



Quality-driven Evolution in Information Integration Systems

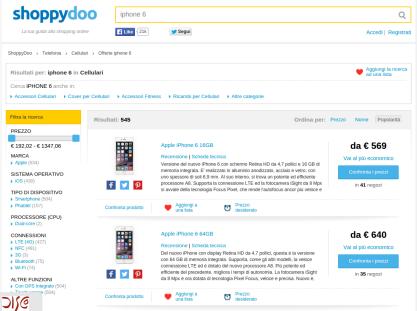
Ph.D. in Computer Science Course - XXVIII Series

Riccardo Porrini

Supervisor: Dott. Palmonari

Tutor: Prof. Messina

Web Information Integration



Multiple Classifications

categories

facets

Country of Origin

USA (320)

France (91)

Italy (40) Spain (18)

Australia (17)

Bulgaria (10)

Chile (8)

+ See more

Vintage

- No Vintage (96)
- **2013** (72)
- 2012 (102)
- 2011 (84)
- 2010 (50)
- + See more

1-24 of 8,933 results for Grocery & Gourmet Food : Wine : Red



Renwood Winter Reds Port, Syrah, Primitivo Mixed Pack, 3 x 750 mL

\$63.91 \$79.89

Eligible for 1¢ Standard Shipping See Details Show only Renwood items



Renwood Delectable Port, Ice Wine, Syrah Mixed Pack, 2 x 750 mL 1 x 375 ml

\$67.88 \$84.85

Eligible for 1¢ Standard Shipping See Details Show only Renwood items







Multiple Classifications in Action - Product Autocomplete



^{*} translated from Italian

demo at http://autocomplete.shoppydoo.com/demo.html

[Porrini et al. WIAS 2014] R. Porrini, M. Palmonari and G. Vizzari, Composite Match Autocompletion (COMMA): a Semantic Result-Oriented Autocompletion Technique for e-Marketplaces. In Web Intelligence and Agent Systems Journal, 2014

[Palmonari et al. WI 2012] M. Palmonari, G. Vizzari, R. Porrini, A. Broglia, N. Lamberti. Comma: A Result-Oriented Composite Autocompletion Method for e-Marketplaces, In Web Intelligence, 2012



Multiple Classifications in Action - Product Autocomplete



support for explorative keyword based queries

* translated from Italian

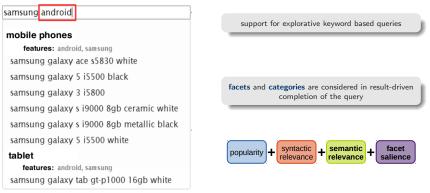
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Multiple Classifications in Action - Product Autocomplete



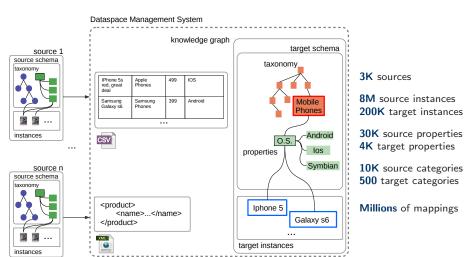
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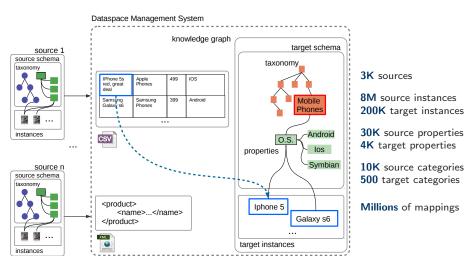
[Porrini et al. WIAS 2014] R. Porrini, M. Palmonari and G. Vizzari, Composite Match Autocompletion (COMMA): a Semantic Result-Oriented Autocompletion Technique for e-Marketplaces. In Web Intelligence and Agent Systems Journal, 2014

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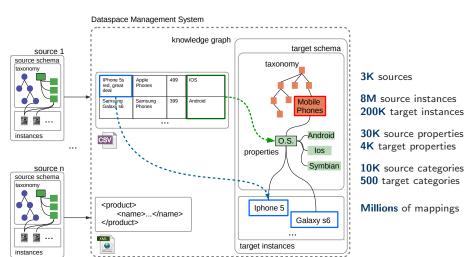


