Part II

Entity Retrieval

Entity retrieval

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

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")

In this part

- Look at a number of entity ranking tasks
  - Motivating real-world use-cases
  - Abstractions at evaluation benchmarking campaigns (TREC, INEX)
  - Methods and approaches
- In all cases
  - Input: (semi-structured) query
  - Output: ranked list of entities
  - Evaluation: standard IR metrics

Outline

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

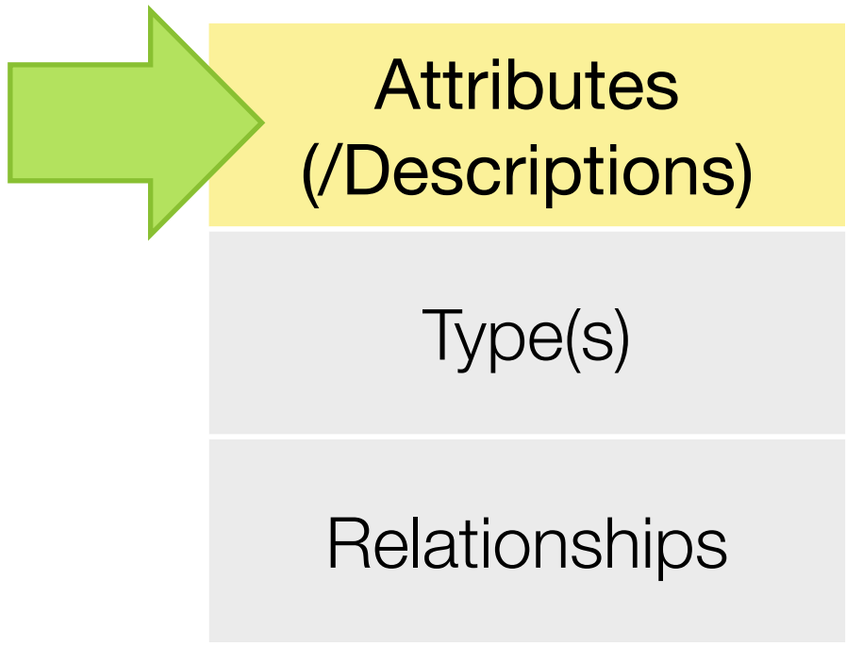
Attributes (/Descriptions)
Type(s)
Relationships

Setting boundaries

We are IR people ...

- ... but that doesn’t mean that we are the only ones who thought about this
- Entity retrieval is an active research area in neighbouring communities
  - Databases
  - Semantic web
  - Natural language processing

Ranking based on entity descriptions



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

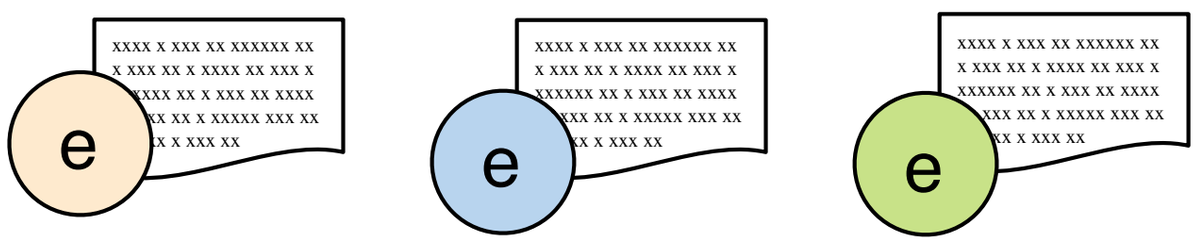
meg ryan war

Worst actor century

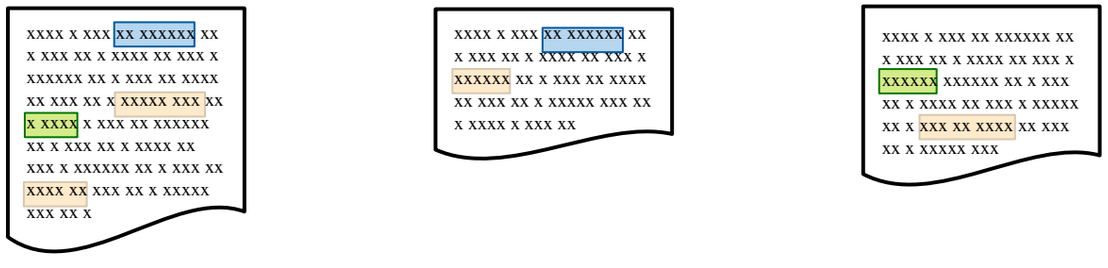
Sweden Iceland currency

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

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

Smoothing parameter

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

Empirical document model

Maximum likelihood estimates

Collection model

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

Here, documents==entities, so

$$P(e|q) \propto P(e)P(q|\theta_e) = \underbrace{P(e)}_{\text{Entity prior}} \prod_{t \in q} \underbrace{P(t|\theta_e)}_{\text{Entity language model}}^{n(t,q)}$$

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

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Dansk
Deutsch

Audi A4

From Wikipedia, the free encyclopedia

The **Audi A4** is a line of compact executive cars produced since late 1994 by the German car manufacturer Audi, a subsidiary of the Volkswagen Group.

The A4 has been built in four generations and is based on Volkswagen's B platform. The first generation A4 succeeded the Audi 80. The automaker's internal numbering treats the A4 as a continuation of the Audi 80 lineage, with the initial A4 designated as the B5-series, followed by the B6, B7, and the current B8. The B8 A4 is built on the Volkswagen Group MLB platform shared with many other Audi models and potentially one Porsche model within Volkswagen Group.[2]

Audi A4

Manufacturer Audi

dbpedia:Audi_A4

foaf:name	Audi A4
rdfs:label	Audi A4
rdfs:comment	The Audi A4 is a compact executive car produced since late 1994 by the German car manufacturer Audi, a subsidiary of the Volkswagen Group. The A4 has been built [...]
dbpprop:production	1994 2001 2005 2008
rdf:type	**dbpedia-owl:MeanOfTransportation** **dbpedia-owl:Automobile**
dbpedia-owl:manufacturer	**dbpedia:Audi**
dbpedia-owl:class	**dbpedia:Compact_executive_car**
owl:sameAs	**freebase:Audi A4**
is **dbpedia-owl:predecessor** of	**dbpedia:Audi_A5**
is **dbpprop:similar** of	**dbpedia:Cadillac_BLS**

Mixture of Language Models

[Ogilvie & Callan, 2003]

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

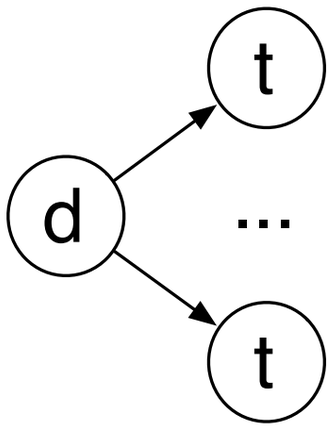
$$P(t|\theta_d) = \sum_{j=1}^{m} \underbrace{\mu_j}_{\text{Field weights}} P(t|\underbrace{\theta_{d_j}}_{\text{Field language model}})$$

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

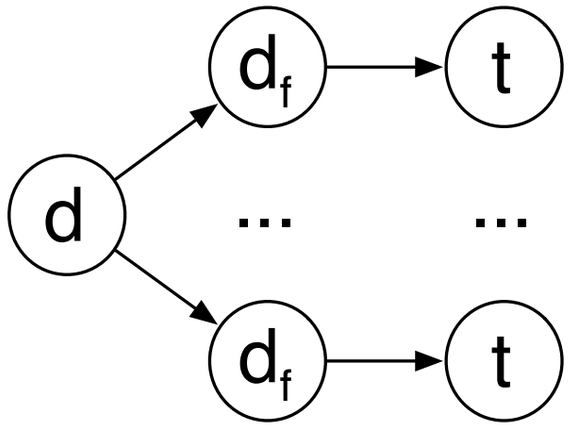
Field weights

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

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]

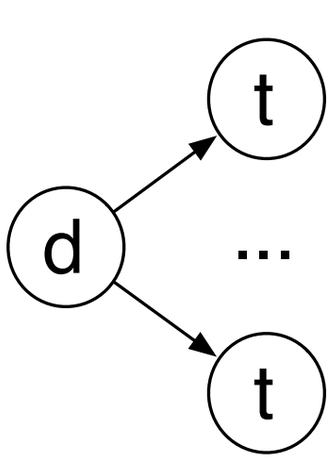
- Organize fields into a 2-level hierarchy
  - Field types (4) on the top level
  - Individual fields of that type on the bottom level
- Estimate field weights
  - Using training data for field types
  - Using heuristics for bottom-level types

Two-level hierarchy

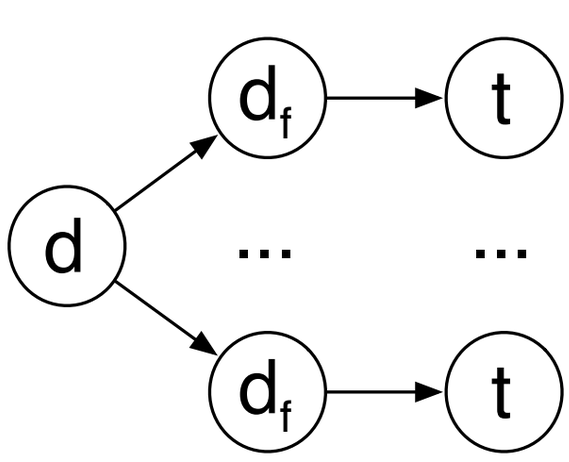
[Neumayer et al. 2012]

