# Semistructured Data Search

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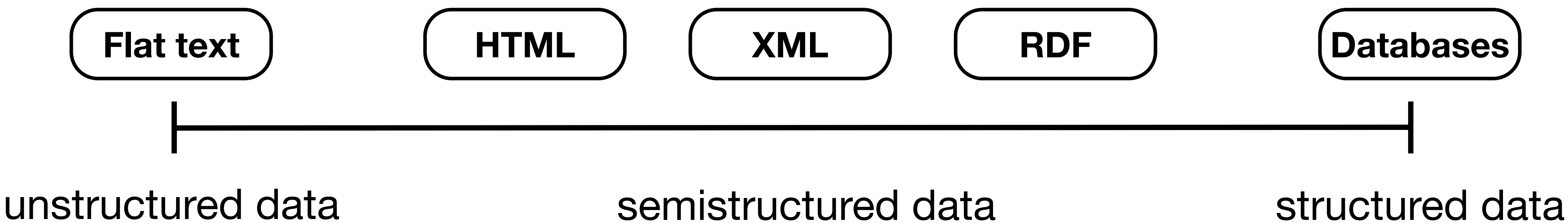
**Promise Winter School 2013** | Bressanone, Italy, February 2013

# The data landscape




- **Semistructured data**
  - Lack of fixed, rigid schema
  - No separation between the data and the schema, self-describing structure (tags or other markers)

# Motivation

- Supporting users who cannot express their need in structured query languages
  - SQL, SPARQL, Inquery, etc.
- Dealing with heterogeneity
  - Users are unaware of the schema of the data
  - No single schema to the data

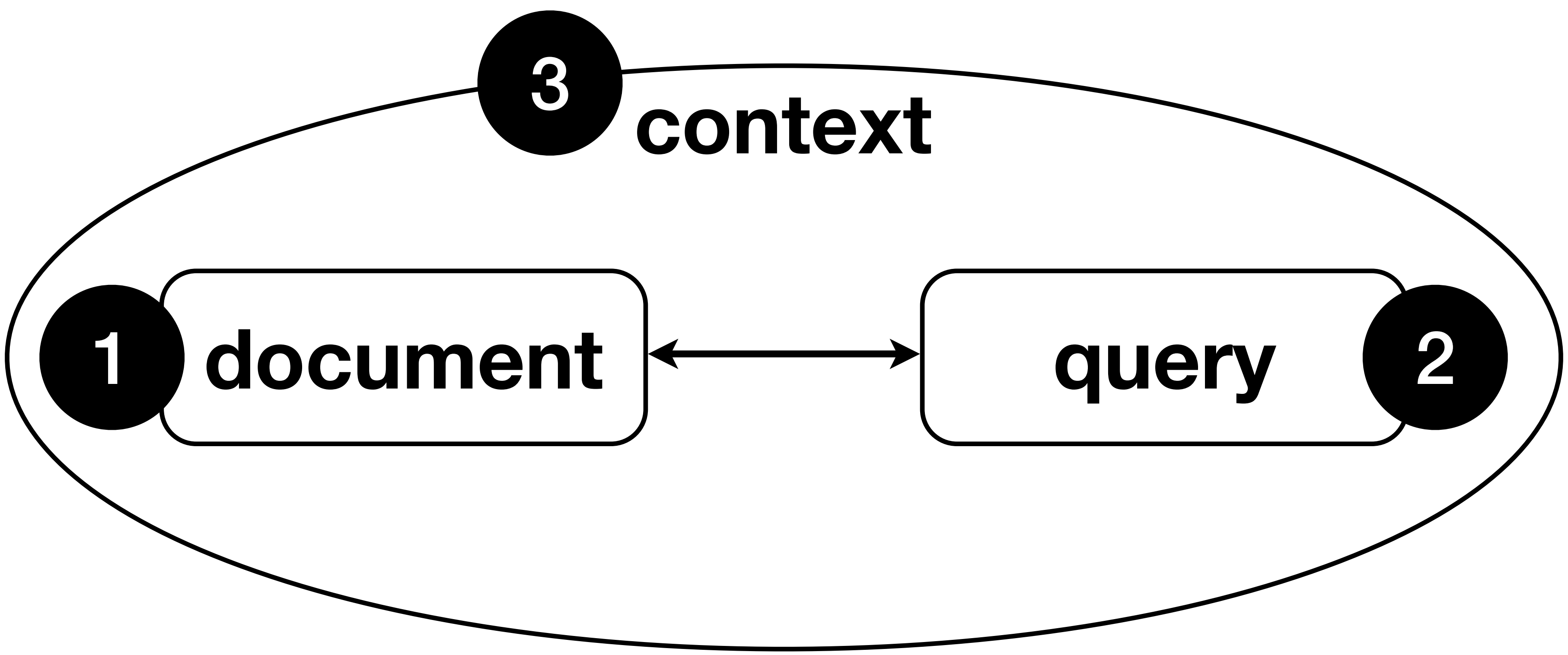
# Semistructured data

- Advantages
  - The data is not constrained by a fixed schema
  - Flexible (the schema can easily be changed)
  - Portable
  - Possible to view structured data as semistructured
- Disadvantages
  - Queries are less efficient than in a constrained structure

