Part II

Entity Retrieval

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Donaldson
Filtration Solutions

BEST BUY

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AMS
Solutions for Life

WELLS FARGO

Medtronic
Alleviating Pain · Restoring Health · Extending Life

Thrivent Financial for Lutherans

MARVIN
Windows and Doors

3M Worldwide

POLARIS
The Way Out.

GENERAL MILLS

What is an entity?

- Uniquely identifiable “thing” or “object”
- Properties:
    - ID
    - Name(s)
    - Type(s)
    - Attributes
    - Relationships to other entities

Entity retrieval tasks

- Ad-hoc entity retrieval
- List completion
- Question answering
  - Factual questions
  - List questions
  - Related entity finding
- Type-restricted variations
  - People, blogs, products, movies, etc.

What’s so special about it?

- Entities are not always directly represented
    - Recognise and disambiguate entities in text
    - Collect and aggregate information about a given entity from multiple documents and even multiple data collections
- More structure
    - Types (from some taxonomy)
    - Attributes (from some ontology)
    - Relationships to other entities (“typed links”)

In this Part

- Focus on the ad-hoc entity retieval task
- Mainly probabilistic models
  - Specifically, Language Models

Outline for Part II

- Crash course into probability theory
- Ranking with ready-made entity descriptions
- Ranking without explicit entity representations
- Evaluation initiatives
- Future directions

Crash course into Probability theory

Basics

- Probability of an event

  $$P(A)$$

- Conditional probability

  $$P(A|B)$$

- Joint probability

  $$P(A, B)$$

Conditional dependence

- Independent events

$$P(A,B) = P(A) \cdot P(B)$$
$$P(A,B|C) = P(A|C) \cdot P(B|C)$$

- Conditionally dependent events

$$P(A,B) = P(A|B) \cdot P(B)$$
$$P(A,B|C) = P(A|B,C) \cdot P(B|C)$$

Bayes' theorem

$$\underbrace{P(A|B)}_{\text{Posterior}} = \frac{\overbrace{P(B|A)}^{\text{Likelihood}} \cdot \overbrace{P(A)}^{\text{Prior}}}{P(B)}$$

Now, back to business...

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

Ranking with ready-made entity descriptions

This is not unrealistic...

Document-based entity representations

- Each entity is described by a document
- Ranking entities 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)

Number of times *t* appears in *q*

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

Document language model
Multinomial probability distribution
over the vocabulary of terms

Smoothing parameter

$$P(t|\theta_d) = (1 - \lambda)\underbrace{P(t|d)} + \overbrace{\lambda}\underbrace{P(t|C)}$$

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

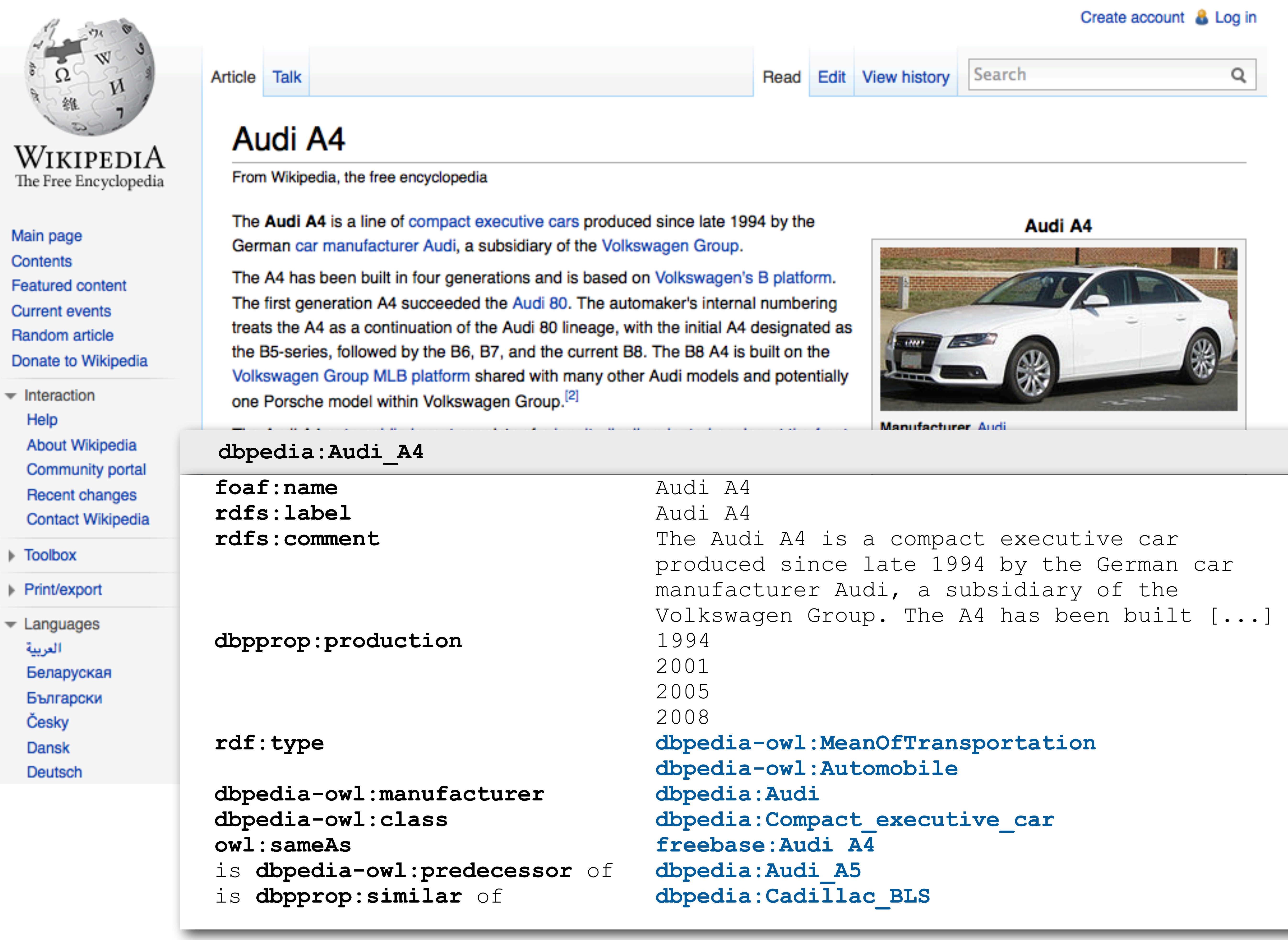
$$P(e|q) \propto P(e)P(q|\theta_e) = \underbrace{P(e)}_{\text{Entity prior}} \prod_{t \in q} \underbrace{P(t|\theta_e)}_{\text{Entity language model}}{}^{n(t,q)}$$