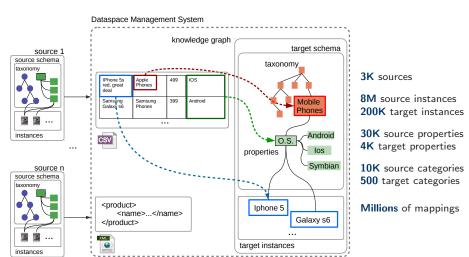












Challenges

target schema and mapping maintenance is hard

need for extensive knowledge of disparate domains

wines and clothes

need for domain experts supervision

quality issues



Challenges

target schema and mapping maintenance is hard

- need for extensive knowledge of disparate domains wines and clothes
- need for domain experts supervision

quality issues

crucial for

- inclusion of new data sources covering different domains
- ▶ pay-as-you-go refinement of the integration

from wines

to italian, cabernet wine bottles, from 2011



Research Challenges

highlighted by seminal works on Dataspaces

[Franklin et al. 2005]

relevant to this thesis

schema enrichment

extraction of properties and categories

```
[Pound et al. 2011, Medelyan et al. 2013, Kong and Allan 2013] . . .
```

category and property profiling

```
[Presutti et al. 2011, Jarrar et al. 2012] . . .
```

mapping discovery

schema and ontology matching (p-to-p, c-to-c)

```
[Bernstein et al. 2011, Shvaiko and Euzenat 2013] . . .
```

▶ web table annotation (sources with weak structure)

```
[Limaye et al. 2010, Venetis et al. 2011] . . .
```



Formalization

Dataspace $\Delta = <\mathcal{S}, T, M>$

- \triangleright S set of sources S with respective schema and instances
- T target knowledge graph (schema and instances)
- ► *M* set of mappings between the sources and the target



Formalization

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schema	$\mathcal{A}^{\mathcal{S}} = <\mathcal{C}^{\mathcal{S}}, \mathcal{P}^{\mathcal{S}}>$	$\mathcal{A}^T = < C^T, P^T >$
instances	$X^S = \{x_1^S, \dots x_h^S\}$	$X^T = \{x_1^T, \dots x_k^T\}$
categories	$C^S = \{c_1^S, \dots, c_m^S\}$	$C^T = \{c_1^T, \dots, c_n^T\}$
properties	$P^S = \{p_1^S, \dots, p_w^S\}$	$P^T = \{p_1^T, \dots, p_j^T\}$

- categories as FOL unary predicates from taxonomy or a lattice MobilePhones(iphone 6)
- ightharpoonup properties $p_i \subseteq X \times V_i$ as FOL binary predicates price(iphone 6, "32 euro")



Formalization

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Horn clauses encoded mappings from sources to target schema

$$a^{T}(\bar{x}) \leftarrow a_{1}^{S}(\bar{x}), \dots, a_{i}^{S}(\bar{x}), c_{1}, \dots, c_{n}$$
 $a^{T} \in \mathcal{A}^{T}, \ a^{S} \in \mathcal{A}^{S}$
 $c_{1}, \dots, c_{n} \text{ constraints}$

C-to-C (category-to-category) $Phones(x) \leftarrow ApplePhones(x)$

p-to-p (property-to-property)

 $year(x, v) \leftarrow yearOfProduction(x, v)$

C-to-p (category-to-property)

 $year(x, "2013") \leftarrow WinesFrom2013(x)$





schema enrichment

extraction of domain specific properties from sources

[Porrini et al. CAiSE 2014]

▶ analysis of property usage within the dataspace

[Palmonari et al. ESWC 2015]



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mapping discovery

establishment of category-to-property mappings

[Porrini et al. CAiSE 2014]

establishment of property-to-property mappings

Paper to be submitted



schema enrichment

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Paper to be submitted

case study from the eCommerce domain

usage of target categories and properties for product autocompletion

[Palmonari et al. WI 2012, Porrini et al. WIAS 2014]



goal

granular characterization of dataspace instances by extracting domain specific properties



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granular characterization of dataspace instances by extracting domain specific properties

Wines



goal

granular characterization of dataspace instances by extracting domain specific properties

