Part II
Entity Retrieval

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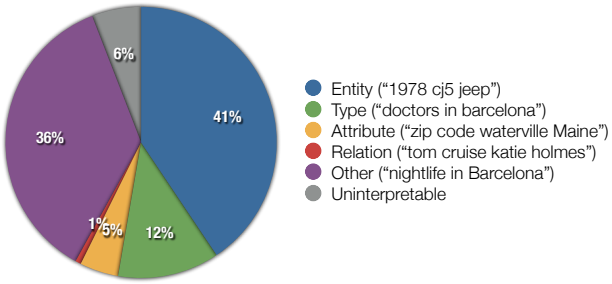
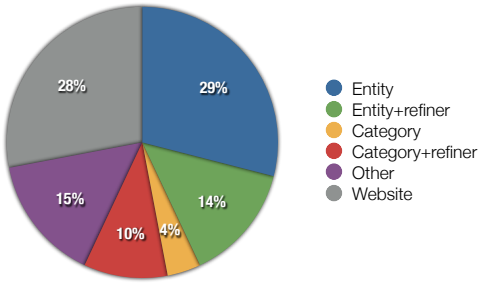
Entity retrieval

*Addressing information needs that are better answered by **returning specific objects** (entities) instead of just any type of documents.*

Distribution of web search queries [Pound et al. 2010]



Distribution of web search queries [Lin et al. 2011]

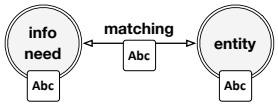


What's so special here?

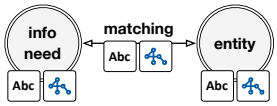
- Entities are not always directly represented
  - Recognize and disambiguate entities in text (that is, entity linking)
  - Collect and aggregate information about a given entity from multiple documents and even multiple data collections
- More structure than in document-based IR
  - Types (from some taxonomy)
  - Attributes (from some ontology)
  - Relationships to other entities ("typed links")

Semantics in our context

- working definition:
  references to meaningful structures
- How to capture, represent, and use structure?
  - It concerns all components of the retrieval process!



Text-only representation



Text+structure representation

Overview of core tasks

	Queries	Data set	Results
(adhoc) entity retrieval	keyword	unstructured/ semistructured	ranked list
adhoc object retrieval	keyword	structured	ranked list
list completion	keyword+++ (examples)	(semi)structured	ranked list
related entity finding	keyword++ (target type, relation)	unstructured & structured	ranked list

In this part

- Input: keyword(++) query
- Output: a ranked list of entities
- Data collection: unstructured and (semi)structured data sources (and their combinations)
- Main RQ: **How to incorporate structure into text-based retrieval models?**

Outline

1. Ranking based on entity descriptions
2. Incorporating entity types
3. Entity relationships

Attributes (/Descriptions)

Type(s)

Relationships

Ranking entity descriptions

Attributes (/Descriptions)

Type(s)

Relationships

Task: ad-hoc entity retrieval

- **Input**: unconstrained natural language query
  - "telegraphic" queries (neither well-formed nor grammatically correct sentences or questions)
- **Output**: ranked list of entities
- **Collection**: unstructured and/or semi-structured documents

Example information needs

- american embassy nairobi
- ben franklin
- Chernobyl
- meg ryan war
- Worst actor century
- Sweden Iceland currency

Two settings

1. With ready-made entity descriptions

2. Without explicit entity representations

Ranking with ready-made entity descriptions

This is not unrealistic...

Document-based entity representations

- Most entities have a "home page"
- I.e., each entity is described by a document
- In this scenario, ranking entities is much like ranking documents
  - unstructured
  - semi-structured

Evaluation initiatives

- INEX Entity Ranking track (2007-09)
  - Collection is the (English) Wikipedia
  - Entities are represented by Wikipedia articles
- Semantic Search Challenge (2010-11)
  - Collection is a Semantic Web crawl (BTC2009)
    - ~1 billion RDF triples
  - Entities are represented by URIs
- INEX Linked Data track (2012-13)
  - Wikipedia enriched with RDF properties from DBpedia and YAGO