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


Create account
Log in
Article
Talk
Read
Edit
View history
Search
WIKIPEDIA
The Free Encyclopedia
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
Main page
Contents
Featured content
Current events
Random article
Donate to Wikipedia
Interaction
Help
About Wikipedia
Community portal
Recent changes
Contact Wikipedia
Toolbox
Print/export
Languages
العربية
Беларуская
Български
Česky
Dansk
Deutsch
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

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

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

Field weights

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

P. Ogilvie and J. Callan. **Combining document representations for known item search**. *SIGIR'03*.

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
  - Type **[Pérez-Agüera et al. 2010]**
  - Manually determined importance **[Blanco et al. 2011]**

R. Blanco, P. Mika, and S. Vigna. **Effective and efficient entity search in RDF data**. *ISWC'11*.
J.R. Pérez-Agüera, J. Arroyo, J. Greenberg, J.P. Iglesias, and V. Fresno. **Using BM25F for semantic search**. *SemSearch'10*.

Hierarchical Entity Model

[Neumayer et al. 2012]

- Organise 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

R. Neumayer, K. Balog and K. Nørvåg. **On the modeling of entities for ad-hoc entity search in the web of data**. *ECIR'12*.

Two-level hierarchy

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**

Formally

$$P(t|\theta_d) = \sum_{F} \underbrace{P(t|F,d)}_{\text{Term importance}} \underbrace{P(F|d)}_{\text{Field type importance}}$$

Field type importance
Taken to be the same for all entities
$P(F|d) = P(F)$

Term importance

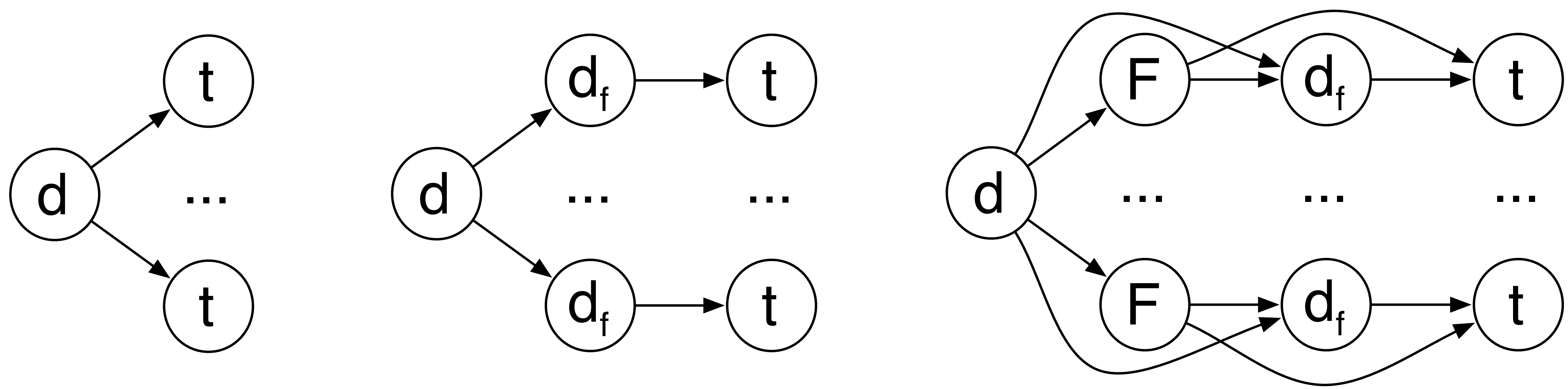
$$P(t|F,d) = \sum_{d_f \in F} \underbrace{P(t|d_f,F)}_{\text{Term generation}} \underbrace{P(d_f|F,d)}_{\text{Field generation}}$$

Term generation
Importance of a term is jointly determined by the field it occurs as well as all fields of that type (smoothed with a coll. level model)