Wines

Winery Country of Origin	Wine Alcohol By Volume	Grape Variety	Wine Bottle Volume
USA	Under 10%	Blend - White	■ 375 mL
China	☐ 10% to 12%	Blend - Other	■ 500 mL
Australia	2% to 14%	Fruit	750 mL
Italy	☐ 14% & Up	Muscadine	
Specialty Wine Type	Wine Vintage	Cabernet Sauvignon	
Sustainable	2011	Pinot Noir	
Small Lot	2010	Chardonnay	
Kosher	2009		
Gluten-Free	2008		
	2007		



goal

granular characterization of dataspace instances by extracting domain specific properties

observations about source categories

- source categories often come from specialized sources
 - (e.g., emarketplaces selling only wine bottles)
- c-to-c mappings typically map specialized to generic categories

 $Wines(x) \leftarrow Barolo(x)$



goal

granular characterization of dataspace instances by extracting domain specific properties

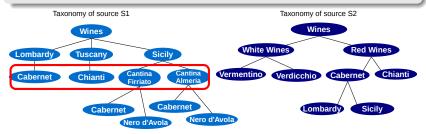
idea: leverage already defined c-to-c mappings

- **1.** fix a target category c^T
- **2.** pick all the source categories c^S such that $c^T(x) \leftarrow c^S(x)$
- **3.** form clusters of **homogeneous** property values V^1, \ldots, V^n
- **4.** output properties $p_i \subseteq X \times V^i$
- **5.** output c-to-p mappings: $p_i(x, v) \leftarrow v(x), v \in V^i$



Source Category Mutual Exclusivity Principle

the more two source categories are mutually exclusive, the more they should be clustered together into the same property value set



given two source categories c_1 and c_2 , their occurrence as siblings indicates that c_1 and c_2 are mutually exclusive



Taxonomy Layer Distance

$$\mathsf{TLD}(c_1, c_2) = 1 - rac{|L_{c_1} \cap L_{c_2}|}{|L_{c_1} \cup L_{c_2}|}$$

Jaccard distance between the two sets of taxonomy layers where two categories c₁ and c₂ occur



cabernet chianti

$$\mathsf{TLD}(\textit{cabernet}, \textit{chianti}) = 1 - \frac{|L_{\textit{cabernet}} \cap L_{\textit{chianti}}|}{|L_{\textit{cabernet}} \cup L_{\textit{chianti}}|} = 1 - \frac{2}{3} = \frac{1}{3}$$



Evaluation

	#Taxonomies	#Mappings
Wines	184	8967
Musical Instruments	128	1306
Grappe, Liquors, Aperitives	115	1254
Beers	58	156
DVD Movies	164	2042
Blu-Ray Movies	55	395
Dogs and Cats Food	80	5592
Rings	138	936
Ski and Snowboards	55	790
Necklaces	148	1156
Overall	688	22594

evaluation using real world data from the Italian PCE TrovaPrezzi

- property values manually grouped by domain experts
- comparison with Leacock and Chodorow similarity

[Leacock and Chodorow 1998]

and with Wu and Palmer similarity

[Wu and Palmer 1994]



Quantitative Evaluation

	Value Effectiveness			Clustering Effectiveness				Quality
	Р	R	F_1	F*	NMI*	Purity	E*	PRF*
LC	0.394	0.953	0.537	0.666	0.709	0.220	0.685	0.531
WP TI D	0.377 0.416	0.984 0.901	0.525 0.541	0.682 0.719	0.714 0.746	0.210 0.286	0.744 0.416	0.520 0.558
ILD	0.710	0.901	0.541	0.713	0.770	0.200	0.710	0.550



Quantitative Evaluation

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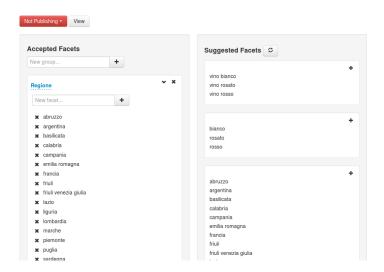
▶ TLD more effective in finding relevant property values and discarding noisy ones (high F_1)

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TLD	0.416	0.901	0.541	0.719	0.746	0.216	0.416	0.558

- ► TLD more effective in finding relevant property values and discarding noisy ones (high F_1)
- ▶ TLD more effective in clustering homogeneous values (high clustering effectiveness)