Standard Language Modeling approach

- Rank documents d according to their likelihood of being relevant given a query q: $P(d|q)$

$$P(d|q) = \frac{P(q|d)P(d)}{P(q)} \propto P(q|d)P(d)$$

Query likelihood
Probability that query q was "produced" by document d

Document prior
Probability of the document being relevant to *any* query

$$P(q|d) = \prod_{t \in q} P(t|\theta_d)^{n(t,q)}$$

Standard Language Modeling approach (2)

$$P(q|d) = \prod_{t \in q} P(t|\theta_d)^{n(t,q)}$$

Number of times t appears in q

Document language model
Multinomial probability distribution over the vocabulary of terms

$$P(t|\theta_d) = (1-\lambda)P(t|d) + \lambda P(t|C)$$

Smoothing parameter

Empirical document model

Maximum likelihood estimates

$$\frac{n(t,d)}{|d|} \qquad \frac{\sum_d n(t,d)}{\sum_d |d|}$$

Collection model

Here, documents==entities, so

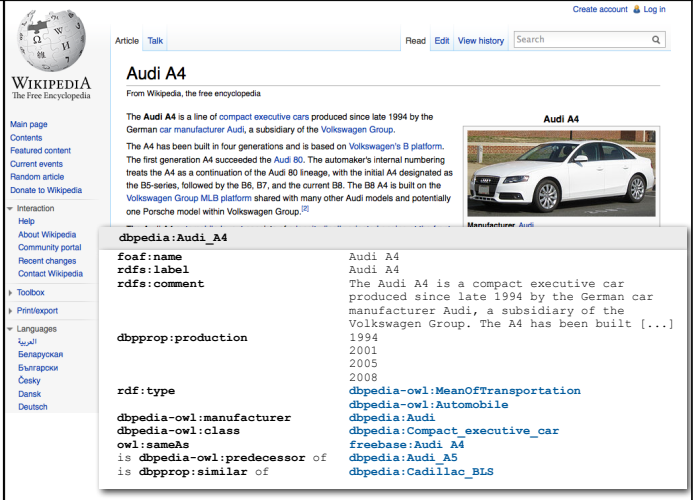
$$P(e|q) \propto P(e)P(q|\theta_e) = P(e) \prod_{t \in q} P(t|\theta_e)^{n(t,q)}$$

Entity prior
Probability of the entity being relevant to *any* query

Entity language model
Multinomial probability distribution over the vocabulary of terms

Semi-structured entity representation

- Entity description documents are rarely unstructured
- Representing entities as
  - Fielded documents – the IR approach
  - Graphs – the DB/SW approach



Mixture of Language Models

[Ogilvie & Callan 2003]

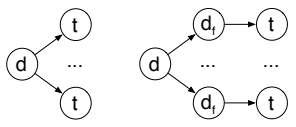
- Build a separate language model for each field
- Take a linear combination of them

$$P(t|\theta_d) = \sum_{j=1}^{m} \mu_j P(t|\theta_{d_j})$$

Field language model
Smoothed with a collection model built from all document representations of the same type in the collection

Field weights
$\sum_{j=1}^{m} \mu_j = 1$

Comparison of models



Unstructured document model

Fielded document model

Setting field weights

- Heuristically
  - Proportional to the length of text content in that field, to the field's individual performance, etc.
- Empirically (using training queries)
- Problems
  - Number of possible fields is huge
    - It is not possible to optimise their weights directly
- Entities are sparse w.r.t. different fields
  - Most entities have only a handful of predicates

Predicate folding

- **Idea**: reduce the number of fields by grouping them together
- Grouping based on (BM25F and)
  - type **[Pérez-Agüera et al. 2010]**
  - manually determined importance **[Blanco et al. 2011]**

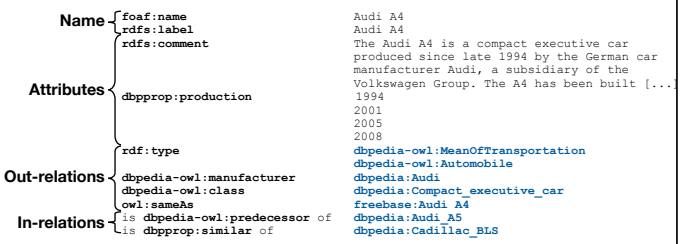
Hierarchical Entity Model

[Neumayer et al. 2012]

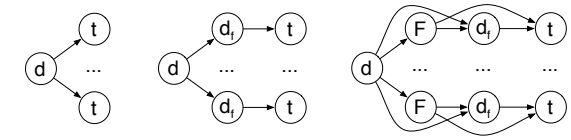
- Organize fields into a 2-level hierarchy
  - Field types (4) on the top level
  - Individual fields of that type on the bottom level
- Estimate field weights
  - Using training data for field types
  - Using heuristics for bottom-level types

Two-level hierarchy

[Neumayer et al. 2012]



Comparison of models



Unstructured document model | **Fielded document model** | **Hierarchical document model**