Field generation
Uniform or estimated heuristically (based on length, popularity, etc)

$$P(t|d_f,F) = (1-\lambda)P(t|d_f) + \lambda P(t|\theta_{d_F})$$

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

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

J. Kim, X. Xue, and W.B. Croft. **A probabilistic retrieval model for semistructured data**. *ECIR'09*.

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

Query: `meg ryan war`

d_j	$P(t \mid d_j)$
cast	0.407
team	0.382
title	0.187

d_j	$P(t \mid d_j)$
cast	0.601
team	0.381
title	0.017

d_j	$P(t \mid d_j)$
genre	0.927
title	0.070
location	0.002

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]**

J. Kamps and M. Koolen. **The importance of link evidence in Wikipedia**. *ECIR'08*.
C. Macdonald and I. Ounis. **Expertise drift and query expansion in expert search**. *CIKM'07*.
P. Serdyukov, S. Chernov, and W. Nejdl. **Enhancing expert search through query modeling**. *ECIR'07*.
J.Y. Kim and W.B. Croft. **A Field Relevance Model for Structured Document Retrieval**. *ECIR'12*.

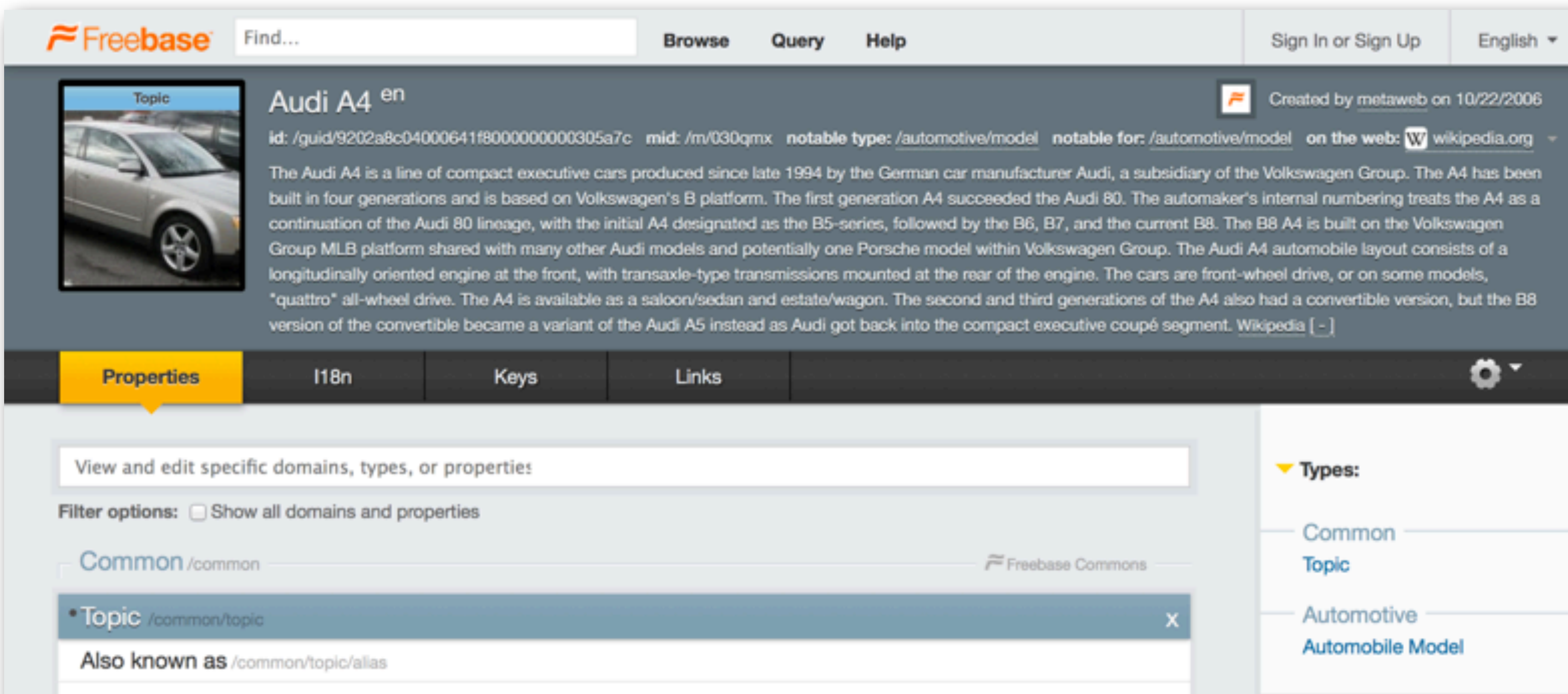
So far...

- Ranking (fielded) documents...
- What is special about entities?
    - Type(s)
    - Relationships with other entities

Entity types

`rdf:type`	`dbpedia-owl:MeanOfTransportation` `dbpedia-owl:Automobile`

Categories: Audi vehicles | Compact executive cars | Euro NCAP large family cars | Sedans | Station wagons | Convertibles | Vehicles with CVT transmission | All-wheel-drive vehicles | Front-wheel-drive vehicles | Vehicles introduced in 1994 | 1990s automobiles | 2000s automobiles | 2010s automobiles | Hybrid electric cars



Using target types
Assuming they have been identified...