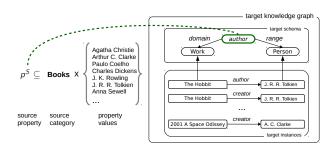
Real World Deployment



in production within the Italian PCE TrovaPrezzi dataspace extracted properties for 16 target categories and counting



Property-to-Property Mapping

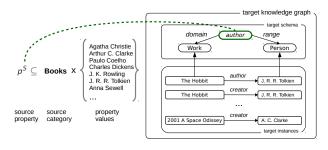


goal

given a source property p^S select a property p^T from the target schema such that the semantics of p^S is compatible with p^T



Property-to-Property Mapping



challenges

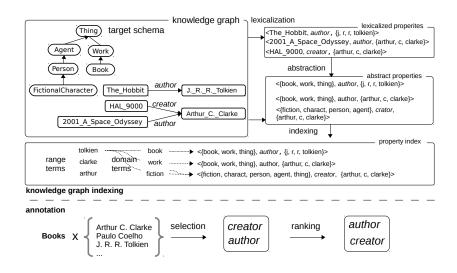
- more than one target property suitable for mapping e.g., ~50000 properties from the DBPedia knowledge graph
- how to resolve ambiguities?

$$p^{S} \subseteq X^{S} \times \{2010, 2011, 2012, ...\}$$
release Year for music albums
vintage for wines

how to capture semantic compatibility between properties?

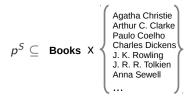


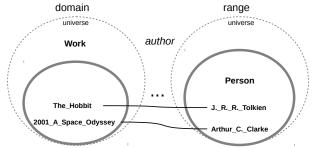
Approach Overview





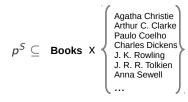
Specificity

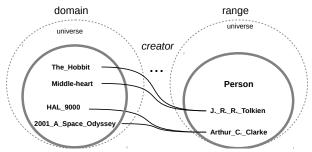






Specificity







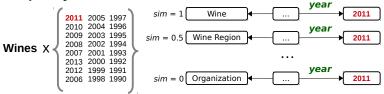
Coverage



Coverage



Frequency



Evaluation

	source properties		t		
	#	categories	#	relevant	fair
dbpedia-numbers	8	7	53195	~4	\sim 19
dbpedia-entities	31	13	53195	\sim 7	\sim 7
dbpedia	39	13	53195	~3	\sim 9
yago-full	83	17	89	1	-
yago-abstract	83	10	89	1	-

- ► DBPedia and YAGO as target knowledge graphs
- ▶ DBPedia based gold standard created through a questionnaire
- YAGO based state-of-the-art gold standard [Limaye et al. 2010, Venetis et al. 2011]



Evaluation Results

Mean Average Precision on the DBPedia Gold Standard

	dbpedia-numbers	dbpedia-entities	dbpedia
majority	0.22	0.50	0.44
maximum likelihood	0.16	0.39	0.34
proposed approach	0.25	0.55*	0.49*

Mean Reciprocal Rank on the YAGO Gold Standard

	yago-full	yago-abstract	
majority	0.76	0.86	
maximum likelihood	0.81	0.85	
proposed approach	0.88*	0.90*	

* p < 0.05

- comparison with the well known majority voting scheme and
- ▶ with maximum likelihood based approach [Venetis et al. 2011]



Research Prototype: STAN

STAN Alpha

Semantic Table Annotation Tool

Annota	tion Ontolo	ogies Namespace					Sav	е Ехро	ert 🕶
School	name	FullName	SchoolName2	ISBE Name	address	Street Direction	address	city	s
400010	Ace Technical Chtr HS	Architecture, Construction, and Engineering(ACE)Technical Charter School	Ace Technical Chtr HS	Ace Technical Charter High School	5410	S	State St	Chicago	IL
609772	Addams	Jane Addams Elementary School	Addams	Addams Elem School	10810	S	Avenue H	Chicago	IL
609773	Agassiz	Louis A Agassiz Elementary School	Agassiz	Agassiz Elem School	2851	N	Seminary Ave	Chicago	IL
610513	Air Force HS	Air Force Academy High School	Air Force HS	Air Force Acad High School	3630	S	Wells St	Chicago	IL
610212	Albany Park	Albany Park Multicultural Academy	Albany Park	Albany Park Multicultural Elem	4929	N	Sawyer Ave	Chicago	IL
609774	Alcott ES	Louisa May Alcott	Alcott ES	Alcott Elem	2625	N	Orchard St	Chicago	IL