# In this talk

- How to **exploit the structure available in the data** for retrieval purposes?
- Different types of structure
  - Document, query, context
- Working in a Language Modeling setting
- Number of different tasks
  - Retrieving entire documents
    - I.e., no element-level retrieval
  - Textual document representation is readily available
    - No aggregation over multiple documents/sources

# Incorporating structure



# Preliminaries

Language modeling

# Language Modeling

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

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

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

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

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

# Language Modeling

## Query likelihood scoring

$$P(q|d) = \prod_{t \in q} \underbrace{P(t|\theta_d)}_{\text{Document language model}}{}^{\overbrace{n(t,q)}^{\text{Number of times } t \text{ appears in } q}}$$

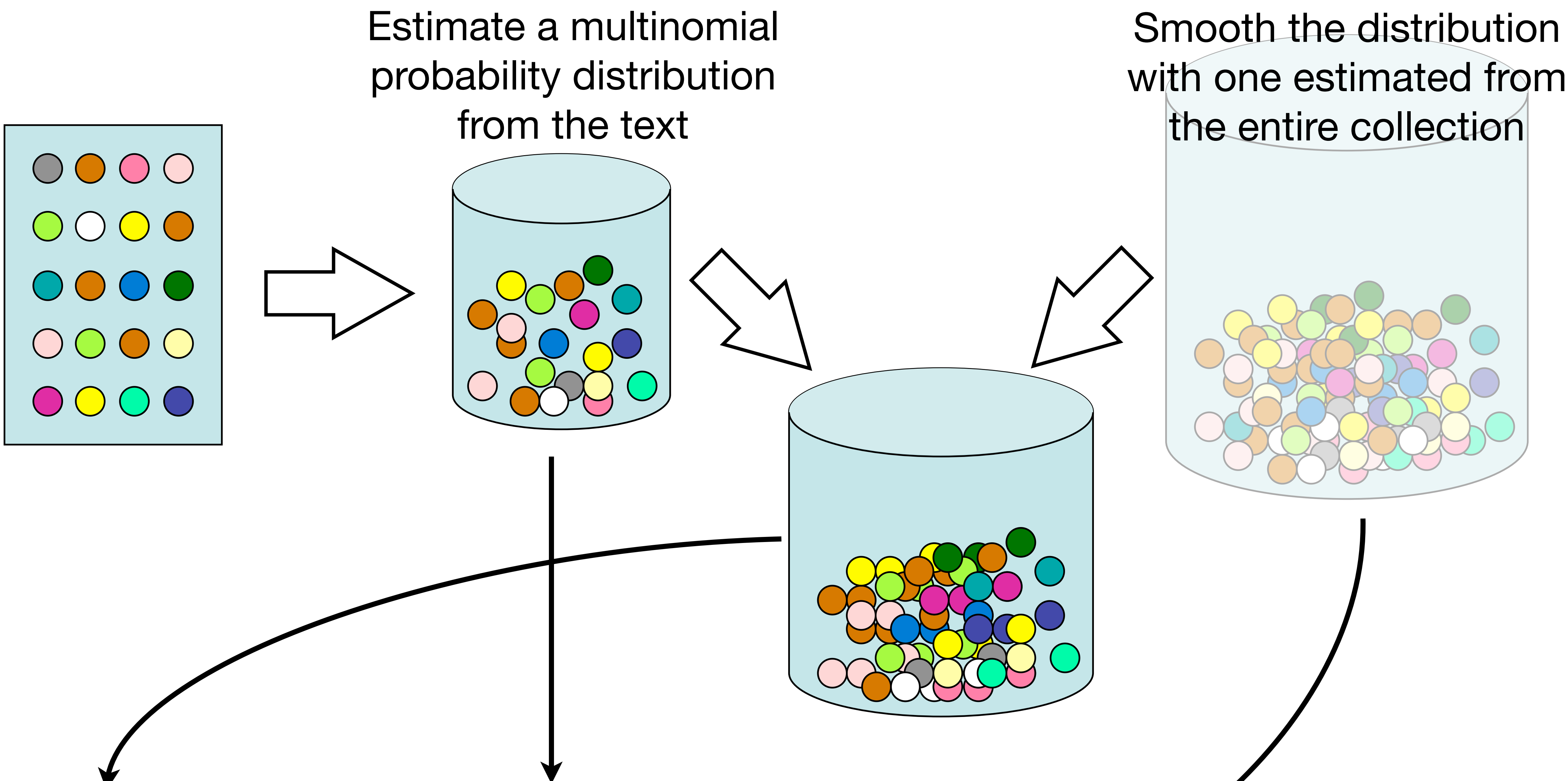
**Document language model**
Multinomial probability distribution over the vocabulary of terms