Probabilistic Retrieval Model for Semistructured data

[Kim et al. 2009]

- Extension to the Mixture of Language Models
- Find which document field each query term may be associated with

$$P(t|\theta_d) = \sum_{j=1}^{m} \mu_j P(t|\theta_{d_j})$$

Mapping probability
Estimated for each query term

$$P(t|\theta_d) = \sum_{j=1}^{m} \overbrace{P(d_j|t)} P(t|\theta_{d_j})$$

Estimating the mapping probability

$$P(t|C_j) = \frac{\sum_d n(t, d_j)}{\sum_d |d_j|}$$

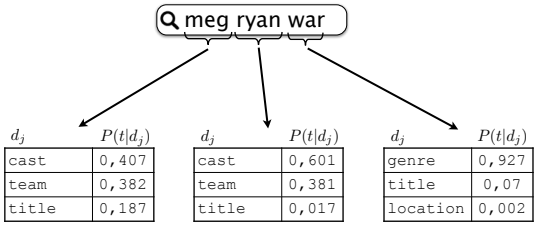
Term likelihood
Probability of a query term occurring in a given field type

Prior field probability
Probability of mapping the query term to this field before observing collection statistics

$$P(d_j|t) = \frac{\overbrace{P(t|d_j)}\overbrace{P(d_j)}}{\underbrace{P(t)}}$$

$$\sum_{d_k} P(t|d_k)P(d_k)$$

Example



d_j	$P(t\|d_j)$
cast	0,407
team	0,382
title	0,187

d_j	$P(t\|d_j)$
cast	0,601
team	0,381
title	0,017

d_j	$P(t\|d_j)$
genre	0,927
title	0,07
location	0,002

Ranking without explicit entity representations

Scenario

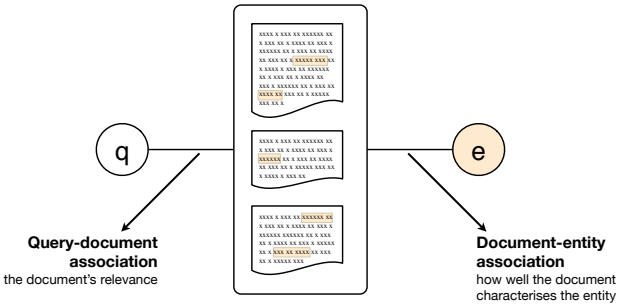
- Entity descriptions are not readily available
- Entity occurrences are annotated
  - manually
  - automatically (~entity linking)

TREC Enterprise track

- Expert finding task (2005-08)
  - Enterprise setting (intranet of a large organization)
  - Given a query, return people who are experts on the query topic
  - List of potential experts is provided
- We assume that the collection has been annotated with **<person>...</person>** tokens

The basic idea

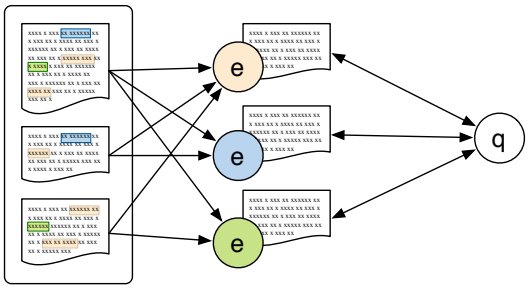
Use documents to go from queries to entities



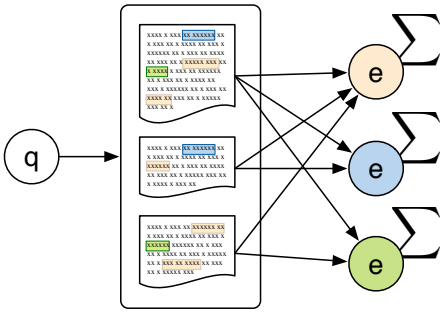
Two principal approaches

- **Profile-based** methods
  - Create a textual profile for entities, then rank them (by adapting document retrieval techniques)
- **Document-based** methods
  - Indirect representation based on mentions identified in documents
  - First ranking documents (or snippets) and then aggregating evidence for associated entities

Profile-based methods



Document-based methods



Many possibilities in terms of modeling

- Generative (probabilistic) models
- Discriminative (probabilistic) models
- Voting models
- Graph-based models

Generative probabilistic models

- Candidate generation models (*P(e|q)*)
  - Two-stage language model
- Topic generation models (*P(q|e)*)
  - Candidate model, a.k.a. Model 1
  - Document model, a.k.a. Model 2
  - Proximity-based variations
- Both families of models can be derived from the Probability Ranking Principle [Fang & Zhai 2007]