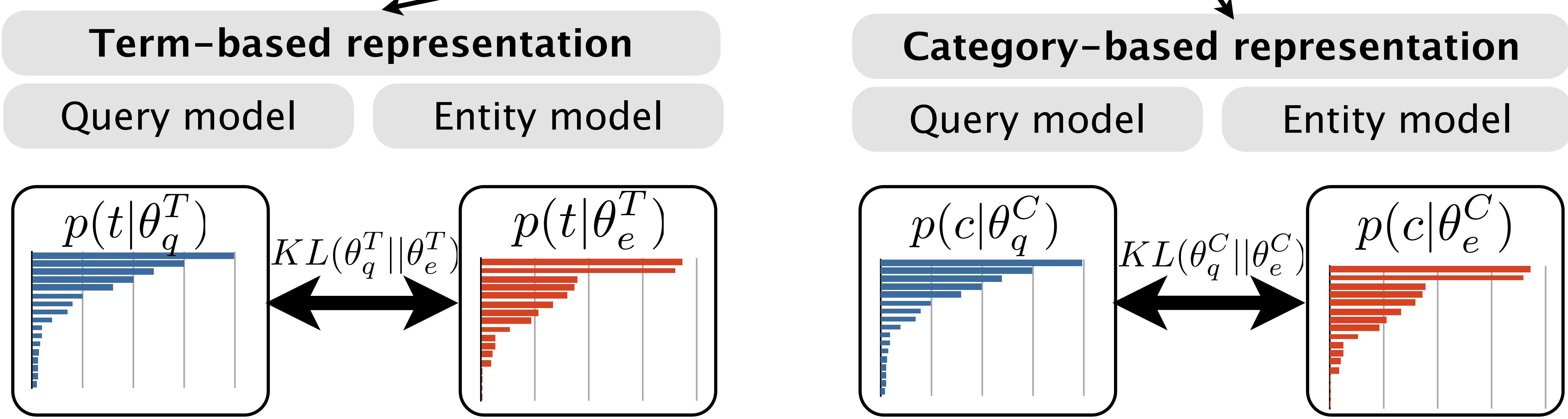
- Constraining results
  - Soft/hard filtering
  - Different ways to measure type similarity (between target types and the types associated with the entity)
    - Set-based
    - Content-based
    - Lexical similarity of type labels
- Query expansion
  - Adding terms from type names to the query
- Entity expansion
  - Categories as a separate metadata field

Modeling terms and categories

[Balog et al. 2011]

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

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



K. Balog, M. Bron, and M. de Rijke. **Query modeling for entity search based on terms, categories and examples**. *TOIS'11*.

Identifying target types

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

D. Vallet and H. Zaragoza. **Inferring the most important types of a query: a semantic approach**. *SIGIR'08*.
K. Balog and R. Neumayer. **Hierarchical target type identification for entity-oriented queries**. *CIKM'12*.
U. Sawant and S. Chakrabarti. **Learning joint query interpretation and response ranking**. *WWW'13*.

Expanding target types

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

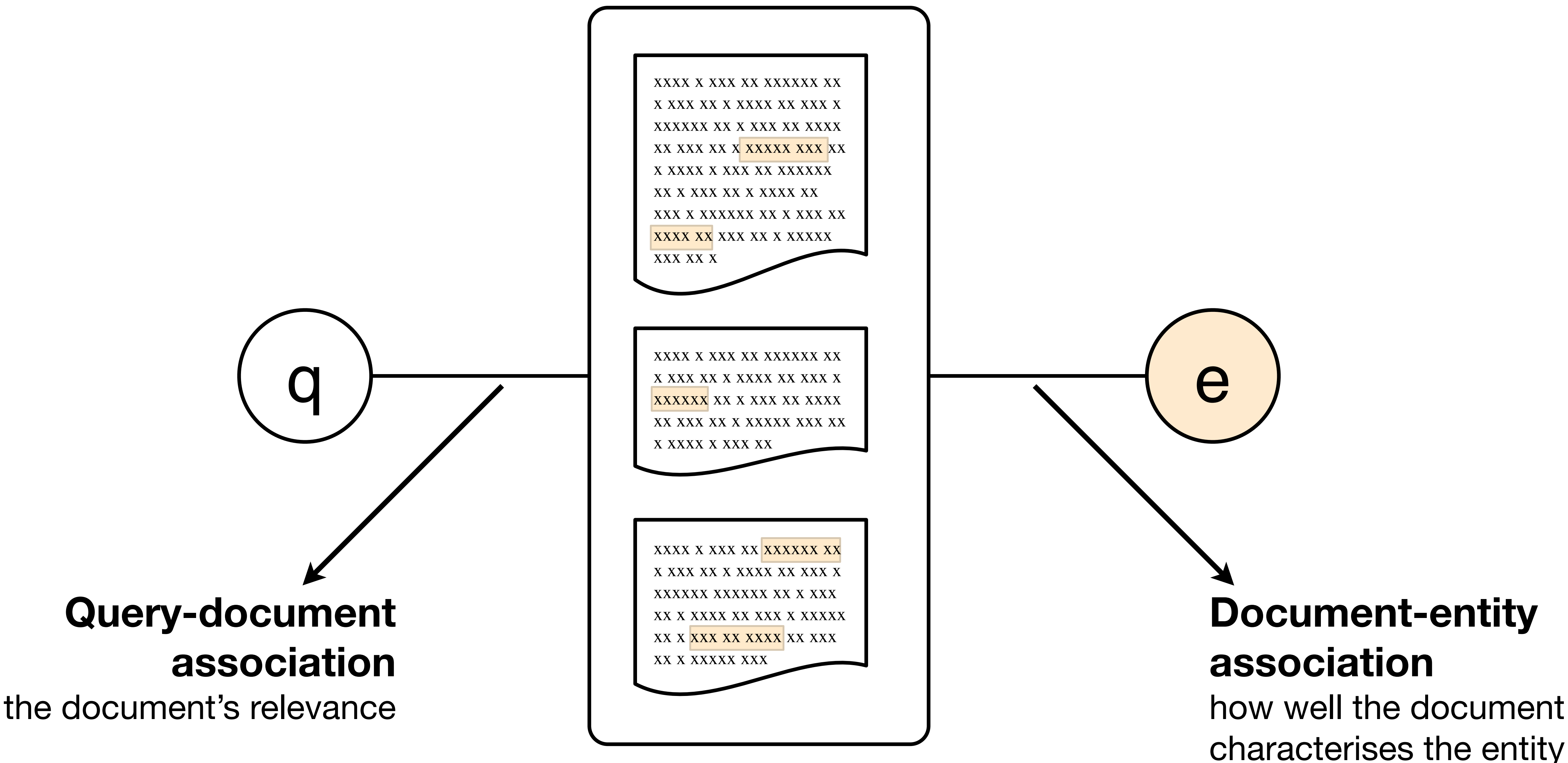
Ranking without explicit entity representations

