks.
 - Evolve over time.
 - Look for possible other types of *ECR* links (i.e., *rdf:seeAlso*).
- ❑ Properties do not have uniform distribution in a dataset.
 - Hence, some properties do not have enough matches or appearances.
 - This is due to rare classes and domains they belong to.
 - We can run the algorithm on instances that these less frequent properties appear iteratively.
- ❑ Current limitations,
 - Requires *ECR links*
 - Requires overlapping datasets
 - Object-type properties
 - Inability to identify property – sub property relationships

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- ❑ We approximate *owl:equivalentProperty* using *Statistical Equivalence* of properties by analyzing property extensions, which is schema independent.
- ❑ This novel extension based approach works well with interlinked datasets.
- ❑ The extension based approach outperforms syntax or dictionary based approaches. F measure gain in the range of **57% - 78%**.
- ❑ It requires many comparisons, but can be easily parallelized evidenced by our Map-Reduce implementation.

Questions ?

Thank You

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