Candidate models ("Model 1")

[Balog et al. 2006]

$$P(q|\theta_e) = \prod_{t \in q} \underbrace{P(t|\theta_e)}^{n(t,q)}$$

Smoothing
With collection-wide background model

$$(1-\lambda)\underbrace{P(t|e)} + \lambda P(t)$$

$$\sum_d \underbrace{P(t|d,e)}\underbrace{P(d|e)}$$

Term-candidate co-occurrence
In a particular document.
In the simplest case: $P(t|d)$

Document-entity association

Document models ("Model 2")

[Balog et al. 2006]

$$P(q|e) = \sum_d \underbrace{P(q|d,e)}\underbrace{P(d|e)}$$

Document relevance
How well document d supports the claim that e is relevant to q

Document-entity association

$$\prod_{t \in q} \underbrace{P(t|d,e)}^{n(t,q)}$$

Simplifying assumption
(t and e are conditionally independent given d)

$$P(t|\theta_d)$$

Document-entity associations

- Boolean (or set-based) approach
- Weighted by the confidence in entity linking
- Consider other entities mentioned in the document

Proximity-based variations

- So far, conditional independence assumption between candidates and terms when computing the probability *P(t|d,e)*
- Relationship between terms and entities that in the same document is ignored
  - Entity is equally strongly associated with everything discussed in that document
- Let's capture the dependence between entities and terms
  - Use their distance in the document

Using proximity kernels

[Petkova & Croft 2007]

$$P(t|d,e) = \underbrace{\frac{1}{Z}}\sum_{i=1}^{N}\underbrace{\delta_d(i,t)}\underbrace{k(t,e)}$$

Normalizing contant

Indicator function
1 if the term at position i is t,
0 otherwise

Proximity-based kernel
- constant function
- triangle kernel
- Gaussian kernel
- step function

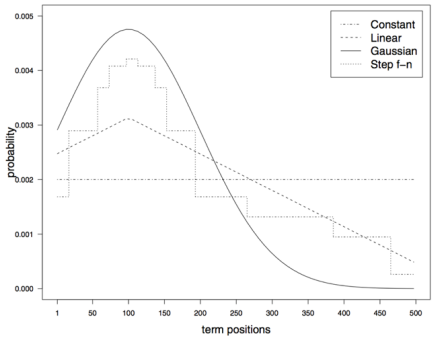


Figure taken from D. Petkova and W.B. Croft. Proximity-based document representation for named entity retrieval. **CIKM'07.**

Many possibilities in terms of modeling

- ~~Generative probabilistic models~~
- Discriminative probabilistic models
- Voting models
- Graph-based models

Discriminative models

- Vs. generative models:
  - Fewer assumptions (e.g., term independence)
  - "Let the data speak"
    - Sufficient amounts of training data required
  - Incorporating more document features, multiple signals for document-entity associations
  - Estimating *P(r=1|e,q)* directly (instead of *P(e,q|r=1)*)
  - Optimization can get trapped in a local maximum/ minimum

Arithmetic Mean Discriminative (AMD) model

[Yang et al. 2010]

$$P_\theta(r=1|e,q) = \sum_d \underbrace{P(r_1=1|q,d)}_{\text{Query-document relevance}} \underbrace{P(r_2=1|e,d)}_{\text{Document-entity relevance}} \underbrace{P(d)}_{\text{Document prior}}$$

logistic function over a linear combination of features

$$\sigma\Big(\sum_{i=1}^{N_f} \alpha_i f_i(q,d_t)\Big) \quad \sigma\Big(\sum_{j=1}^{N_g} \beta_j g_j(e,d_t)\Big)$$

standard logistic function; weight parameters (learned); features

Learning to rank && entity retrieval

- Pointwise
  - AMD, GMD **[Yang et al. 2010]**
  - Multilayer perceptrons, logistic regression **[Sorg & Cimiano 2011]**
  - Additive Groves **[Moreira et al. 2011]**
- Pairwise
  - Ranking SVM **[Yang et al. 2009]**
  - RankBoost, RankNet **[Moreira et al. 2011]**
- Listwise
  - AdaRank, Coordinate Ascent **[Moreira et al. 2011]**

Voting models

[Macdonald & Ounis 2006]

- Inspired by techniques from data fusion
  - Combining evidence from different sources
- Documents ranked w.r.t. the query are seen as "votes" for the entity

Voting models

Many different variants, including...