Scenario

- Entity descriptions are not readily available
- Entity occurrences are annotated

The basic idea

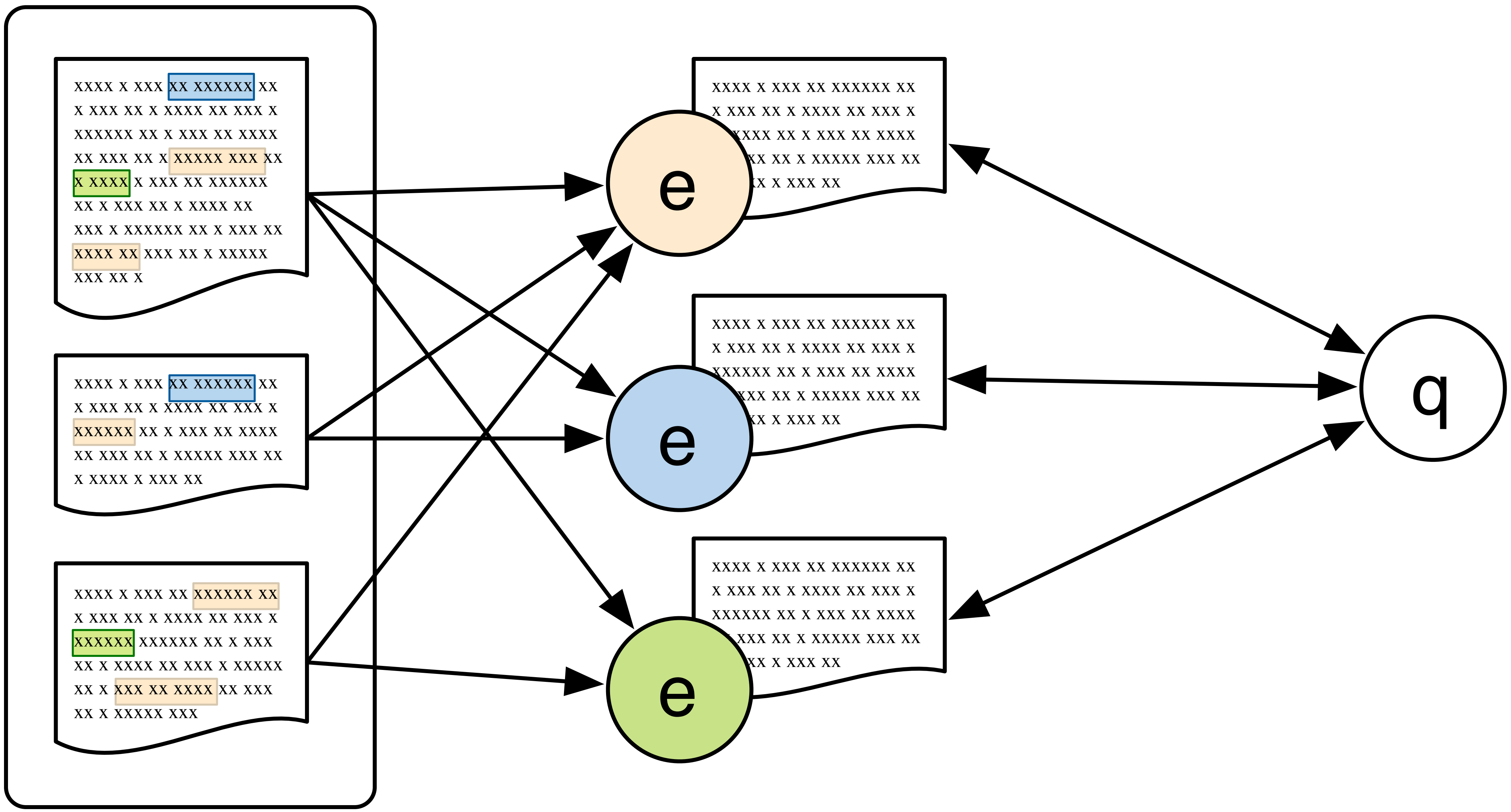
Use documents to get from queries to entities



