

Gianluca Demartini Ph.D. Defense

Hannover, April 6th, 2011

FROM PEOPLE TO ENTITIES: TYPED SEARCH IN THE ENTERPRISE AND THE WEB



Motivation

As the Web grows, Search Engines are the main entry points

- Search Engines are good for document ranking
- Provide more than just documents (e.g., pictures, videos, maps, etc.)

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Everything	News for rihanna Katy Perry And Lady Gaga? Competition Is None For Rihanna Q		
Videos	31 minutes ago By Paul Cantor, Mar 23, 2011 11:17 pm Permalink Rihanna covers the latest issue of UK mag Fabulous. In the accompanying article, she speaks about her		
Realtime Blogs	Complex.com - 2201 related articles <u>Rihanna wants to launch make-up, fashion line</u> Calcutta Tube - 73 related articles <u>Rihanna to live with Farrell?</u>		
Search near Enter location Set	Rihanna - Wikipedia, the free encyclopedia Robyn Rihanna Fenty (born February 20, 1988), better known as simply Rihanna is a Barbadian R&B recording artist and songwriter. Born in Saint Michael, Discography - Loud - Songs - What's My Name? en.wikipedia.org/wiki/Rihanna - Cached - Similar		
Any time Latest Past 24 hours Past 3 days Past week	Rihannanow.com Tune into E! tonight at 11pm EST to check out Rihanna as she dishes with Chelsea handler about her birthday party and more! www.rihannanow.com/ - Cached - Similar		
Past month Past year Custom range	Videos for rihanna - Report videos The OFFICIAL "Run This Town" Rihanna - What's My Name - Video Video The X Factor Live Final Video		
More search tools	5 min - 21 Aug 2009 Uploaded by jayz youtube.com 4 min - 11 Dec 2010 Uploaded by missdiva152 youtube.com		
Something different beyonce fergie christina aguilera	Rihanna Free Music, Tour Dates, Photos, Videos Q Rihanna's official profile including the latest music, albums, songs, music videos and more updates.		

 Ist Mariner Arena
 Sat, Jun 4
 Baltimore, MD

 Air Canada Centre
 Mon, Jun 6
 Toronto, ON, CANADA

 Air Canada Centre
 Tue, Jun 7
 Toronto, ON, CANADA

 www.myspace.com/rihanna - Cached - Similar
 Similar

shakira avril lavigne



Library > Miscellaneous > Who2 Biographies Born: 20 February 1988 Birthplace: Saint Michael Barbados Best Known As: Singer of the hit single "Umbrella" Name at hirth

Las Vegas



Problem Statement

- Many queries (50%) search for specific entities instead of documents [Kumar&Tomkins09]
- Web Search Engines do not satisfy users needing specific entities
- Retrieve a list of entities instead of a list of documents





Ph.D. Overview

Entity Retrieval





Outline

Motivation

Part I - Retrieving Entities in the Enterprise

- A Vector Space Model for Ranking Entities
- Application to Expert Finding

Part II - Retrieving Entities in Wikipedia

- Evaluation of Entity Retrieval in Wikipedia
- Structure-based techniques
- NLP-based techniques

Part III - Additional Dimensions of Entity Retrieval: Time and Opinion

- Time-Aware Entity Retrieval
- Mining Opinions about Entities on the Web

Part IV - Test Collections for Entity Retrieval

Conclusions



PART I RETRIEVING ENTITIES IN THE ENTERPRISE

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Expert Finding - Motivation

Scenario



- In large companies competencies and skills are spread
- Executives need to create a team for a new project: find staff with the right expertise
- Someone needs to solve a problem
- Example: I need an expert on ontology engineering

Goal

- Use the digital content available in the enterprise
- Create a ranking of people who are experts in the given topic



Related Work

- P@noptic Expert [Craswell et al. Ausweb01]
- Balog's Model 1 [Balog et al. SIGIR06]
- Voting Model [Macdonald and Ounis CIKM06, ECIR07, ECIR08]
- Experise evidence [Macdonald et al. ECIR08]
- Topic drift: ProjSim allows multiple expertises