Name	**foaf:name**	Audi A4
	rdfs:label	Audi A4
Attributes	**rdfs:comment**	The Audi A4 is a compact executive car produced since late 1994 by the German car manufacturer Audi, a subsidiary of the Volkswagen Group. The A4 has been built [...]
	dbpprop:production	1994 2001 2005 2008
Out-relations	**rdf:type**	**dbpedia-owl:MeanOfTransportation** **dbpedia-owl:Automobile**
	dbpedia-owl:manufacturer	**dbpedia:Audi**
	dbpedia-owl:class	**dbpedia:Compact_executive_car**
	owl:sameAs	**freebase:Audi A4**
In-relations	is **dbpedia-owl:predecessor** of	**dbpedia:Audi_A5**
	is **dbpprop:similar** of	**dbpedia:Cadillac_BLS**

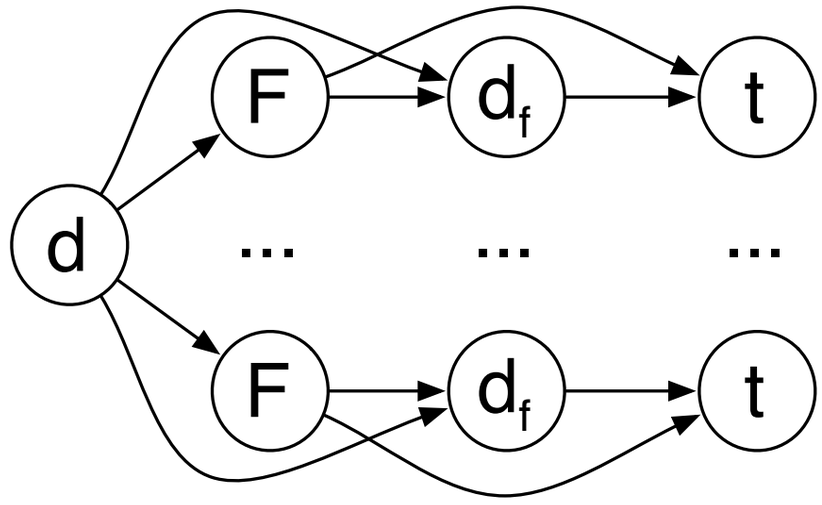
Comparison of models



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

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

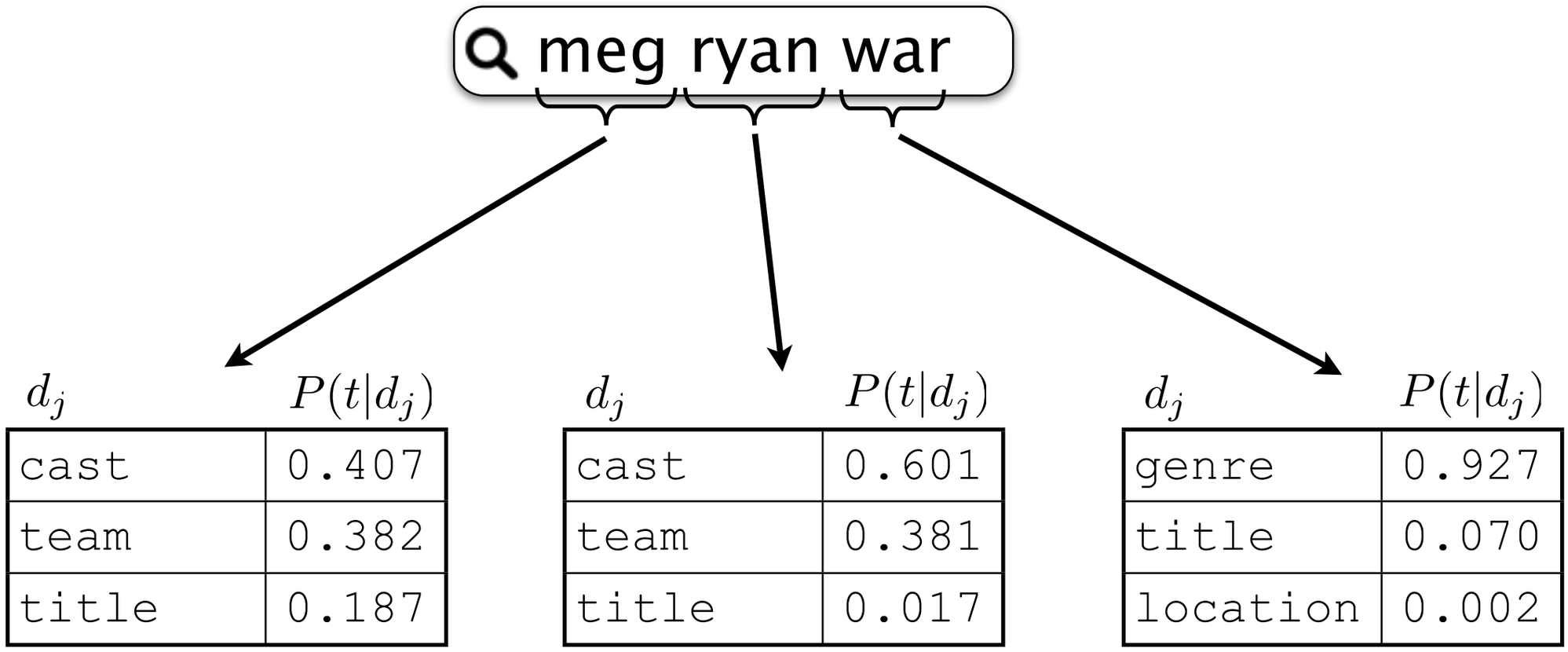
Term likelihood
Probability of a query term occurring in a given field type

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	0.070
location	0.002

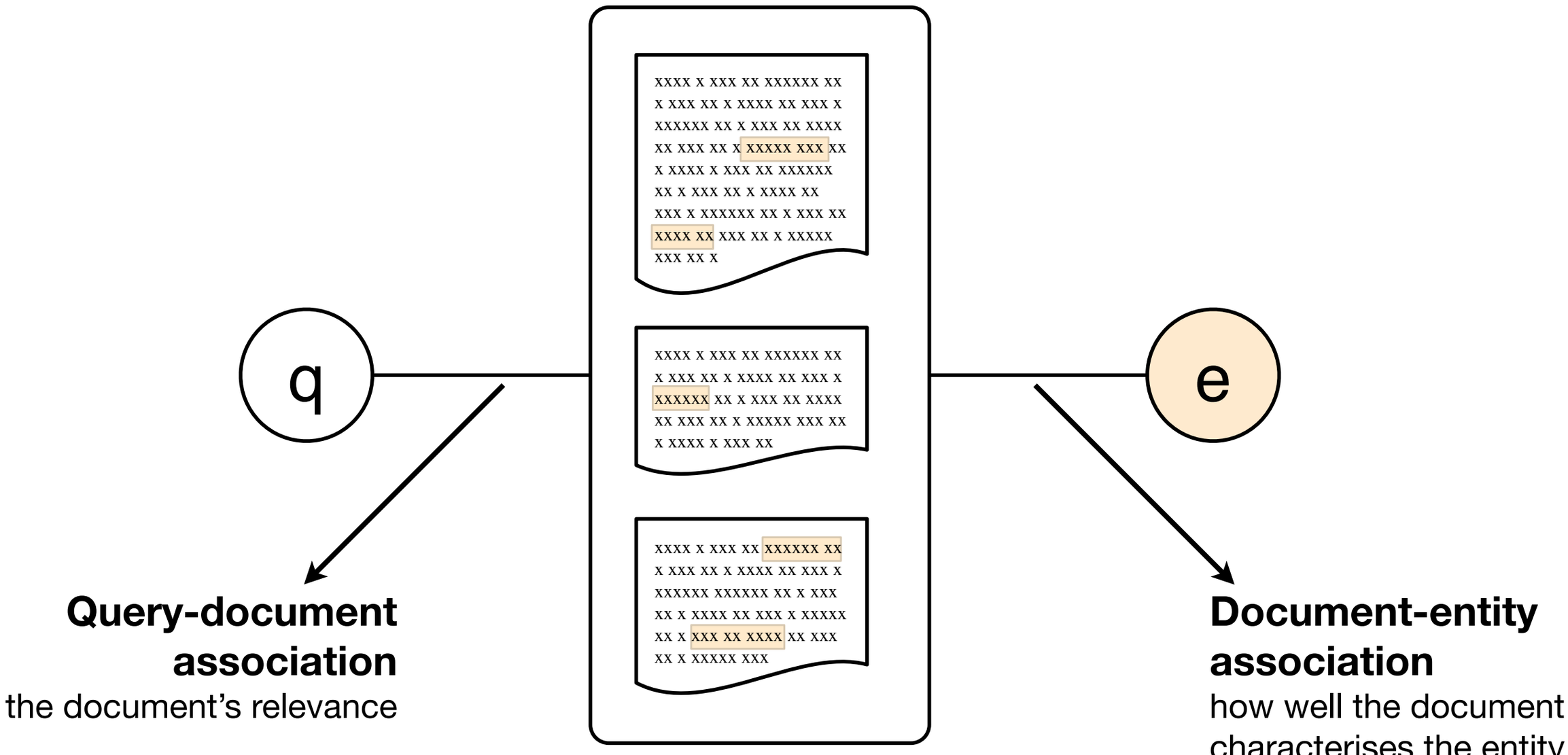
Ranking without explicit entity representations