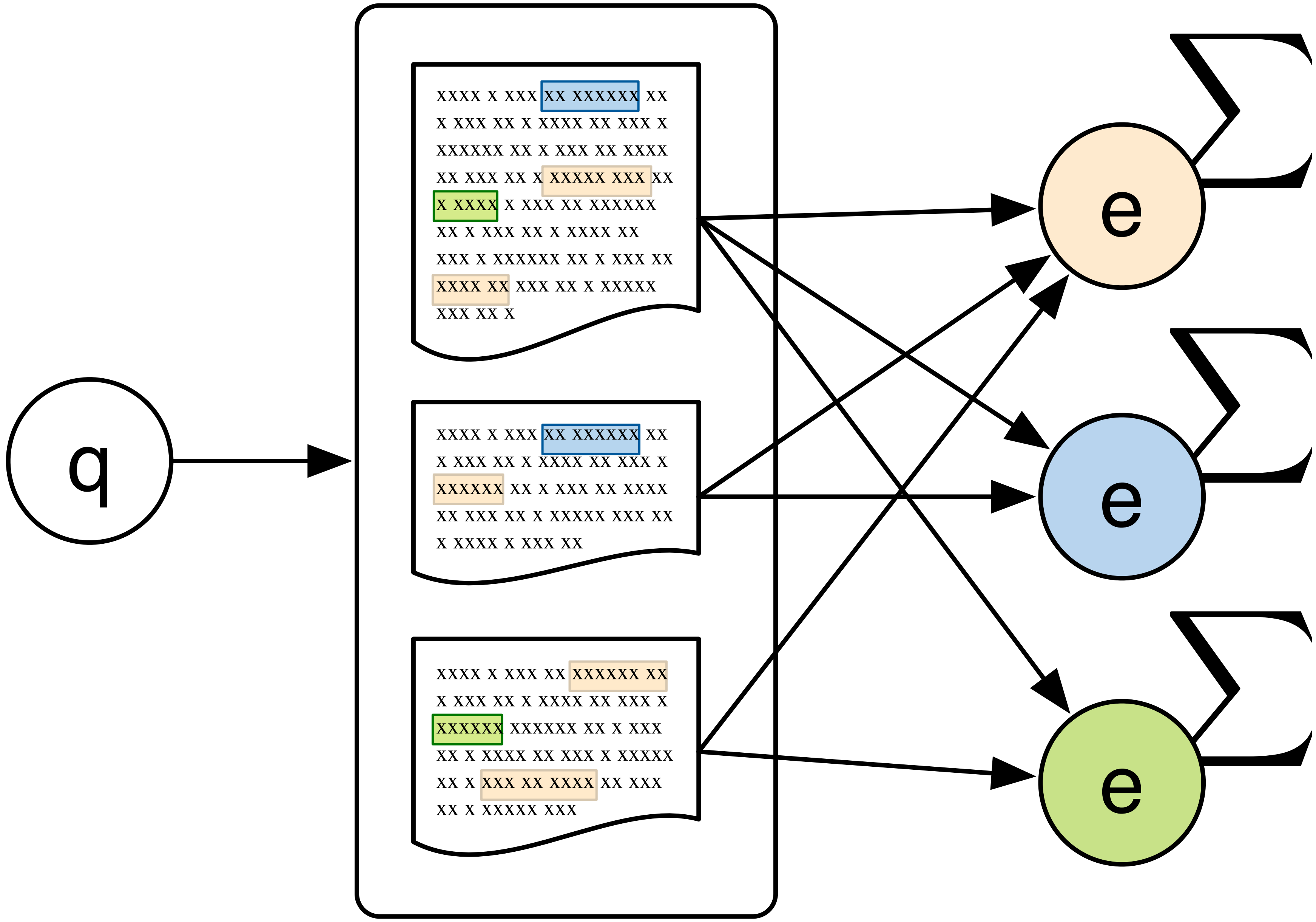
Two principal approaches

- **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]**

H. Fang and C. Zhai. **Probabilistic models for expert finding**. *ECIR'07*.

Candidate models ("Model 1")

[Balog et al. 2006]

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

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

K. Balog, L. Azzopardi, and M. de Rijke. **Formal Models for Expert Finding in Enterprise Corpora**. *SIGIR'06*.

Document models ("Model 2")

[Balog et al. 2006]

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

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

Document-entity association

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

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

$$P(t|\theta_d)$$

K. Balog, L. Azzopardi, and M. de Rijke. **Formal Models for Expert Finding in Enterprise Corpora**. *SIGIR'06*.

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]

$$P(t|d,e) = \underbrace{\frac{1}{Z}}_{\text{Normalising contant}} \sum_{i=1}^{N} \underbrace{\delta_d(i,t)}_{\text{Indicator function}} \underbrace{k(t,e)}_{\text{Proximity-based kernel}}$$