- Votes
  - Number of documents mentioning the entity

    $Score(e,q) = |M(e) \cap R(q)|$
- Reciprocal Rank
  - Sum of inverse ranks of documents

    $$Score(e,q) = \sum_{\{M(e)\cap R(q)\}} \frac{1}{rank(d,q)}$$
- CombSUM
  - Sum of scores of documents

    $$Score(e,q) = |\{M(e) \cap R(q)\}| \sum_{\{M(e)\cap R(q)\}} s(d,q)$$

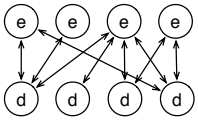
Graph-based models

[Serdyukov et al. 2008]

- One particular way of constructing graphs
  - Vertices are documents and entities
  - Only document-entity edges
- Search can be approached as a random walk on this graph
  - Pick a random document or entity
  - Follow links to entities or other documents
  - Repeat it a number of times

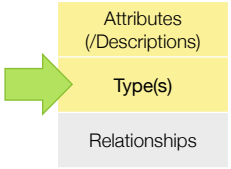
Infinite random walk

[Serdyukov et al. 2008]



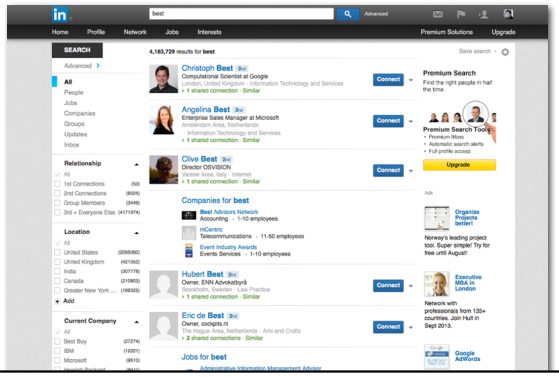
$$\begin{aligned} P_i(d) &= \lambda P_J(d) + (1-\lambda) \sum_{e\to d} P(d|e) P_{i-1}(e), \\ P_i(e) &= \sum_{d\to e} P(e|d) P_{i-1}(d), \\ P_J(d) &= P(d|q), \end{aligned}$$

Incorporating entity types



For a handful of types

grouping results by entity type is a viable solution



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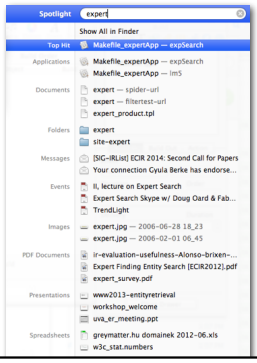
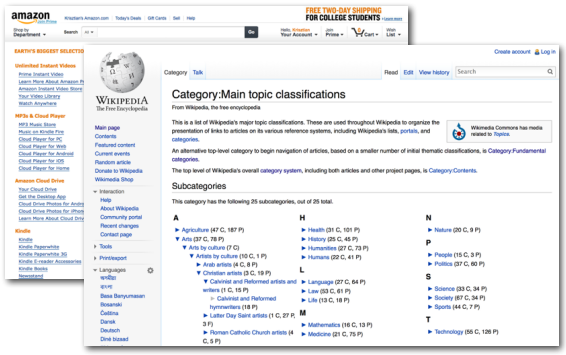


But what about very many types?

which are typically hierarchically organized



Challenges

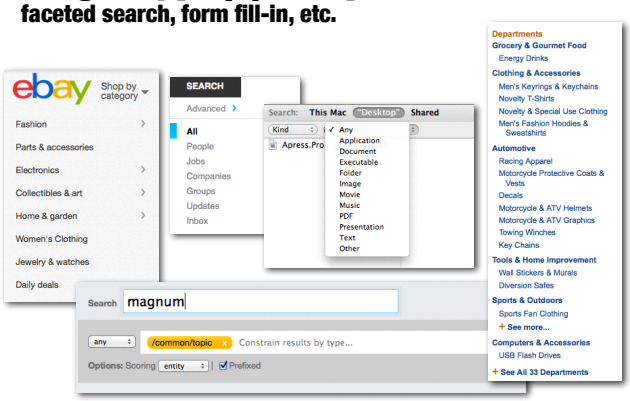
- Users are not familiar with the type system
  - (Often) user input is to be treated as a hint, not as a strict filter
- Type system is imperfect
  - Inconsistencies
  - Missing assignments
  - Granularity issues
    - Entities labeled with too general or too specific types
- In general, categorizing things can be hard
  - E.g. is King Arthur “British royalty”, “fictional character”, or “military person”?