Scenario

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

The basic idea

Use documents to go from queries to entities



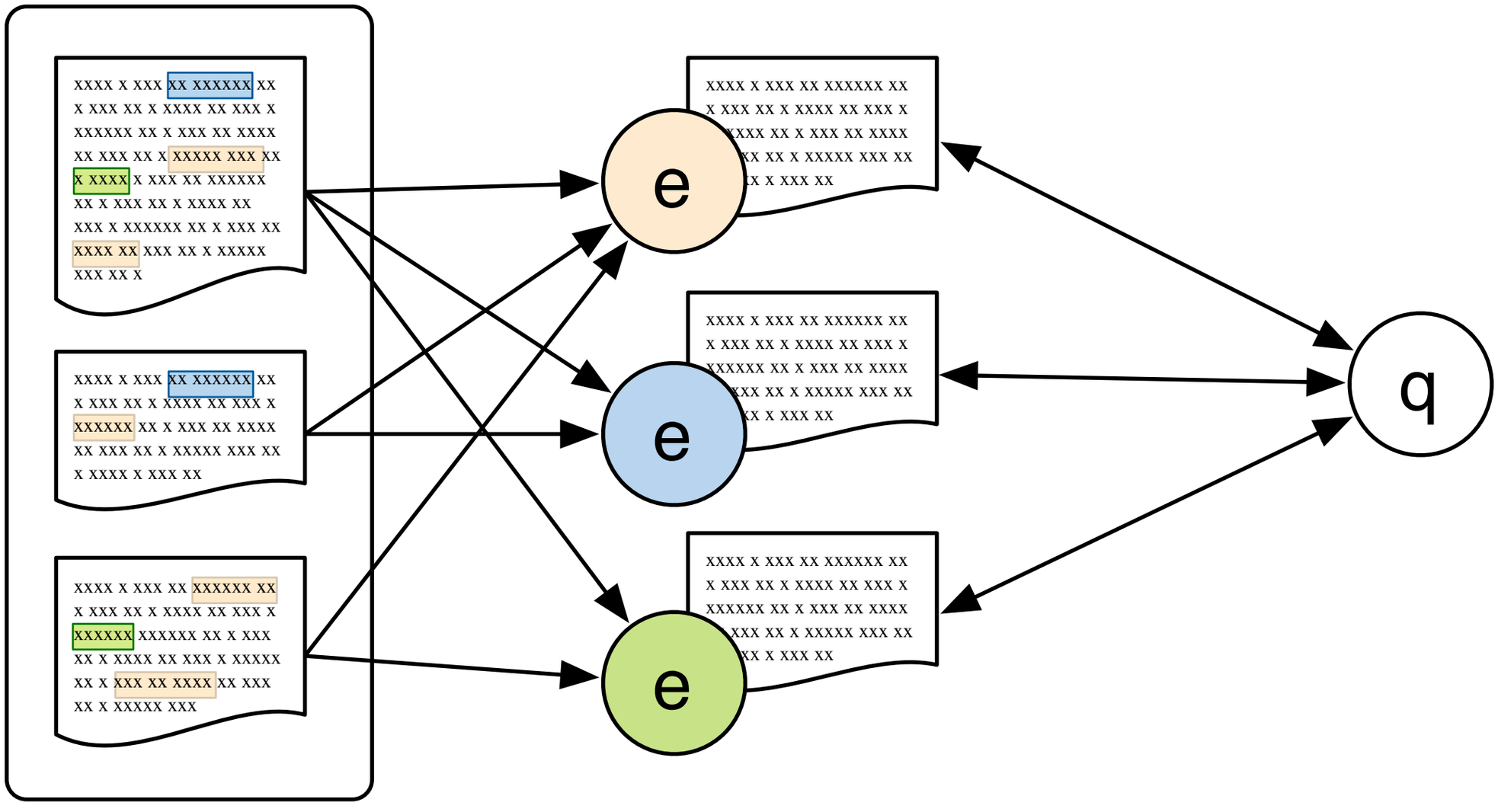
Query-document association
the document's relevance

Document-entity association
how well the document characterises the entity

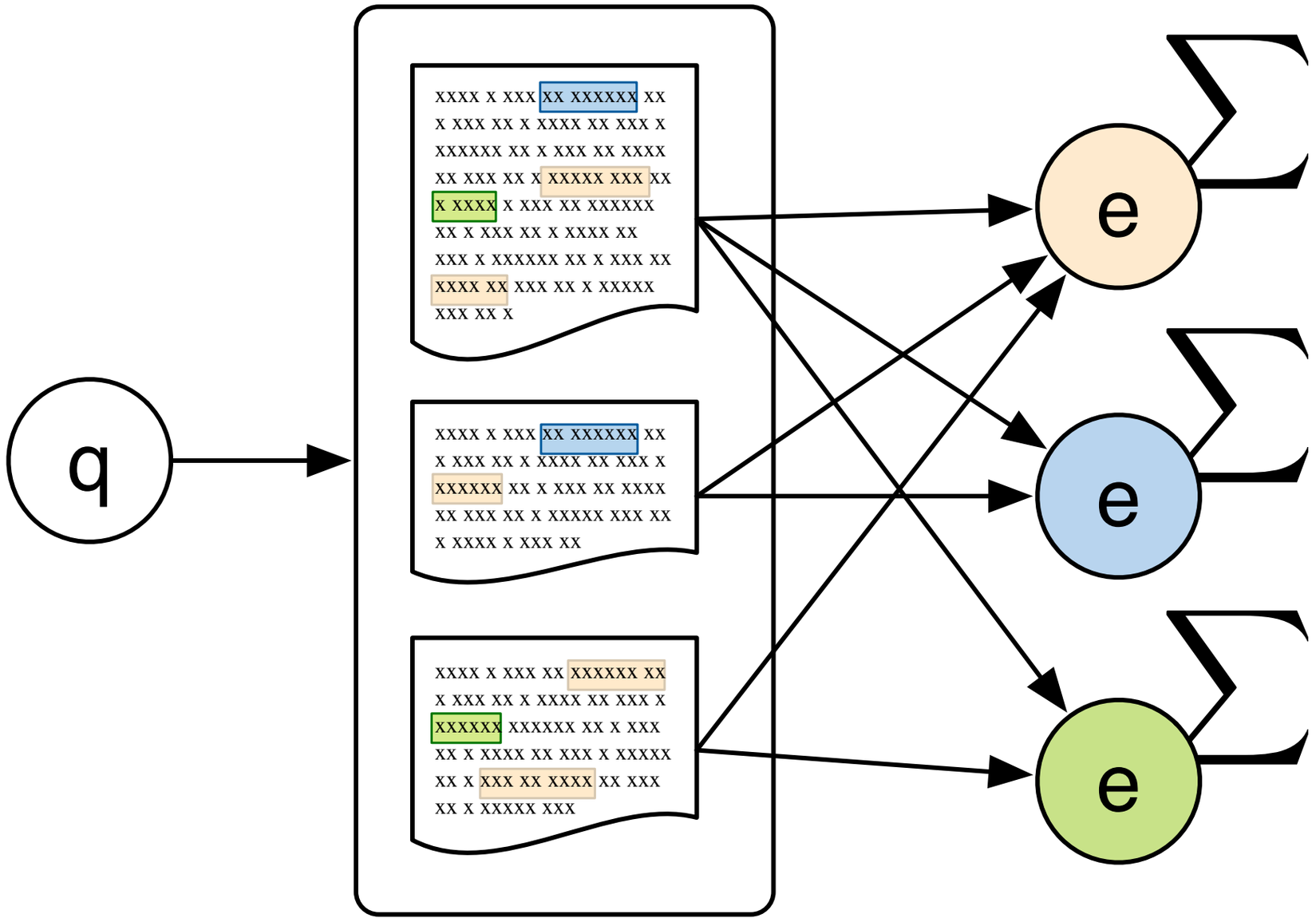
Two principal approaches

- **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]

$$P(q|e) = \sum_d \underbrace{P(q|d,e)}_{\text{Document relevance}} \underbrace{P(d|e)}_{\text{Document-entity association}}$$

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

Document-entity association

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

Simplifying assumption (t and e are conditionally independent given 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]