Normalising 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

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

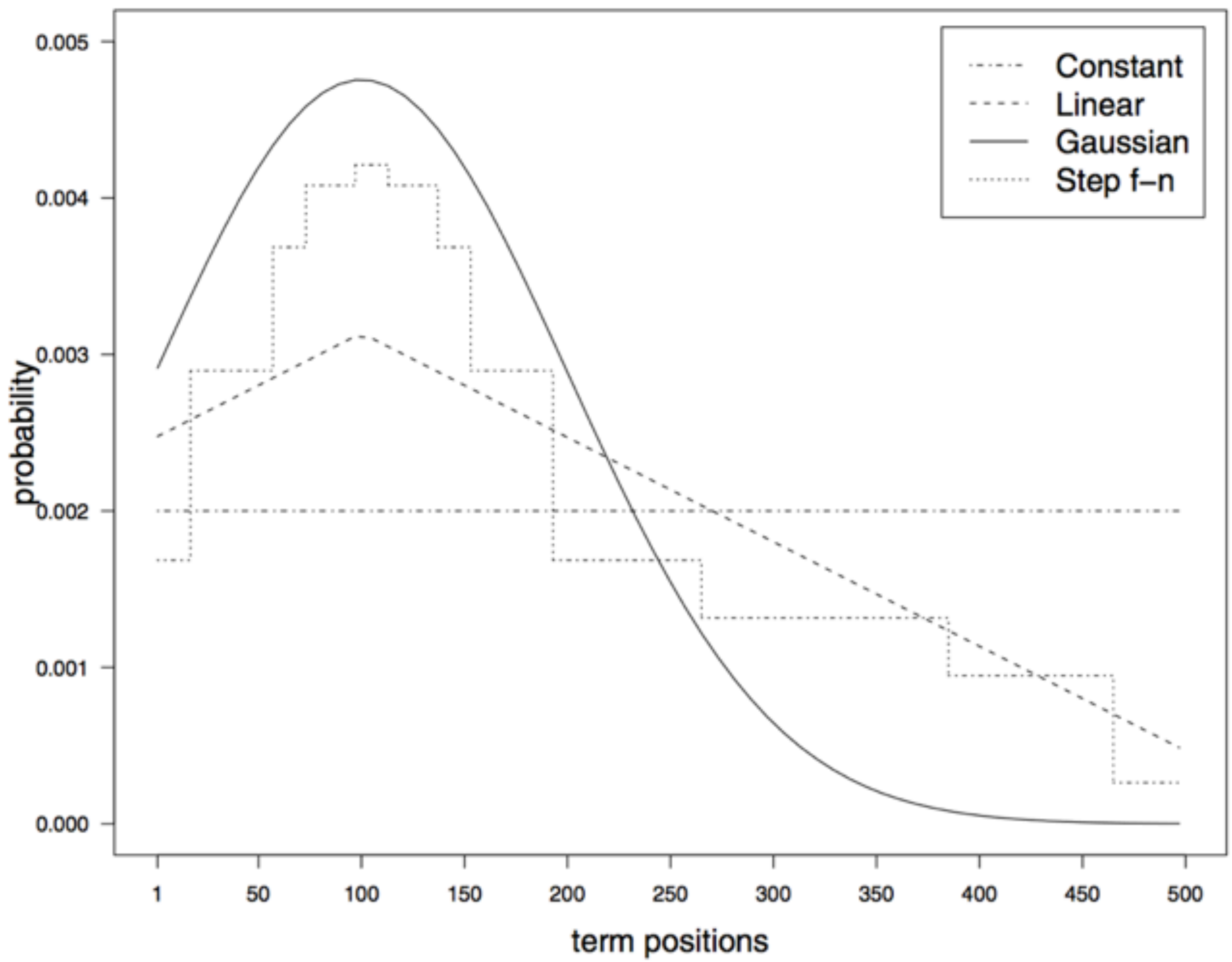


Figure taken from D. Petkova and W.B. Croft. **Proximity-based document representation for named entity retrieval**. *CIKM'07*.

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 $P(e,q|r=1)$)
  - Optimisation can get trapped in a local optimum

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

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

Y. Fang, L. Si, and A. P. Mathur. **Discriminative models of integrating document evidence and document-candidate associations for expert search**. *SIGIR'10*.

Learning to rank

- 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]**

P. Sorg and P. Cimiano. **Finding the right expert: Discriminative models for expert retrieval**. *KDIR'11*.
C. Moreira, P. Calado, and B. Martins. **Learning to rank for expert search in digital libraries of academic publications**. *PAI'11*.
Z. Yang, J. Tang, B. Wang, J. Guo, J. Li, and S. Chen. **Expert2bole: From expert finding to bole search**. *KDD'09*.

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

C. Macdonald and I. Ounis. **Voting for candidates: Adapting data fusion techniques for an expert search task**. *CIKM'06*.

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

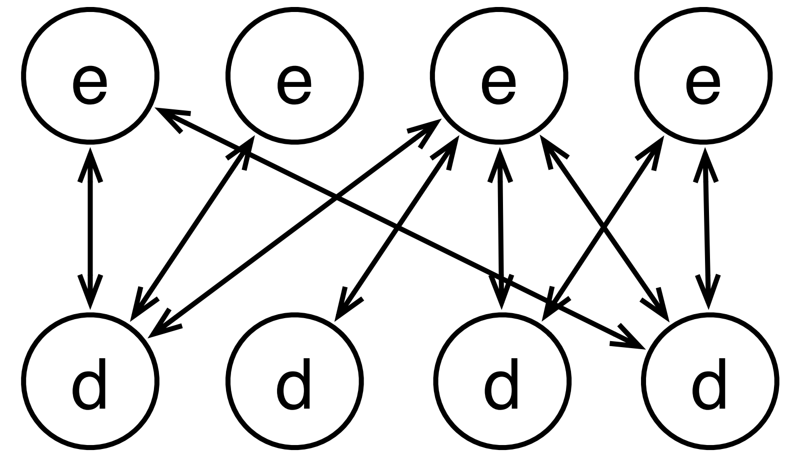
[Serdyukov et al. 2008]