Two settings

- Target type(s) are provided by the user
  - keyword++ query
- Target types need to be automatically identified
  - keyword query

Target type(s) are provided

faceted search, form fill-in, etc.



INEX Entity Ranking track

- Entities are represented by Wikipedia articles
- Topic definition includes target categories

Movies with eight or more Academy Awards
best picture oscar | british films | american films

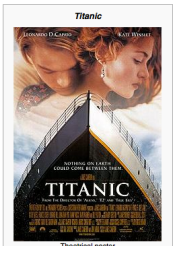
Titanic (1997 film)

From Wikipedia, the free encyclopedia

Titanic is a 1997 American epic romance and disaster film directed, written, co-produced, and co-edited by James Cameron. A fictionalized account of the sinking of the RMS *Titanic*, it stars Leonardo DiCaprio as Jack Dawson and Kate Winslet as Rose DeWitt Bukater, members of different social classes who fall in love aboard the ship during its ill-fated maiden voyage. Although the central roles and love story are fictitious, some characters are based on genuine historical figures. Gloria Stuart portrays the elderly Rose, who narrates the film in a modern-day framing device, and Billy Zane plays Cal Hockley, the overbearing fiancé of the younger Rose. Cameron saw the love story as a way to engage the audience with the real-life tragedy.

Production on the film began in 1995, when Cameron shot footage of the actual *Titanic* wreck. The modern scenes were shot on board the *Akademik Mstislav Keldysh*, which Cameron had used as a base when filming the actual wreck. A reconstruction of the *Titanic* was built at Playas de Rosarito, Baja California, and scale models and computer-generated imagery were also used to recreate the sinking. The film was partially funded by Paramount Pictures and 20th Century Fox – respectively, its American and international distributor – and at the time, it was the most expensive film ever made, with an estimated budget of US$200 million.[3][4][5][6]

The film was originally scheduled to open on July 2, 1997, however, post-production delays pushed back its release to December 19 instead.[7] *Titanic* was an enormous critical and commercial success. It was nominated for fourteen Academy Awards, eventually winning eleven, including Best Picture and Best Director.[8] It became the highest-grossing film of all time, with a worldwide gross of over $1.8 billion, and remained so for twelve years until Cameron's next directorial effort, *Avatar*, surpassed it in 2010.[9][10] *Titanic* also has been ranked as the sixth best epic film of all time in AFI's 10 Top 10 by the American Film Institute.[11] The film is due for theatrical re-release in 2012 after Cameron completes its conversion into 3-D.[12]



Categories: 1997 films | American films | English-language films | American disaster films | Best Drama Picture Golden Globe winners | Best Picture Academy Award winners | Best Song Academy Award winners | Films directed by James Cameron | Films set in 1912 | Films that won the Best Sound Mixing Academy Award | Films that won the Best Visual Effects Academy Award | Films whose art director won the Best Art Direction Academy Award | Films whose cinematographer won the Best Cinematography Academy Award | Films whose director won the Best Director Academy Award | Films whose director won the Best Director Golden Globe | Films whose editor won the Best Film Editing Academy Award | Epic films | RMS Titanic | Romantic epic films | Romantic period films | Seafaring films based on actual events | Films shot in Nova Scotia | Films shot in Vancouver | Paramount films | 20th Century Fox films | Lightstorm Entertainment films | 2-D films converted to 3-D

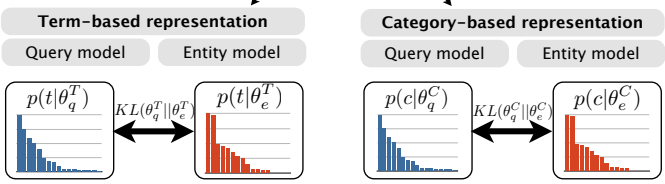
Using target type information

- Constraining results
  - Soft/hard filtering
  - Different ways to measure type similarity
    - Set-based
    - Content-based
    - Lexical similarity of type labels
    - Distance based on the hierarchy
- Query expansion
  - Adding terms from type names to the query
- Entity expansion
  - Types added as a separate metadata field

Modeling terms and categories

[Balog et al. 2011]

$$P(e|q) \propto P(q|e)P(e)$$
$$P(q|e) = (1-\lambda)\underbrace{P(\theta_q^T|\theta_e^T)}_{\text{Term-based representation}} + \lambda\underbrace{P(\theta_q^C|\theta_e^C)}_{\text{Category-based representation}}$$