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

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

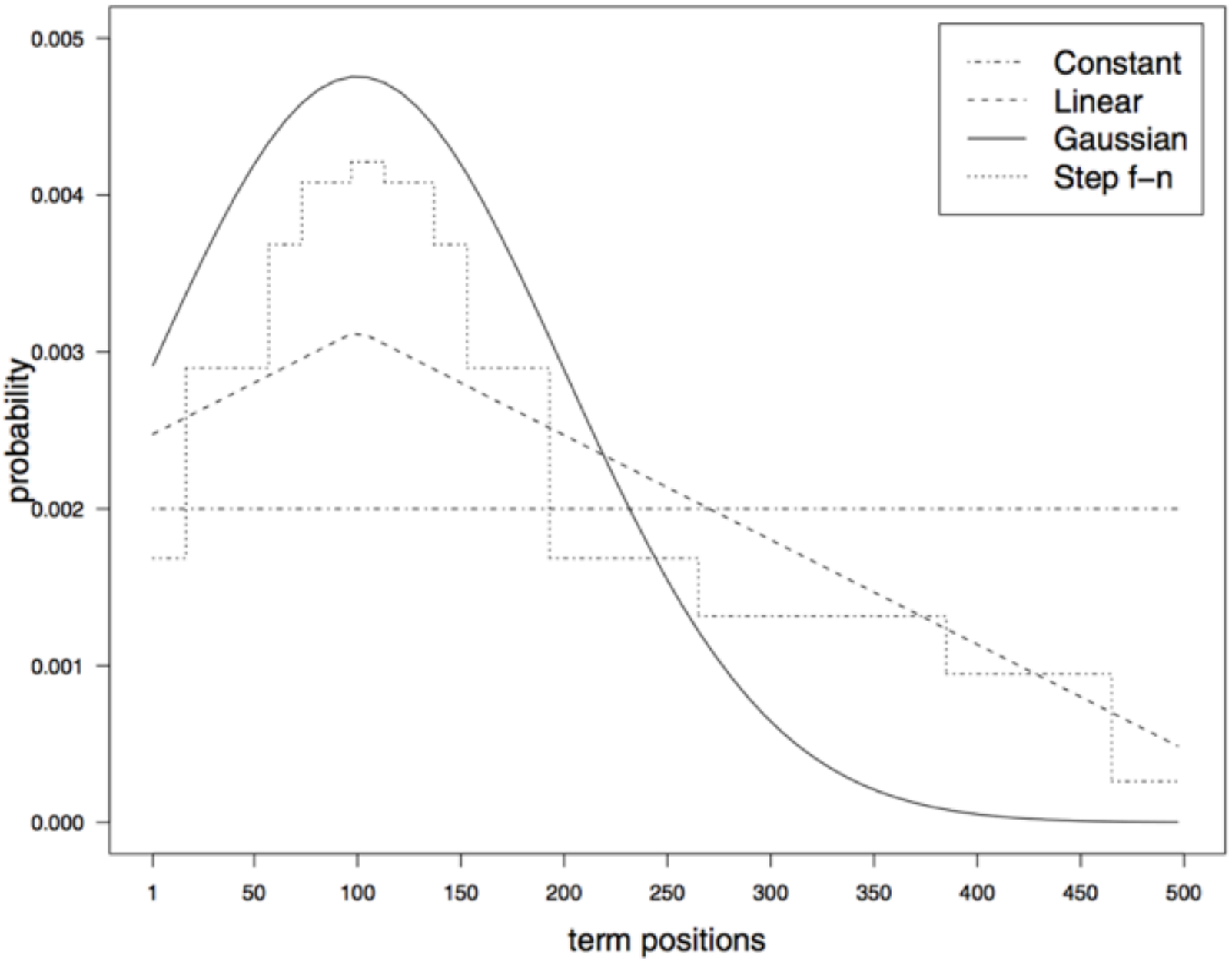


Figure taken from D. Petkova and W.B. Croft. **Proximity-based document representation for named entity retrieval**. *CIKM'07*.

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

$$\underbrace{\sigma}_{\text{standard logistic function}}\Big(\sum_{i=1}^{N_f} \underbrace{\alpha_i}_{\text{weight parameters (learned)}} \underbrace{f_i(q,d_t)}_{\text{features}}\Big) \qquad \sigma\Big(\sum_{j=1}^{N_g} \beta_j g_j(e,d_t)\Big)$$

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

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

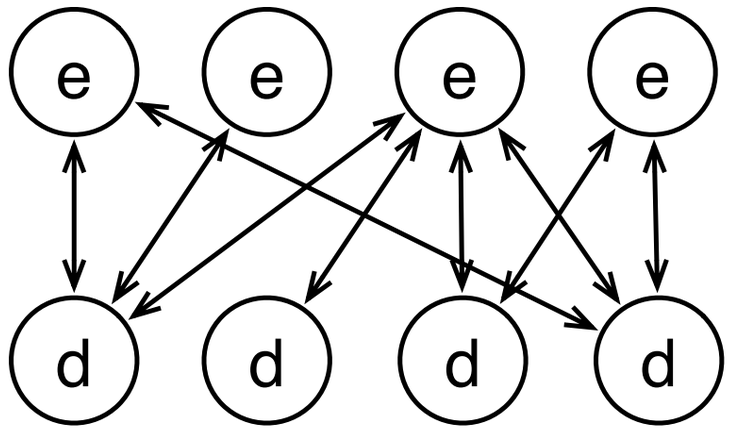
Graph-based models

[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

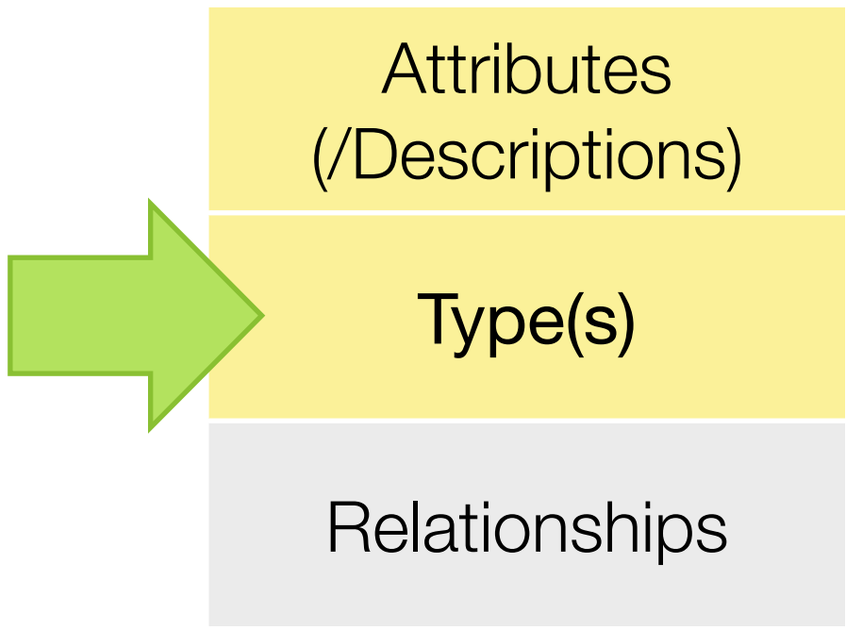
Infinite random walk

[Serdyukov et al. 2008]

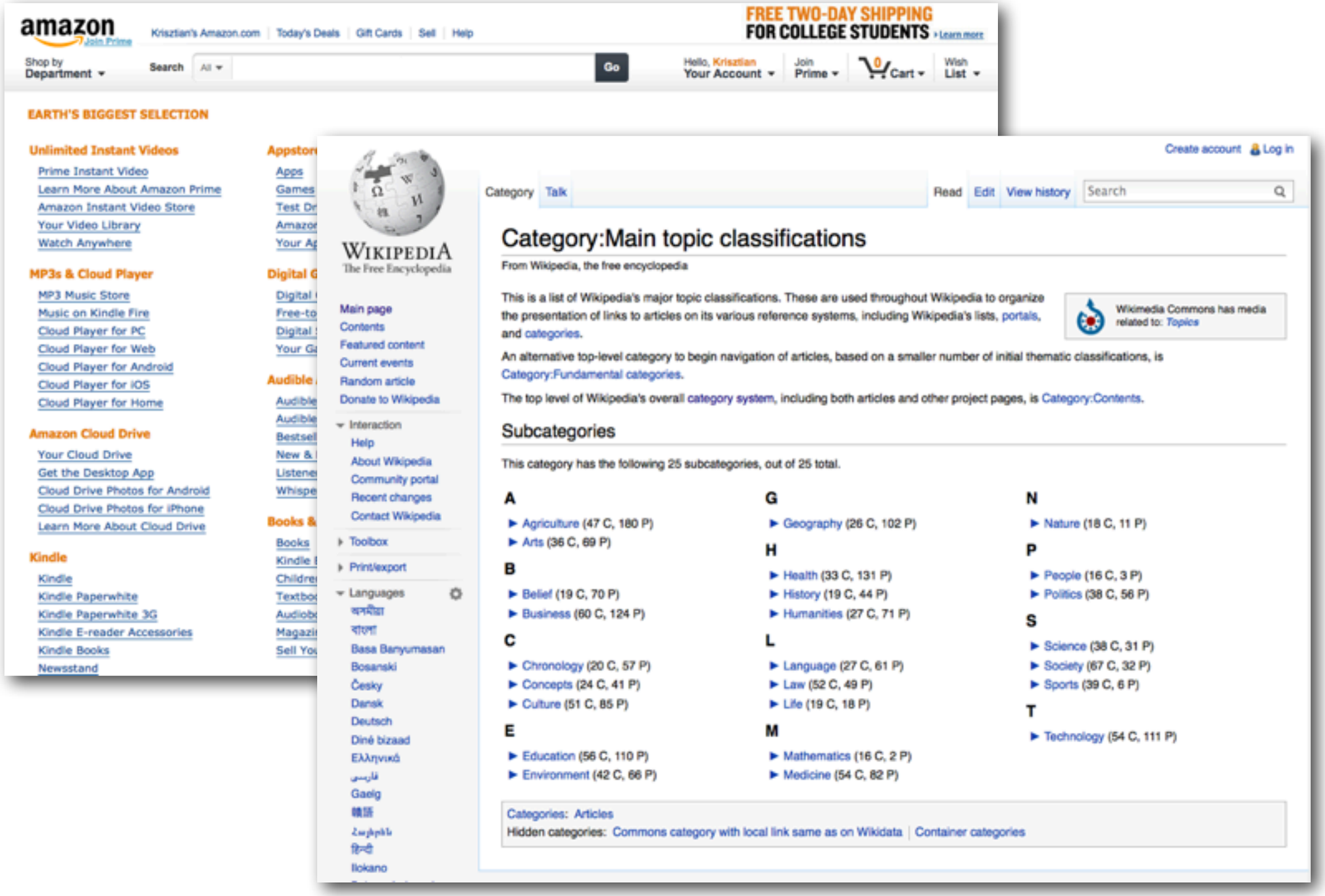


$$
\begin{aligned}
P_i(d) &= \lambda P_J(d) + (1-\lambda) \sum_{e \to d} P(d|e) P_{i-1}(e), \\
P_i(e) &= \sum_{d \to e} P(e|d) P_{i-1}(d), \\
P_J(d) &= P(d|q),
\end{aligned}
$$

Incorporating entity types



Entities are typed...