Gianluca Demartini, Julien Gaugaz, and Wolfgang Nejdl. A Vector Space Model for Ranking Entities and Its Application to Expert Search. In: 31st European Conference on Information Retrieval (ECIR 2009), Toulouse, France, April 2009. ECIR 2009

A Vector Space Model for Entity Retrieval

A general model for ranking entities in a document collection

- Allowing integration of known techniques
- For any type of entity
- An application to the expert finding task



A Vector Space Model for Entity Retrieval

- 1. Send entities into the space (*I*-dimensional) $d_i = d_{1,i}t_1 + ... + d_{l,i}t_l$
 - a) Documents as vectors

$$f:(d_i,e_j) \to r_{ij}$$

- b) Relationship between (n) entities and (m) documents
- c) Entities as vectors



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Extensions of the Model

A lot of expertise evidence may be available in the Enterprise

Document dependent

$$E = D \times (diag(x) \times R)$$

- Importance of each document (e.g., doc type)
- diag(x) is m x m with x_{ii} is the weight for d_i

Entity dependent

- Cost function for entities (e.g., salary)
- diag(cf) is n x n and cf_{ii} is the cost of e_i

$$E' = E \times diag(cf)$$



Experiments - Dataset

TREC

- Evaluation initiative for text retrieval
- Document collections
- Queries
- Relevance judgements

<num> Number: EX52 <title>Ontology engineering</title>

<desc> Description: Find individuals with expertise regarding ontology engineering. </desc>

<narr> Narrative:

This topic attempts to find individuals with expertise regarding to ontology engineering. Ontology engineering concerns the whole life-cycle of ontologies, such as ontology construction, ontology learning, ontology mapping, and ontology evolution. We want people with expertise about ontology engineering rather then other things related to ontology. </narr>



Experiments - Dataset

TREC Enterprise track 2006

- http://www.ins.cwi.nl/projects/trec-ent/
- W3C website (crawl of w3.org sites in June 2004)
- 331k documents (mailinglists, homepages, developers, etc.)
- 1092 (official) candidate experts
- 55 topics with manual relevance assessments







- Reputation of documents
- PageRank

$$E = D \times (diag(x) \times R)$$



Discussion – Part I

We presented a model for Entity Ranking

- It is based on the Vector Space Model
- Can be applied where entities are available
- Can be extended with different types of evidence

Main observations for task of Expert Finding

- Occurences in the author field are more important
- Our similarity measure performs better than cosine similarity
- Document dependent extensions improve effectiveness

Open Issue

■ It only considers a single entity type (i.e., people)



PART II RETRIEVING ENTITIES IN WIKIPEDIA



Wikipedia

Encyclopedia

- Multilingual
- Web-based
- Free-content
- Openly-editable: errors are promptly corrected

Categories / sub-categories

Links, anchor text (Germany --> Albert Einstein)





Entities in Wikipedia

Art museums and galleries Countries

Famous people (Actors, Singers)

Monarchs

Artists Magicians

. . .





Example Entity Ranking Scenarios

Impressionist art museums in the Netherlands

German car manufacturers

Countries involved in WWI

Actors who played Hamlet

English monarchs who married French women

Harry Potter Quidditch Gryffindor character



Web Science – Investigating the Future of Information and Communication Gianluca Demartini, Claudiu S. Firan, Tereza Iofciu, Ralf Krestel, and Wolfgang Nejdl. Why Finding Entities in Wikipedia is Difficult, Sometimes. In: "Information Retrieval" 13(5): 534-567, Springer, October 2010.

Part II Overview



We proposed algorithms for ER on top of Wikipedia

It is possible to search for many different entity types with one system!