Advantages

- Transparent combination of term-based and category-based information
- Sound modeling of uncertainty associated with category information
- Category-based feedback is possible (analogously to the term-based case)

Expanding target types

- Pseudo relevance feedback
- Based on hierarchical structure
- Using lexical similarity of type labels

Two settings

- ~~Target type(s) are provided by the user~~
  - ~~keyword + query~~
- Target types need to be automatically identified
  - keyword query

Identifying target types for queries

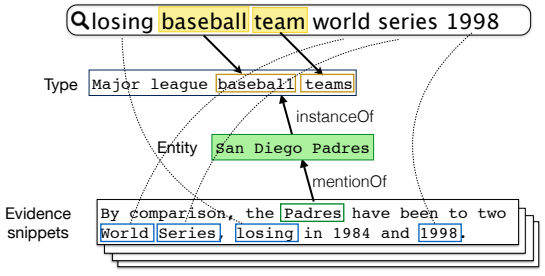
- Types of top ranked entities [Vallet & Zaragoza 2008]
- Types can be ranked much like entities [Balog & Neumayer 2012]
  - Direct term-based vs. indirect entity-based representations ("Model 1 vs. Model 2")
  - Hierarchical case is difficult

Joint type detection and entity ranking [Sawant & Chakrabarti 2013]

- Assumes "telegraphic" queries with target type
  - woodrow wilson president university
  - dolly clone institute
  - lead singer led zeppelin band
- Type detection is integrated into the ranking
  - Multiple query interpretations are considered
- Both generative and discriminative formulations

Approach

- Each query term is either a "type hint" ($h(\vec{q}, \vec{z})$) or a "word matcher" ($s(\vec{q}, \vec{z})$)
  - Number of possible partitions is manageable ($2^{|q|}$)



Generative approach

Generate query from entity

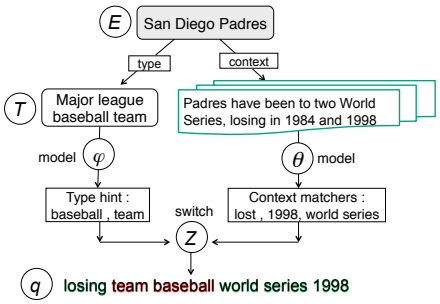


Figure taken from Sawant & Chakrabarti (2013). Learning Joint Query Interpretation and Response Ranking. In WWW '13. (see presentation)

Generative formulation

$$P(e|q) \propto \underbrace{P(e)}_{\text{Entity prior}} \sum_{t,\vec{z}} \underbrace{P(t|e)}_{\text{Type prior}} \underbrace{P(\vec{z})}_{\text{Query switch}} \underbrace{P(h(\vec{q},\vec{z})|t)}_{\text{Type model}} \underbrace{P(s(\vec{q},\vec{z})|e)}_{\text{Entity model}}$$

Type prior
Estimated from answer types in the past

Query switch
Probability of the interpretation

Entity prior

Type model
Probability of observing t in the type model

Entity model
Probability of observing t in the entity model

Discriminative approach

Separate correct and incorrect entities

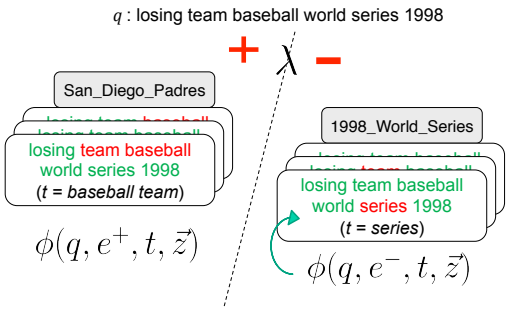
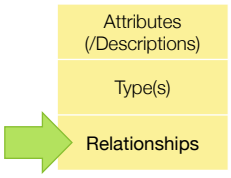


Figure taken from Sawant & Chakrabarti (2013). Learning Joint Query Interpretation and Response Ranking. In WWW '13. (see presentation)