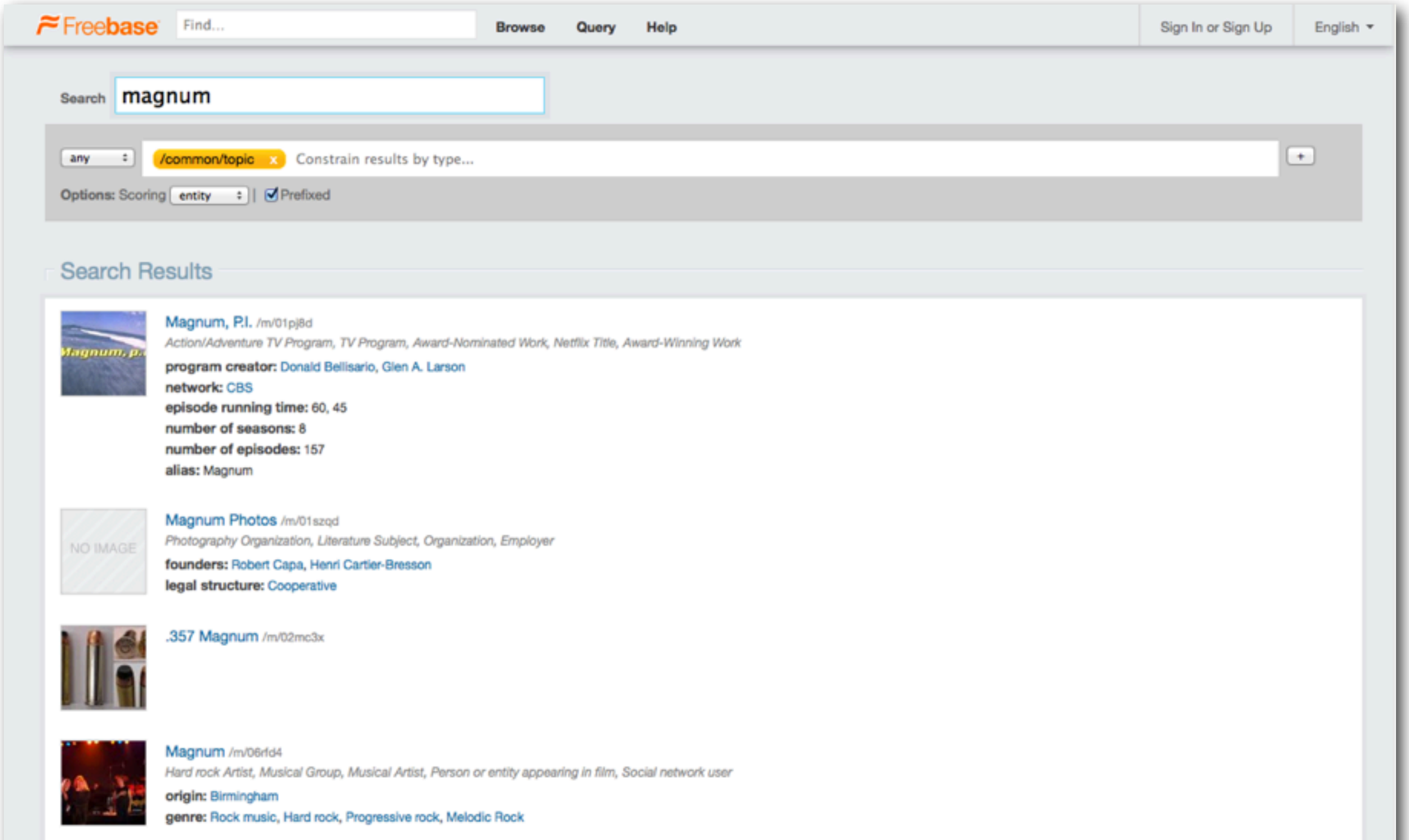
If target type is not provided

Rely on techniques from...

- Federated search
  - Obtain a separate ranking for each type of entity, then merge **[Kim & Croft 2010]**
- Aggregated search
  - Return top ranked entities from each type **[Lalmas 2011]**

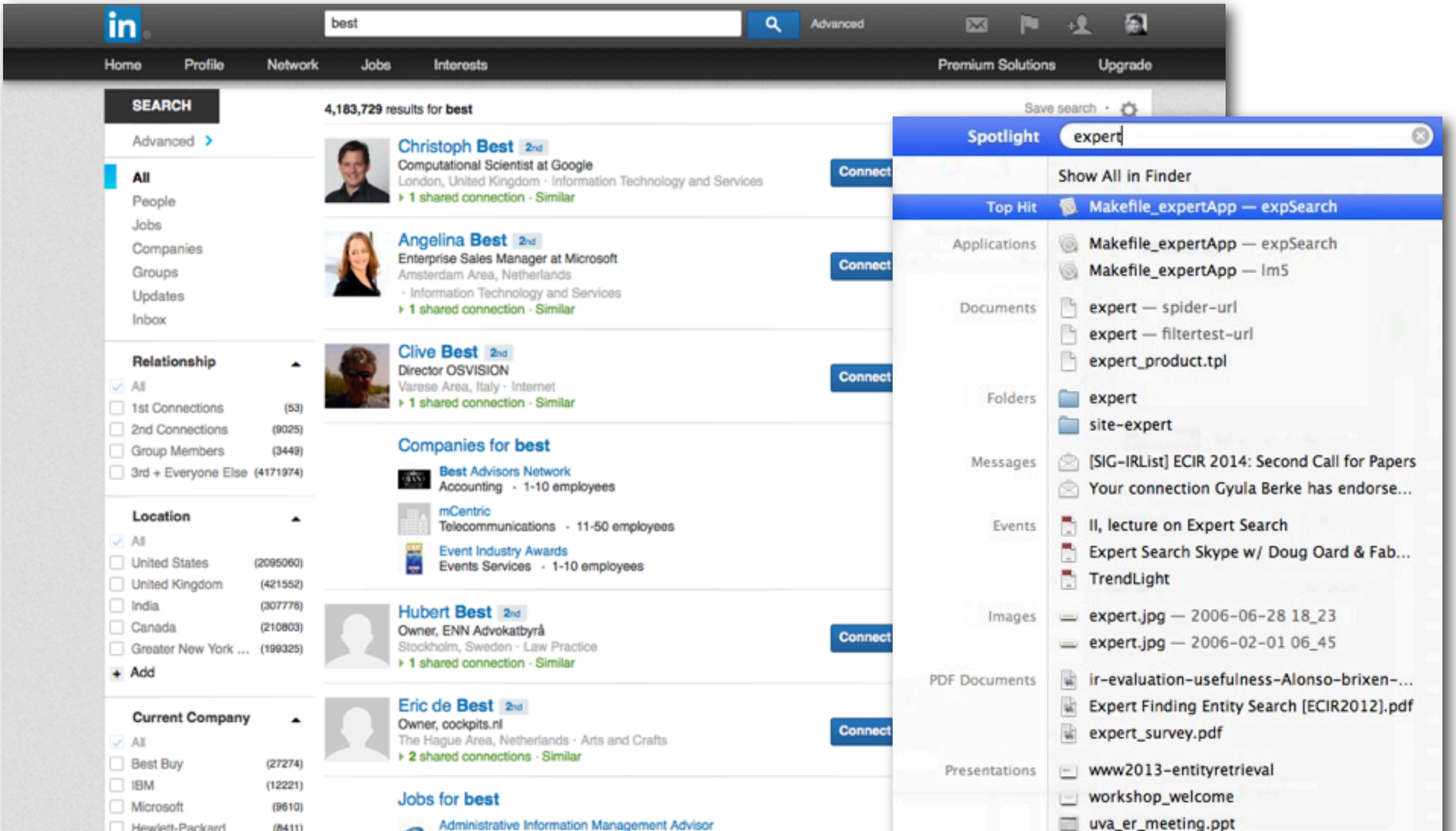
Example (1)

Mixing all types together (“federated search”)