Main observations

- Link information is important
- Cleaning the category structure of Wikipedia is critical (YAGO)
- NLP-based techniques on the user query improve effectiveness

Open issues

- No temporal evolution of content is considered
- Wikipedia is meant to be objective

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- NLP-based techniques

Part III - Additional Dimensions of ER: Time and Opinion

- Time-Aware Entity Retrieval
- Mining Opinions about Entities on the Web
- Part IV Test Collections for ER

Conclusions



PART III ADDITIONAL DIMENSIONS OF ER: TIME AND OPINION

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Web Science – Investigating the Future of Information and Communication Gianluca Demartini, Malik Muhammad Saad Missen, Roi Blanco, Hugo Zaragoza. Entity Summarization of News Articles. In: 33rd Annual ACM SIGIR Conference, Geneva, Switzerland, July 2010. Gianluca Demartini, Malik Muhammad Saad Missen, Roi Blanco, Hugo Zaragoza. TAER: Time Aware Entity Retrieval. In: The 19th ACM International Conference on Information and Knowledge Management (CIKM 2010), Toronto, Canada, October 2010.

Motivation

Techniques for static document collections do not apply everywhere

News stories evolve over time and entities appear/disappear

- Analyse and exploit relevance evolution
- Decide about relevance at document level

SIGIR 2010 CIKIN 2010



Scenario

An event

Charles Schulz dies

Get Relevant Docs

Entities

Peanuts, his wife, media companies, hometown, other cartoonists, ... Timeline of relevant news:

- 10/1999-09/2000:
 - 11/99 cancer diagnosted
 - 12/99 he retires
 - 02/00 he dies
 - 03/00 peanuts future discussed
 - ... Honors, museums, statues, airports, ...



Time-Aware Entity Retrieval

Find the entities e_i that best describe document d wrt a query q

Charles Schulz Dies	Search
	Important Entities:
	- Charles_Schulz
	- Congressional_Gold_Medal
AP Online	- Santa_Rosa
02 15 2000	- Peanuts
02-13-2000	
House Honors 'Peanuts' Creator	

WASHINGTON (AP) -- ``Peanuts'' creator <u>Charles Schulz</u> was remembered today as a genius who touched the lives of millions of Americans as the House adopted a resolution to award him a <u>Congressional Gold Medal</u>.

The 77-year-old cartoonist died in his sleep Saturday at his <u>Santa Rosa</u>, Calif., home, a day before Schulz's last strip featuring <u>Snoopy</u> and the gang was published. He had announced in November he would retire after being diagnosed with colon cancer.

"On Saturday night, millions of Americans lost their security blanket," said Rep. Lynn Woolsey, D-Calif. "Life won't be the same without Charles ...

Find e_i for d wrt a query q given history $d_i < d$



Related Work

Entity Retrieval on Wikipedia

- Ranking entities in a static collection
- Links and structure is important

Finding related Entities

Using Web content

■ TREC Entity Track (Airlines that currently use Boeing 747 plane)

Time-based IR: doc search in collections over time



Experimental Setting





Dataset and Analysis

TREC Novelty Track 2004

- 25 event topics
- 779 relevant news

Entity annotations (7481 entities) Relevance judgements

How useful is to find relevant sentences?

P(e is Rel)	0.411 [0.404-0.417]
P(e is NotRel)	0.168 [0.163-0.173]
P(e is Rel s is Rel)	0.547 [0.534-0.559]

- Sentences:
 - 21727 total
 - 5122 relevant

- 1.46 entity occurences
- 1.88 entity occurences



Data Analysis

How useful is looking at the past?

- P(e|d₁) 0.893 [0.881-0.905]
- P(e|d₋₁) 0.701 [0.677-0.726]

Is useful to consider sentence co-occurence?

P(e ₁ ,e ₂)	Relevant	Related	NotRelevant	NotAnEntity
Relevant	0.24	0.08	0.03	0.07
Related		0.07	0.03	0.03
NotRelevant			0.07	0.05
NotAnEntity				0.04



Approach

Entity Ranking features for News articles

- Local Features
 - F(e,d)
 - FirstSenLen
 - FirstSenPos
 - Fsubj
 - AvgBM25(q,s)
 - SumBM25(q,s)
- History Features

Feature combination

Linear and Machine Learning



Local Features

Feature	P5	MAP
F(e,d)	.56	.60
FirstSenLen	.36	.45
FirstSenPos	.31	.43
F _{subj}	.44	.50
AvgBM25(q,s)	.30	.41
SumBM25(q,s)	.44	.52

Feature	P5	MAP
All Tied	.34	.42



Is the past useful?