demo @ http://stan.disco.unimib.it

algorithm source code @ http://bitbucket.org/rporrini/cluster-labelling



credits to Brando Preda (MSc student) for the web app development

Knowledge Graph Summarization

goal

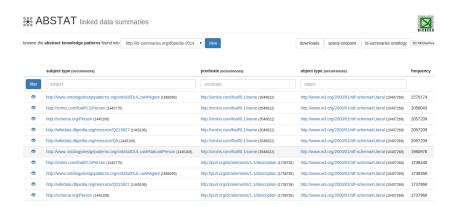
support the analysis of property usage in a knowledge graph

- what categories are described in the knowledge graph?
- what properties are used to characterize the instances?
- ▶ how frequent is the use of a given property?

[Palmonari et al. ESWC 2015] M. Palmonari, A. Rula, R. Porrini, A. Maurino, B. Spahiu and V. Ferme. ASBTAT: Linked Data Summaries with ABstraction and STATistics. In ESWC Posters and Demos, 2015



Research Prototype: ABSTAT



demo @ http://abstat.disco.unimib.it source code @ http://github.com/rporrini/abstat



Conclusions

studied the problem of **property management** in dataspaces

- extraction of domain specific properties
- establishment of c-to-p and p-to-p mappings
- evaluation on different application domains

eCommerce - LOD

algorithms deployed in production or in research prototypes

last mile(s)

- refine the formal framework of the thesis
- experiment p-to-p mapping approach in the eCommerce domain



Scientific Activities

Publications

- [1] M. Palmonari, A. Rula, R. Porrini, A. Maurino, B. Spahiu and V. Ferme. ASBTAT: Linked Data Summaries with ABstraction and STATistics. In ESWC. 2015
- [2] R. Porrini, M. Palmonari and C. Batini, Extracting Facets from Lost Fine-Grained Classifications in Dataspaces. In CAiSE, 2014
- [3] R. Porrini, M. Palmonari and G. Vizzari. Composite Match Autocompletion (COMMA): a Semantic Result-Oriented Autocompletion Technique for e-Marketplaces. In Web Intelligence and Agent Systems Journal, 2014
- [4] M. Palmonari, G. Vizzari, R. Porrini, A. Broglia, N. Lamberti. Comma: A Result-Oriented Composite Autocompletion Method for e-Marketplaces. In Web Intelligence, 2012

Conference Paper Reviews (as sub-reviewer)

- ISWC 2015: 15th International Semantic Web Conference
- ESWC 2015: 12th Extended Semantic Web Conference
- EDBT 2015: 18th International Conference on Extending Database Technology
- ► AAAI-15: 23th AAAI Conference on Artificial Intelligence
- EKAW 2014: 19th International Conference on Knowledge Engineering and Knowledge Management
- ► ISWC 2014: 14th International Semantic Web Conference
- ▶ WI 2014: 2014 IEEE/WIC/ACM International Conference on Web Intelligence
- AAAI-14: 22th AAAI Conference on Artificial Intelligence
- ► ESWC 2014: 11th Extended Semantic Web Conference
- ► CAISE 2014: 26th International Conference on Advanced Information Systems Engineering
- ▶ ODBASE 2013: 12th International Conference on Ontologies, DataBases, and Applications of Semantics
- WI 2013: 2013 IEEE/WIC/ACM International Conference on Web Intelligence



Educational Activities

Courses and Schools

- The Impact of Logic: from Proof Systems to Databases Politecnico di Milano (evaluation pending)
- Recommender Systems DISCo (final report submitted)
- Cluster Analysis DISCo
- Third ESWC Summer School Kalamaky Crete (GR)
- Foundations of Data Exchange and Integration Politecnico di Milano
- Advanced Analytics and Behavior Informatics DISCo