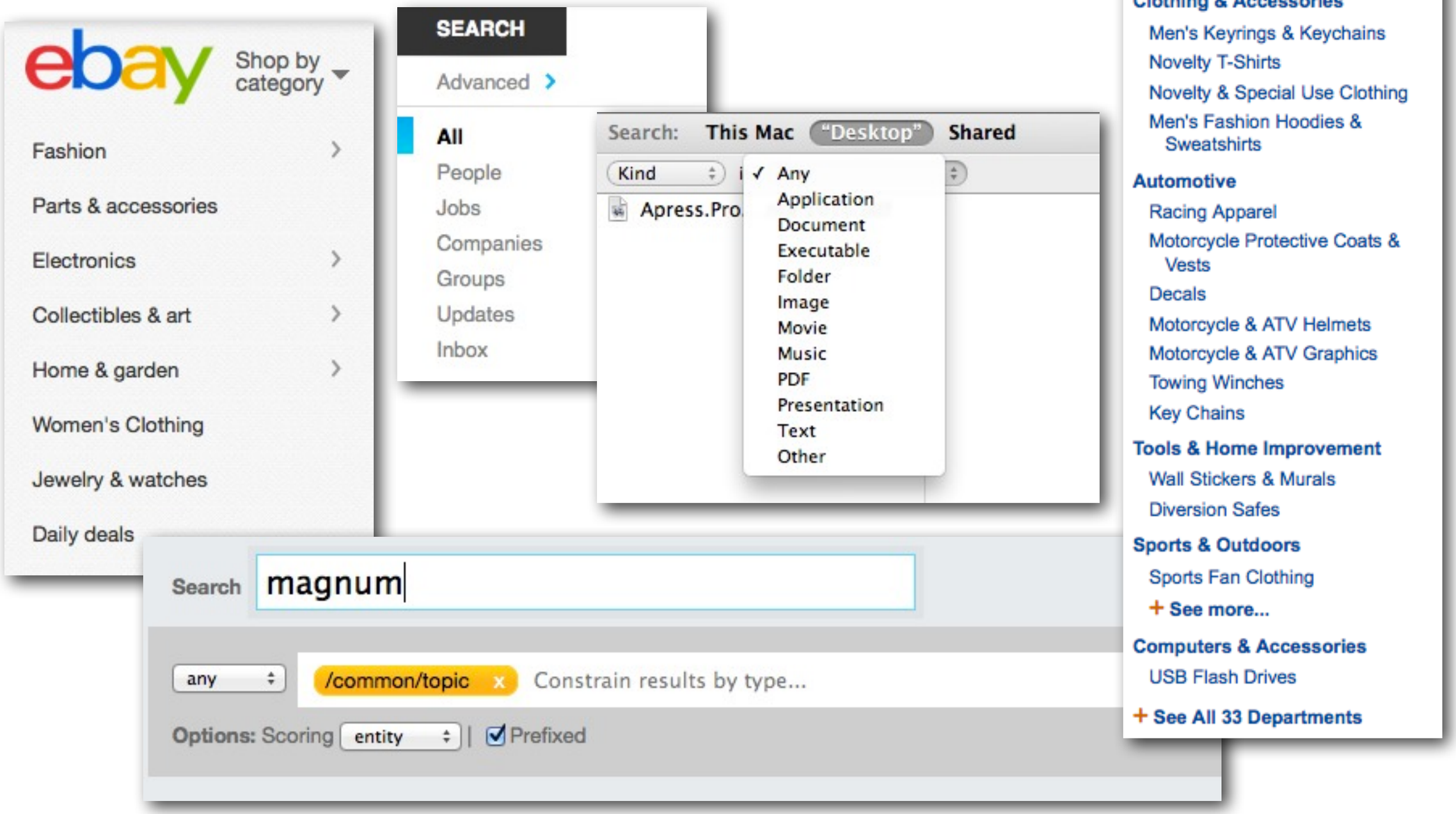


Example (2)

Grouping results by entity type (“aggregated search”)



Often, users provide target types explicitly



Type-aware entity ranking

- Assume that the user provides target type(s)
- Challenges
  - Target type information is imperfect
    - Users are not familiar with the classification system
  - Categorisation of entities is imperfect
    - Entity might belong to multiple categories
      - E.g. is King Arthur “British royalty”, “fictional character”, or “military person”?
  - Types can be hierarchically organised
    - Although it may not be a strict “is-a” hierarchy

INEX Entity Ranking track

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

Titanic (1997 film)

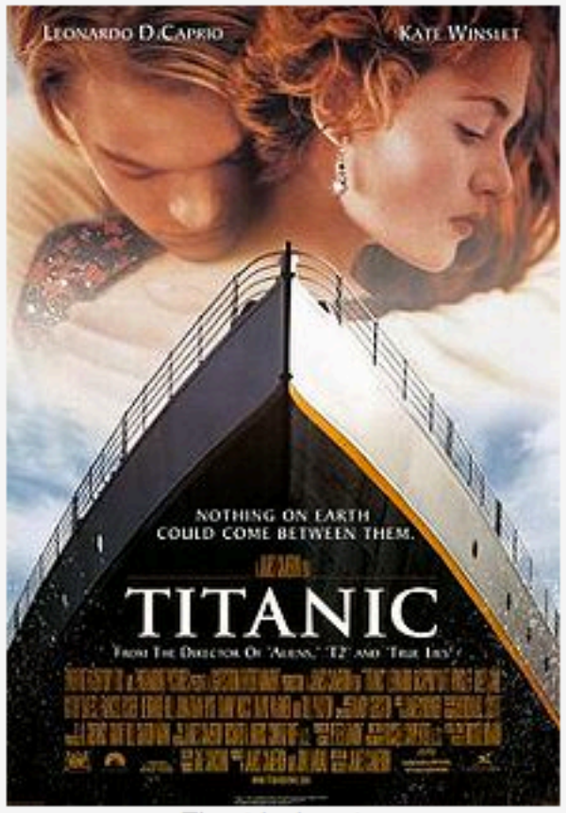
From Wikipedia, the free encyclopedia

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]

Titanic



Theatrical poster

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 (between target types and the types associated with the entity)
    - Set-based
    - Content-based
    - Lexical similarity of type labels
- Query expansion
  - Adding terms from type names to the query
- Entity expansion
  - Categories as a separate metadata field

Modeling terms and categories

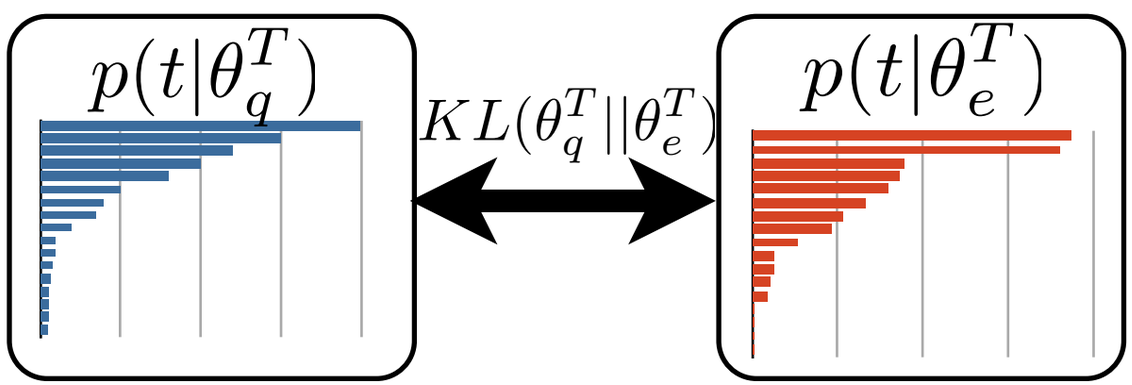
[Balog et al. 2011]

$$P(e|q) \propto P(q|e)P(e)$$

$$P(q|e) = (1-\lambda)\underbrace{P(\theta_q^T|\theta_e^T)} + \lambda\underbrace{P(\theta_q^C|\theta_e^C)}$$

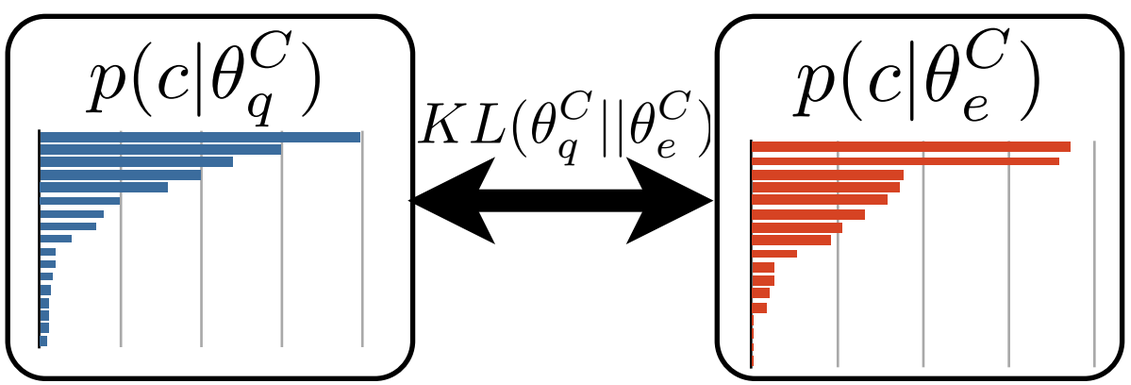
Term-based representation

Query model | Entity model



Category-based representation

Query model | Entity model



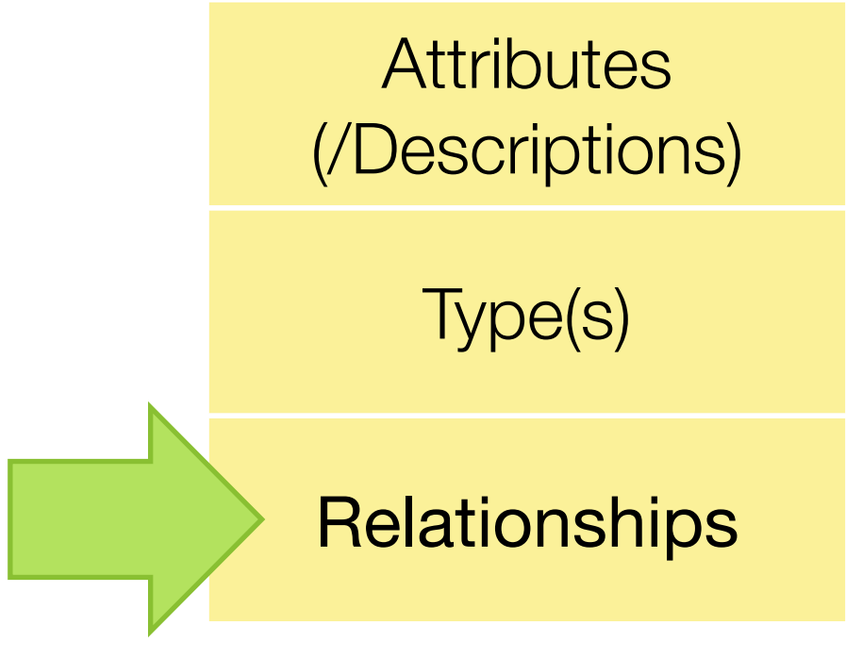
Identifying target types for queries

- Types of top ranked entities **[Vallet & Zaragoza 2008]**
- Direct term-based vs. indirect entity-based representations **[Balog & Neumayer 2012]**
- Hierarchical case is difficult... **[Sawant & Chakrabarti 2013]**