Looking at previous documents

- Entity occurences so far F(e,H)
- Docs where the entity appeared so far DF(e,H)
- Entity occurrences in the previous doc F(e,d₋₁)
- Frequency of entity the first time **F(e,d**₁)
- Number of other entities with which the entity co-occured so far CoOcc(e,H)



History Features

Feature	P5	MAP
F(e,d)	.56	.60
F(e,d ₁)	.53	.56
F(e,d ₋₁)	.56	.62*
F(e,H)	.59**	.66**
CoOcc(e,H)	.57	.65**
DF(e,H)	.57*	.65**

- * t-test p value < 0.05 as compared with F(e,d)
- ** t-test p value < 0.01 as compared with F(e,d)



Using the History

Conclusion

- Evidence from past documents is very important
- Effectiveness should improve over time (run F(e,H))





Combining Features with ML

Logistic Regression for ranking entities 5-folds cross validation on 25 topics Similar results for combinations of 2 features

Local Doc Features	History Features	Feature s	P3	P5	AvgPrec
F(e,d)	F(e,d ₁)	F(e,d)	.65	.56	.60
FirstSenLen	F(e,d ₋₁)	Local	.65	.56	.62
FirstSenPos	F(e,H)	History	.66	.60	.67
F _{subj}	CoOcc(e,H)	All	.69	.62	.68
AvgBM25s	DF(e,H)				
SumBM25s					



Discussion

Defined new search task: Time-Aware Entity Retrieval

Constructed evaluation benchmark

Experimental Evaluation

- Investigated some features and combinations
- Information from the past helps most
- Obtain 15% improvement over F(e,d)



Gianluca Demartini, Stefan Siersdorfer, Sergiu Chelaru, and Wolfgang Nejdl. **Analyzing Political Trends in the Blogosphere**. To appear in: Fifth International AAAI Conference on Weblogs and Social Media (ICWSM 2011), Barcelona, Spain, July 2011.

Estimating public opinion about entities

Motivation



- Wikipedia is objective, while opinions are expressed on the Web
- Blogs as forum for sharing experiences and opinions
- Public opinion is usually estimated by surveys
 - Limited sample
 - High cost for companies and interviewed people

We propose models for estimating public opinions from the blogosphere

- mining opinions
- aggregating information over time
- exploiting Time Series Analysis



Scenario

US Presidential Elections 2008

- 2 competing entities: Obama vs McCain
- Estimate public opinion over time
- Ground truth:
 - Professional telephonic polls (Gallup)





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Public Opinion Estimation





Related Work

Opinion Mining

- TREC Blog track
- Retrieve opinionated postings and their polarity
- Opinion aggregation over Twitter Data (O'Connor et al. 2010)

Time Series Analysis

Only looks at data series and trends



Our Approach

Extracting opinions

- Lexicon of opinionated words
- Training a learning model using opinionated text

Aggregating opinions

- Unsupervised
 - Only blogs
- Supervised (using history of polls)
 - Learn model parameters
 - Learn prediction models



Model parameters

Lag

Time delay between telephonic polls and blogs

Bias

Difference in opinions due to the biased sample

Scale

"Strength" of opinions

 $poll(t, lag, bias, scale) = (poll(t + lag) + bias) \cdot scale$

Smoothing

Remove noise

$$poll(t,k) = \frac{\sum_{j=0}^{k-1} poll(t-j)}{k}$$



The collection

Blogs08

- 28M permalink documents
 - 65% are in English
 - 671K posts contain obama/mccain
- January 2008 February 2009

Gallup polls

- 1500 US adults
- March-November 2008 (230 polls)
- Normalized scores to avoid "undecided voters"