$$P(t|\theta_d) = (1-\lambda)\underbrace{P(t|d)}_{\text{Empirical document model}} + \overbrace{\lambda}^{\text{Smoothing parameter}}\underbrace{P(t|C)}_{\text{Collection model}}$$

Maximum likelihood estimates

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

# Language Modeling




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

# Example

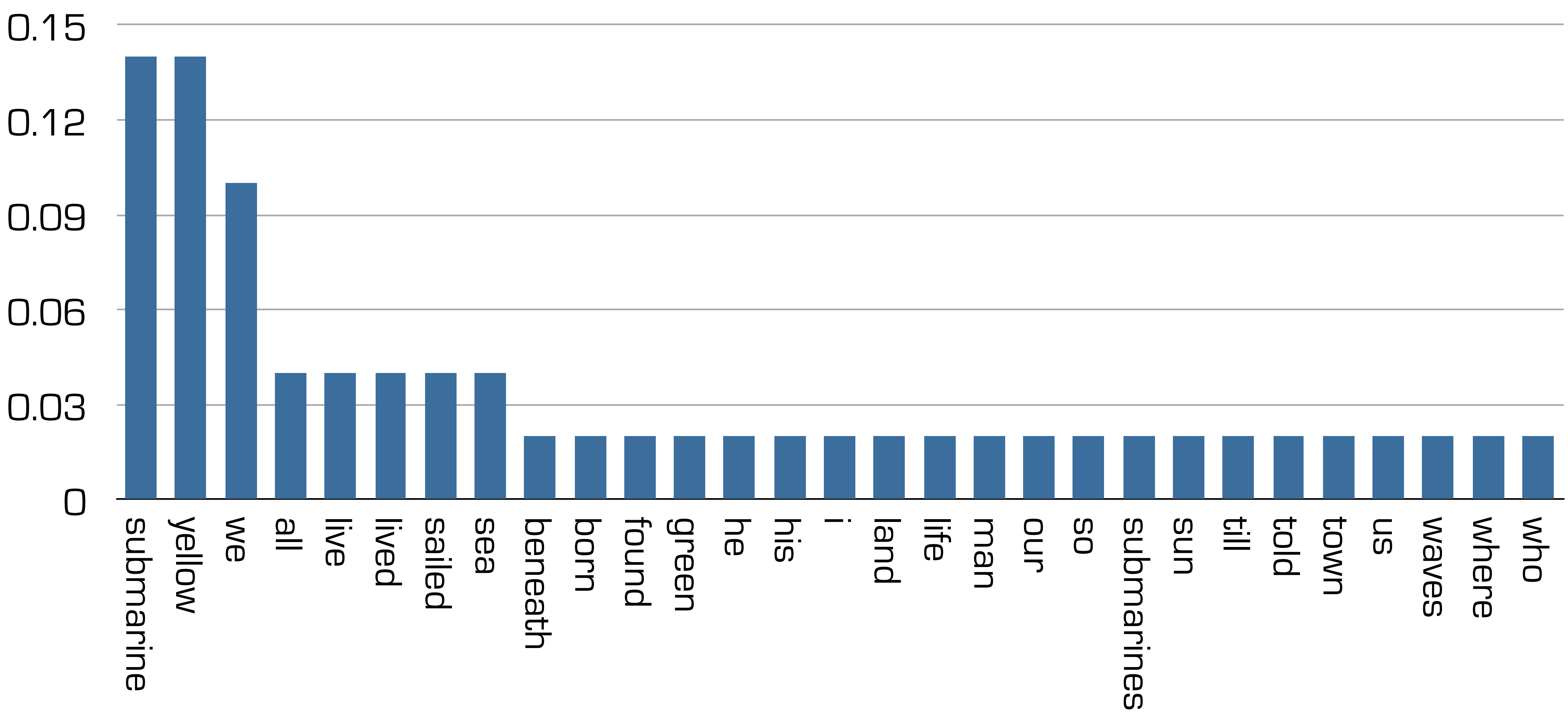
In the town where I was born,
Lived a man who sailed to sea,
And he told us of his life,
In the land of submarines,