Expanding target types

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

Entity relationships



Google

tom cruise a

tom cruise **and katie holmes**
tom cruise **age**
tom cruise **and cameron diaz**
tom cruise **and nicole kidman**

Google tom cruise wives

Krisztian Balog + Share

Web Images Maps Shopping More Search tools

About 2,650,000 results (0.23 seconds)

Tom Cruise Spouse

Katie Holmes
(m. 2006–2012)

Nicole Kidman
(m. 1990–2001)

Mimi Rogers
(m. 1987–1990)

Feedback / More info

Each of **Tom Cruise's wives** has been 11 years younger than the ...
www.omg-facts.com › Celebrity Facts
Mimi Rogers was born in 1956, **Nicole Kidman** was born in 1967, and **Katie Holmes** was born in 1978. **Tom** himself was born in 1962, meaning that he was six ...

Tom Cruise

Actor

Follow

Thomas Cruise Mapother IV, widely known as Tom Cruise, is an American film actor and producer. He has been nominated for three Academy Awards and has won three Golden Globe Awards. He started his career at age 19 in the 1981 film Taps.
Wikipedia

Born: July 3, 1962 (age 51), Syracuse, New York, United States

Height: 5' 7" (1.70 m)

Upcoming movies: All You Need Is Kill, Mission: Impossible 5

Spouse: Katie Holmes (m. 2006–2012), Nicole Kidman (m. 1990–2001), Mimi Rogers (m. 1987–1990)

Children: Suri Cruise, Isabella Jane Cruise, Connor Cruise

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

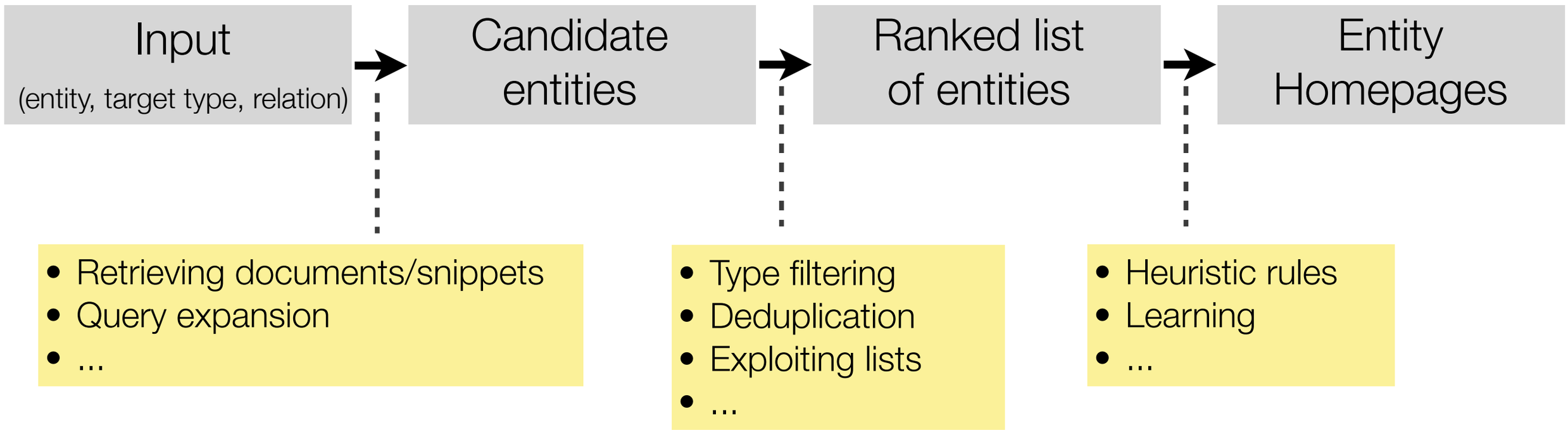
Members of The Beaux Arts Trio

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

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

Anything else?

The usual suspects from document retrieval...

- Priors
  - HITS, PageRank
  - Document link indegree **[Kamps & Koolen 2008]**
- Pseudo relevance feedback
  - Document-centric vs. entity-centric **[Macdonald & Ounis 2007; Serdyukov et al. 2007]**
    - sampling expansion terms from top ranked documents and/or (profiles of) top ranked candidates
  - Field-based **[Kim & Croft 2011]**

Tools & services

Public Toolkits and Web Services for Entity Retrieval

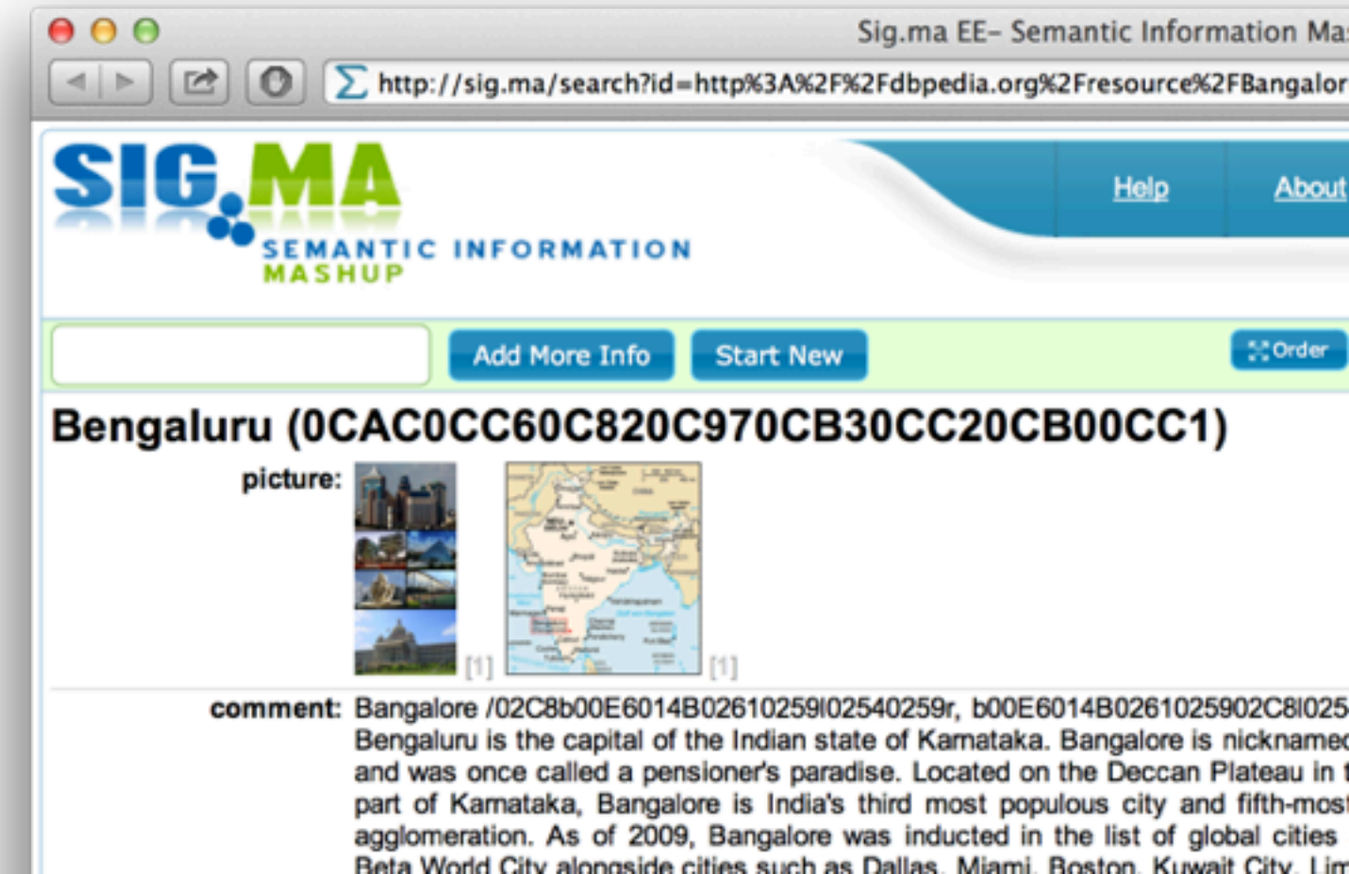
- EARS
- Sig.ma
- Sindice & SIREn

EARS

- Entity and Association Retrieval System
  - open source, built on top of Lemur in C++
    - not actively maintained anymore (but still works)
- Entity-topic association finding models
  - suited for other tasks, e.g. blog distillation
  - focuses on two entity-related tasks:
    - finding entities:
      - "Which entities are associated with topic X?"
    - profiling entities:
      - "What topics is an entity associated with?"
- See https://code.google.com/p/ears/

Sig.ma

- Search, aggregate, and visualize LOD data
- Powered by Sindice
- See http://sig.ma/