Experimental Evaluation

Root Mean Square Error between estimation and telephonic polls





Experimental Evaluation

Method	RMSE		
	unsupervised	supervised	
LexAvg	0.0642	0.0556	
ClassifyAvg	0.0619	0.0608	
LexCount	0.0572	0.0483	
ClassifyCount	0.1980 0.048 2		
LexCountLinFor	0.0394 ($\lambda = 0.2$)		



Discussion

Problem of estimate the public opinion about target entities

We proposed unsupervised and supervised methods exploiting the Blogoshpere based on

- Lexicon
- Text classification

Effective as compared to standard telephonic polls



STANDARD REUSABLE TEST COLLECTIONS

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Comparing and evaluating IR Systems

Availability of standard and reusable test collections is critical

- For comparing systems and algorithms
- For evaluating a model in different settings/collections

We contributed to the creating of such collections by

- Organizing and evaluation initiative
- Creating a test collection for TAER



Gianluca Demartini, Arjen P. de Vries, Tereza Iofciu, and Jianhan Zhu. Overview of the INEX **2008 Entity Ranking Track.** In: 7th International Workshop of the Initiative for the Evaluation of XML Retrieval, INEX 2008 Dagstuhl, Germany, December 2008. Gianluca Demartini, Tereza Iofciu, and Arjen P. de Vries. Overview of the INEX 2009 Entity Ranking Track. In: 8th International Workshop of the Initiative for the Evaluation of XML Retrieval, INEX 2009 Brisbane, Australia, December 2009.

Evaluating ER in Wikipedia

INEX Entity (XER) track 2007-2009

- http://www.inex.otago.ac.nz/tracks/entity-ranking/entity-ranking.asp
- http://www.L3S.de/~demartini/XER08
- INEX 2008 http://www.L3S.de/~demartini/XER09

Standard test collection using

- Wikipedia dump from 2006
- Wikipedia dump from 2009 + extracted entities and types from Wordnet



Evaluating ER in Wikipedia

35+55 Queries and manual relevance judgements

<inex_topic topic_id="113"> <title>Formula 1 drivers that won the Monaco Grand Prix</title> <description>I want a list of Formula 1 drivers. Each of them must have won at least once the Monaco Grand Prix held in Monte Carlo.</description> <narrative>The Monaco Grand Prix (GP) is a Formula 1 competition held in Monte Carlo since 1929. I want to find all the drivers that won the GP over the years.</narrative> </inex_topic>

Pooling techniques and evaluation measures to compare sytems 2008 and 2009 Overview papers: 15+5 citations



Dataset for Evaluating ER over Time

TREC Novelty Track 2004

- Sentence retrieval
- 25 event topics
- 779 relevant news

Entity annotations (7481 entities)

Persons (26%), Locations (10%), Organizations (57%), Products (7%)

Relevance judgements

- Of each entity with respect to the topic in this current news
- 21,213 judgements on 3 levels
- Cohen's Kappa 0.59

http://www.L3S.de/~demartini/deert/



CONCLUSIONS





Ph.D. Contributions

We contributed in going beyond document retrieval in Search Engines Extensive study of the Entity Retrieval problem

■ in different settings: Enterprise, Wikipedia, News, Blogs

We addressed

- The problem of Expert Finding exploiting Enterprise content
- The problem of multi-type Entity Retrieval on top of Wikipedia
- The problem of entity relevance evolving over time
- The problem of different opinions expressed about entities

Created reusable evaluation collections for Entity Retrieval

- Organizing evaluation initiatives
- Releasing new standard datasets



Ph.D. Summary

- Demartini et al. A Vector Space Model for Ranking Entities and Its Application to Expert Search. In: 31st European Conference on Information Retrieval (ECIR 2009), Toulouse, France, April 2009.
- Demartini et al. Why Finding Entities in Wikipedia is Difficult, Sometimes. In: "Information Retrieval" 13(5): 534-567, Springer, October 2010.
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40 publications

- 2 in Journals
- 10 papers and 8 posters in Conference proceedings
- 14 in peer-reviewed Workshops