Seminars

- From Sentiment Analysis to Continuous Learning DISCo.
- Introduzione alla Logica nella Rappresentazione della Conoscenza DISCo
- La Misurazione Della Felicità al Tempo dei Big Data DISCo
- Optimum Hyperpaths in Directed Hypergraphs DISCo
- Phase Transitions in Social and Economic Systems DISCo.
- Progettare e Fare Open Data. Metodologia e tools sviluppati in Evodevo a partire dall'esperienza Open Data INPS - DISCo
- Semantic Constraints for Data Quality Assessment and Cleaning DISCo.
- ▶ Big Data e la forza degli eventi DISCo
- ► WOA 2012: 13th National Workshop "Dagli Oggetti agli Agenti" DISCo

Teaching

- Tutor for Data and Web Semantics couse (MSc and PhD, Fall 2014) University of Illinois at Chicago
- Co-Advisor of two BSc thesis and two MSc thesis
- Lecturer (2 lectures) for the "Artificial Intelligence" course (MSc A.A. 2012/2013 and 2013/2014) DISCo
- Tutor for Distributed Systems course (BSc A.A. 2012/2013) DISCo



Questions?



Challenges

Source taxonomies are:

- many 3900 within the TrovaPrezzi italian price comparison engine
- noisy type > white > by vine > chardonnay > producer > firriato
- heterogeneous type > white > by vine > chardonnay > producer > firriato wines > white wines > greco di tufo
- ▶ ambiguous different semantics for different contexts red is a wine type for wines and a color for shirts



Related Work - Property Extraction

- document corpora focus on property hierarchies - specific for unstructured data [Stoica et al. 2007, Dakka and Ipeirotis 2008, Wei et al. 2013, Medelyan et al. 2013]
- search engines' query logs and documents user search queries as a primary source of information [Li et al. 2009, Pasca and Alfonseca 2009, Pound et al. 2011]
- search engines' query results integrate and rank properties already present in web documents [Yan et al. 2010, Dou et al. 2011, Kawano et al. 2012, Kong and Allan 2013]

Similarity-Relatedness between taxonomy categories

- ► Leacock and Chodorow similarity [Leacock and Chodorow 1998]
- ► Wu and Palmer similarity [Wu and Palmer 1994]
- not designed for taxonomies



Related Work - p-to-p Mapping

from ontologies

- ▶ intensional matchers focus on schema, neglect instances [Cheatham and Hitzler 2014] ...
- extensional matchers focus on the instances, neglect the schema [Zhang et al. 2015] ...

from tabular data

- custom knowlege graphs knowledge graphs with special features [Venetis et al. 2011, Wang et al. 2012] ...
- holistic approaches annotate the table as a whole [Limaye et al. 2010, Mulwad et al. 2013, Zhang 2015] . . .



References I

General References

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- [Bernstein et al. 2011] P. A. Bernstein, J. Madhavan and E. Rahm. Generic Schema Matching, Ten Years Later. In PVLDB, 2011
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- [Shvaiko and Euzenat 2013] Pavel Shvaiko and Jérôme Euzenat. Ontology Matching: State of the Art and Future Challenges. In IEEE Trans. Knowl. Data Eng., 2013

Property Extraction References

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- [Leacock and Chodorow 1998] C. Leacock and M. Chodorow, Combining local context and wordnet similarity for word sense identification. In MIT Press, 1998
- [Stoica et al. 2007] E. Stoica, M.A. Hearst and M. Richardson. Automating creation of hierarchical faceted metadata structures. In HLT-NAACL, 2007
- [Dakka and Ipeirotis 2008] W. Dakka and P.G. Ipeirotis. Automatic extraction of useful facet hierarchies from text databases. In ICDE, 2008
- [Li et al. 2009] X. Li, Y.Y. Wang, A. Acero. Extracting structured information from user queries with semi-supervised conditional random fields. In SIGIR, 2009
- [Pasca and Alfonseca 2009] M. Pasca and E. Alfonseca. Web-derived resources for web information retrieval: from conceptual hierarchies to attribute hierarchies. In SIGIR, 2009



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- [Yan et al. 2010] N. Yan, C. Li, S.B. Roy, R. Ramegowda and G. Das. Facetedpedia: enabling query-dependent faceted search for wikipedia. In CIKM, 2010
- [Pound et al. 2011] J. Pound, S. Paparizos and P. Tsaparas, Facet discovery for structured web search: a query-log mining approach. In SIGMOD, 2011
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