Sindice/SIREn

- Handling of semi-structured data
  - efficient, large scale
  - typically based on DBMS backends
  - uses Lucene for semi-structured search
- Open source
- Online demo, local install
- See http://siren.sindice.com/

Test collections

Test collections

Campaign	Task	Collection	Entity repr.	#Topics
TREC Enterprise (2005-08)	Expert finding	Enterprise intranets (W3C, CSIRO)	Indirect	99 (W3C) 127 (CSIRO)
TREC Entity (2009-11)	Rel. entity finding	Web crawl (ClueWeb09)	Indirect	120
	List completion			70
INEX Entity Ranking (2007-09)	Entity search	Wikipedia	Direct	55
	List completion			
SemSearch Chall. (2010-11)	Entity search	Semantic Web crawl (BTC2009)	Direct	142
	List search			50
INEX Linked Data (2012-13)	Ad-hoc search	Wikipedia + RDF (Wikipedia-LOD)	Direct	100 (’12) 144 (’13)

Test collections (2)

- Entity search as Question Answering
  - TREC QA track
  - QALD-2 challenge
  - INEX-LD Jeopardy task
- DBpedia entity search **[Balog & Neumayer 2013]**
  - synthesized queries and assessments, distilled from previous campaigns
  - from short keyword queries to natural language questions
  - 485 queries in total; mapped to DBpedia

Open challenges

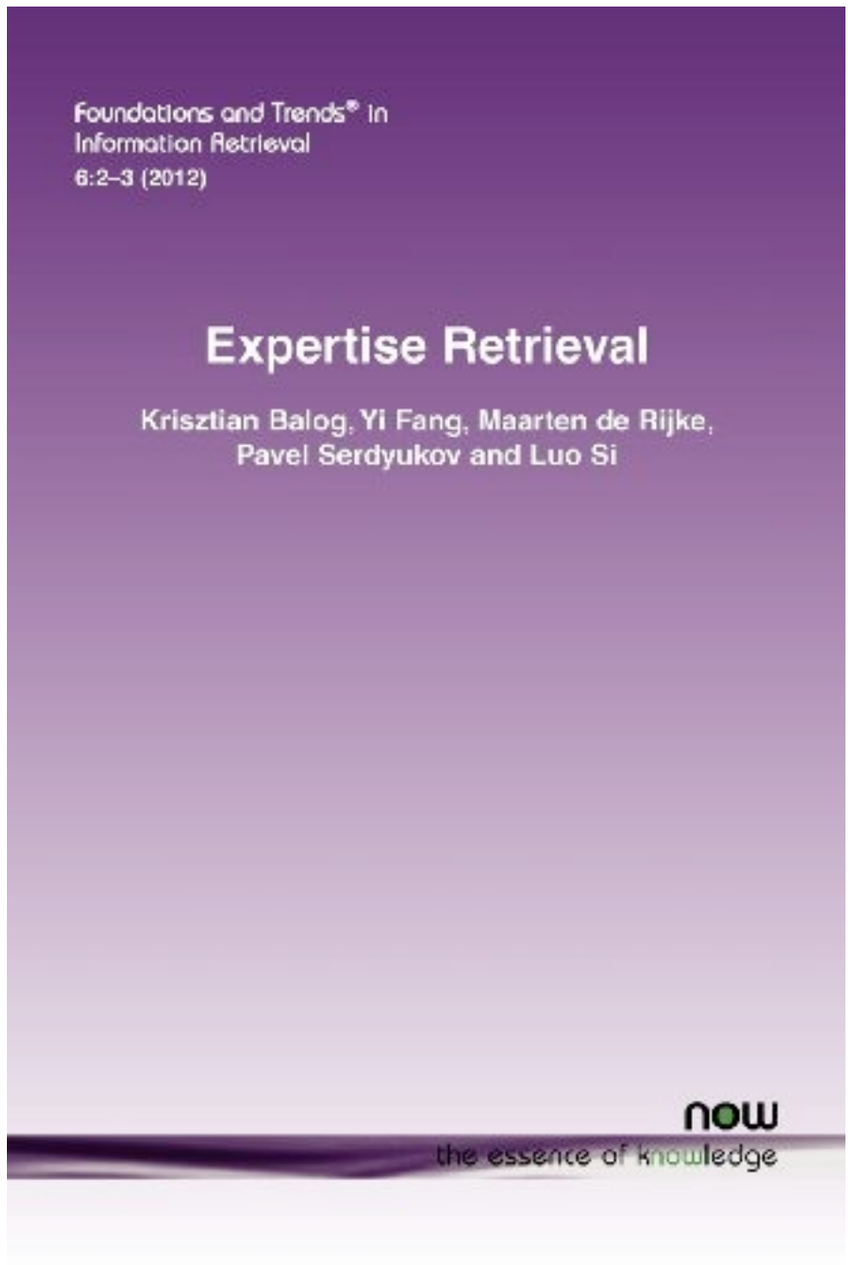
Open challenges

- Combining text and structure
  - Knowledge bases and unstructured Web documents
- Query understanding and modeling
- UI/UX/Result presentation
  - How to interact with entities
- Hyperlocal
  - Siri/Google Now/...
  - Recommendations

Open challenges (2)

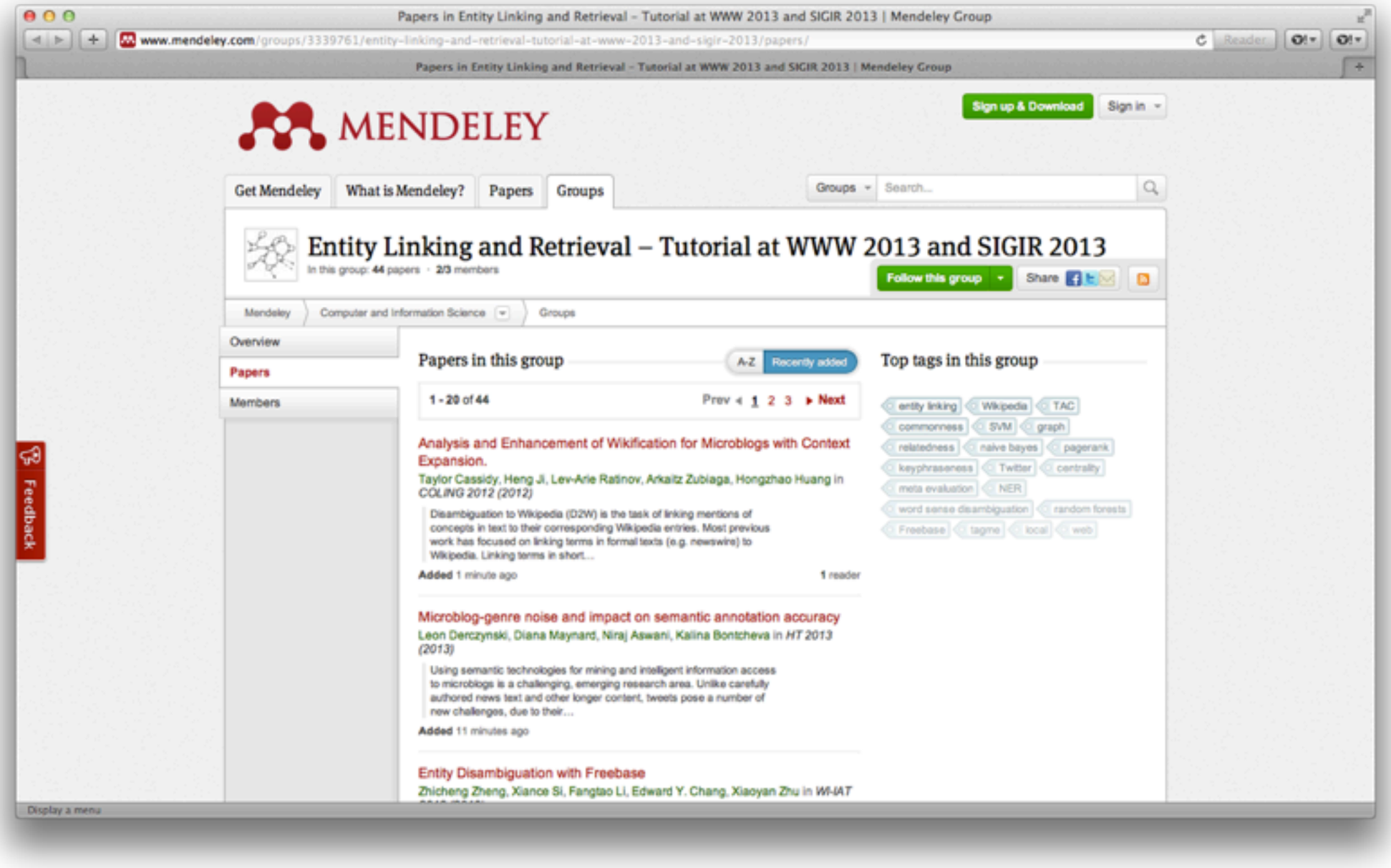
- There is more to types than currently exploited
  - Multiple category systems, hierarchy, ...
- Entity retrieval is typically part of some more complex task
  - Buying a product, planning a vacation, etc.

Follow-up reading



K. Balog, Y. Fang, M. de Rijke, P. Serdyukov, and L. Si. **Expertise Retrieval**. *FnTIR'12*.

References – Entity retrieval



http://www.mendeley.com/groups/3339761/entity-linking-and-retrieval-tutorial-at-www-2013-and-sigir-2013/papers/added/0/tag/entity+retrieval/