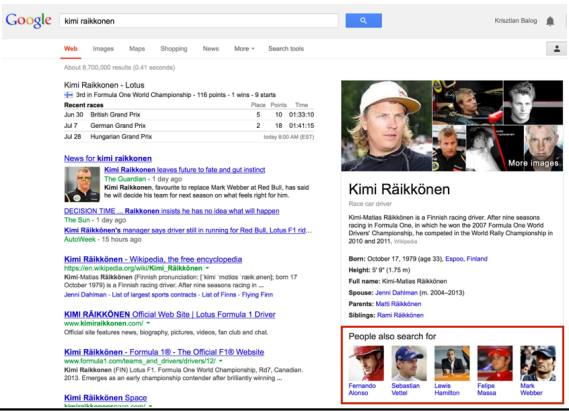
Discriminative formulation

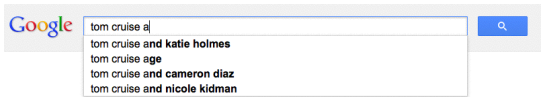
$$\phi(q, e, t, \vec{z}) = \langle \underbrace{\phi_1(q,e)}_{\text{Models the type prior P(t|e)}}, \underbrace{\phi_2(t,e)}_{\text{Models the entity prior P(e)}}, \underbrace{\phi_3(q,\vec{z},t)}_{\text{Comparability between hint words and type}}, \underbrace{\phi_4(q,\vec{z},e)}_{\text{Comparability between matchers and snippets that mention e}} \rangle$$

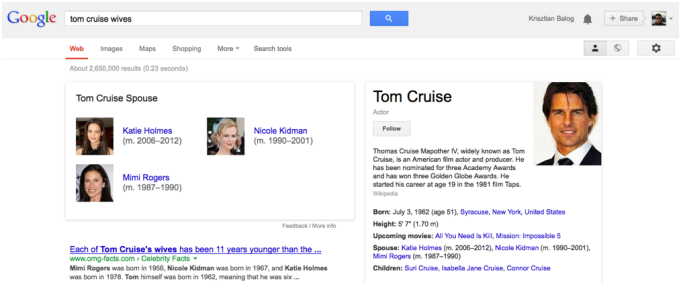
Entity relationships

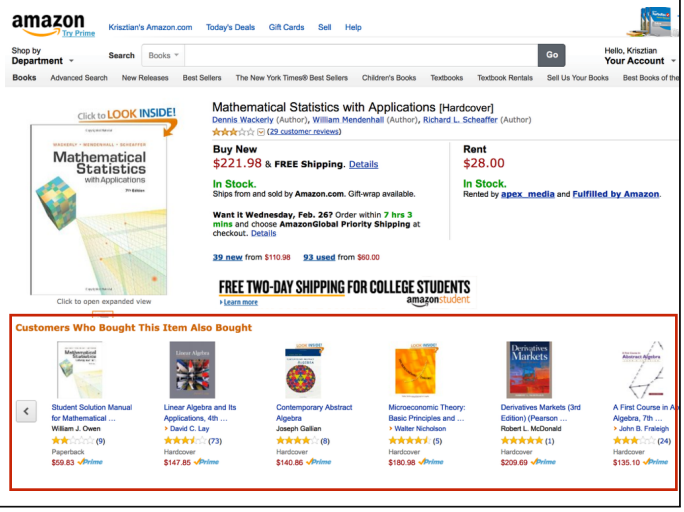


Related entities









TREC Entity track

- Related Entity Finding task
- Given
  - Input entity (defined by name and homepage)
  - Type of the target entity (PER/ORG/LOC)
  - Narrative (describing the nature of the relation in free text)
- Return (homepages of) related entities

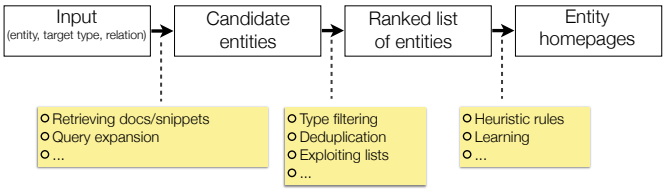
Example information needs

airlines that currently use Boeing 747 planes
ORG Boeing 747

Members of The Beaux Arts Trio
PER The Beaux Arts Trio

What countries does Eurail operate in?
LOC Eurail

A typical pipeline



Modeling related entity finding

[Bron et al. 2010]

- Three-component model

$$p(e|E,T,R) \propto \underbrace{p(e|E)}_{\text{Co-occurrence model}} \cdot \underbrace{p(T|e)}_{\text{Type filtering}} \cdot \underbrace{p(R|E,e)}_{\text{Context model}}$$

Wrapping up

- Increasingly more discriminative approaches over generative ones
  - Increasing amount of components (and parameters)
  - Easier to incrementally add informative but correlated features
  - But, (massive amounts of) training data is required!

Future challenges

- It's "easy" when the "query intent" is known
  - Desired results: single entity, ranked list, set, …
  - Query type: ad-hoc, list search, related entity finding, …
- Methods specifically tailored to specific types of requests
- Understanding query intent still has a long way to go