- 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

P. Serdyukov, H. Rode, and D. Hiemstra. **Modeling multi-step relevance prop- agation for expert finding**. *CIKM'08*.

Infinite random walk model

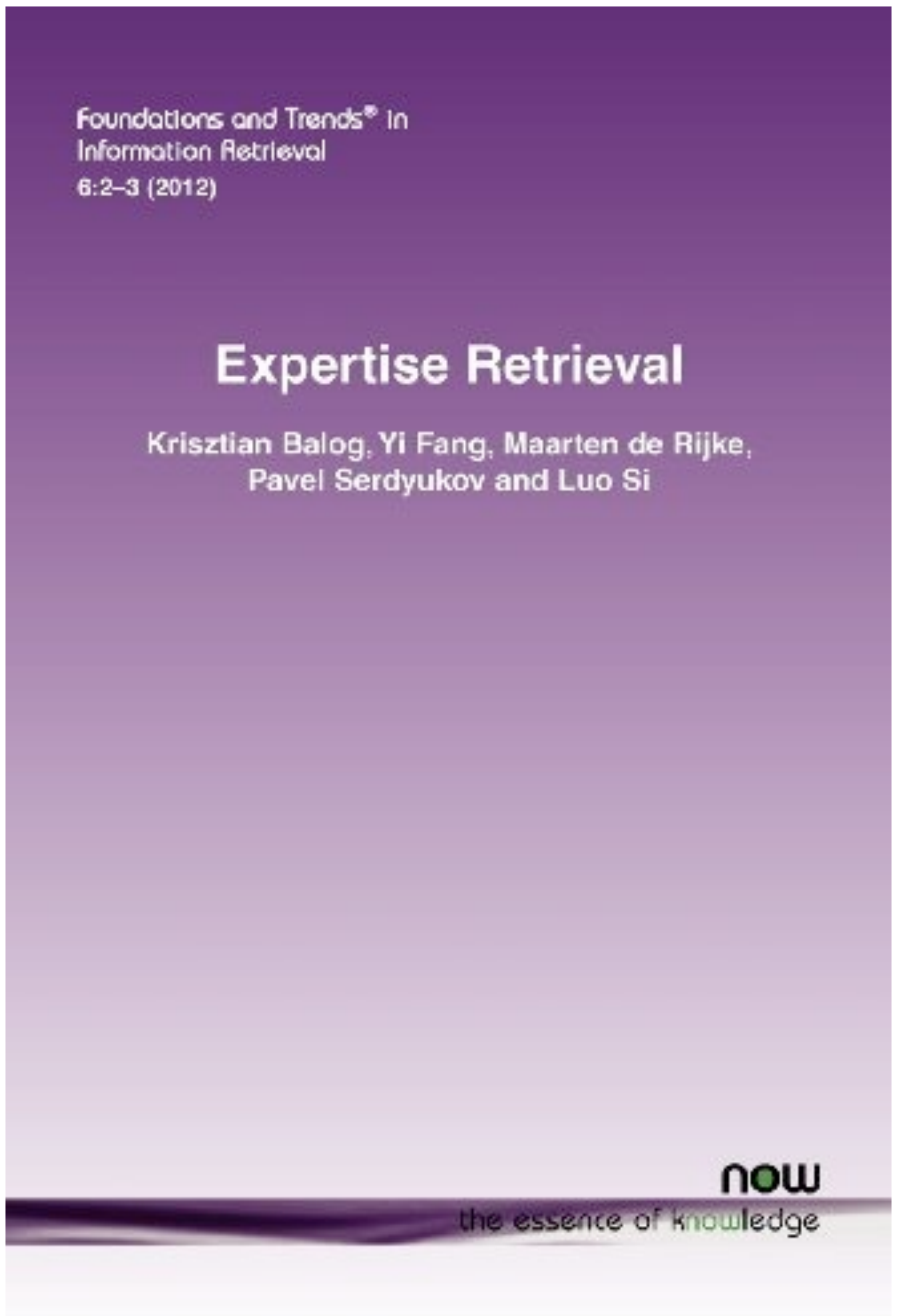
[Serdyukov et al. 2008]



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

P. Serdyukov, H. Rode, and D. Hiemstra. **Modeling multi-step relevance propagation for expert finding.** *CIKM'08*.

Further reading



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

Evaluation initiatives

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

Entity search in DBpedia

[Balog & Neumayer 2013]

- Synthesising queries and relevance assessments from previous eval. campaigns
- From short keyword queries to natural language questions
- 485 queries in total
- Results are mapped to DBpedia

K. Balog and R. Neumayer. **A test collection for entity search in DBpedia**. *SIGIR'13*

Open challenges

- Combining text and structure
  - Knowledge bases and unstructured Web documents
- Query understanding and modeling
  - See **[Sawant & Chakrabarti 2013]** at the main conference
- Result presentation
  - How to interact with entities

U. Sawant and S. Chakrabarti. **Learning joint query interpretation and response ranking**. *WWW'13*.