So we sailed on to the sun,
Till we found the sea green,
And we lived beneath the waves,
In our yellow submarine,

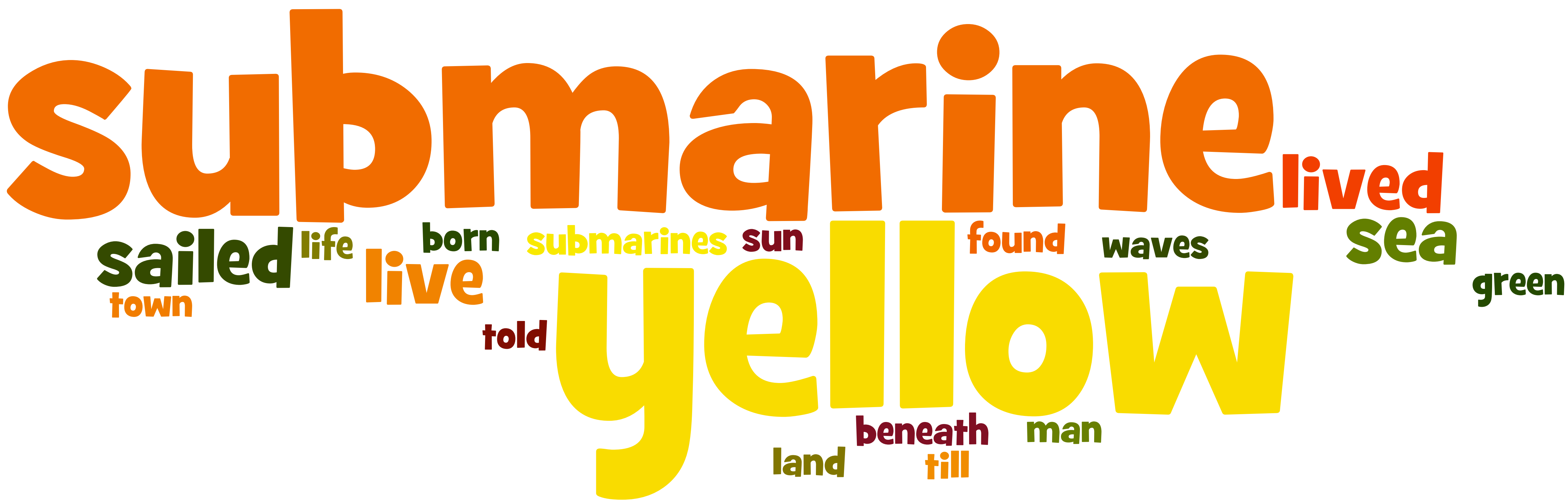
We all live in yellow submarine, yellow submarine, yellow submarine, We all live in yellow submarine, yellow submarine, yellow submarine.

# Empirical document LM

$$P(t|d) = \frac{n(t,d)}{|d|}$$



# Alternatively...



# Scoring a query

$$q = \{\text{sea}, \text{submarine}\}$$

$$P(q|d) = P(\text{``sea''}|\theta_d) \cdot P(\text{``submarine''}|\theta_d)$$

# Scoring a query

$$q = \{\text{sea}, \text{submarine}\}$$

$$P(q|d) = \underbrace{\overset{0.03602}{P(\text{“sea”}|\theta_d)}}_{} \cdot P(\text{“submarine”}|\theta_d)$$

$$\overset{0.9}{(1-\lambda)}\overset{0.04}{P(\text{“sea”}|d)} + \overset{0.1}{\lambda}\overset{0.0002}{P(\text{“sea”}|C)}$$

| t | P(t\|d) |
|---|---|
| submarine | 0.14 |
| sea | 0.04 |
| ... | |

| t | P(t\|C) |
|---|---|
| submarine | 0.0001 |
| sea | 0.0002 |
| ... | |

# Scoring a query

$$q = \{\text{sea}, \text{submarine}\}$$

$$\overset{0.04538}{P(q|d)} = \overset{0.03602}{P(\text{“sea”}|\theta_d)} \cdot \underbrace{\overset{0.12601}{P(\text{“submarine”}|\theta_d)}}$$

$$\overset{0.9}{(1-\lambda)}\overset{0.14}{P(\text{“submarine”}|d)} + \overset{0.1}{\lambda}\overset{0.0001}{P(\text{“submarine”}|C)}$$

| t | P(t\|d) |
|---|---|
| submarine | 0.14 |
| sea | 0.04 |
| ... | |

| t | P(t\|C) |
|---|---|
| submarine | 0.0001 |
| sea | 0.0002 |
| ... | |

# Part I

Document structure

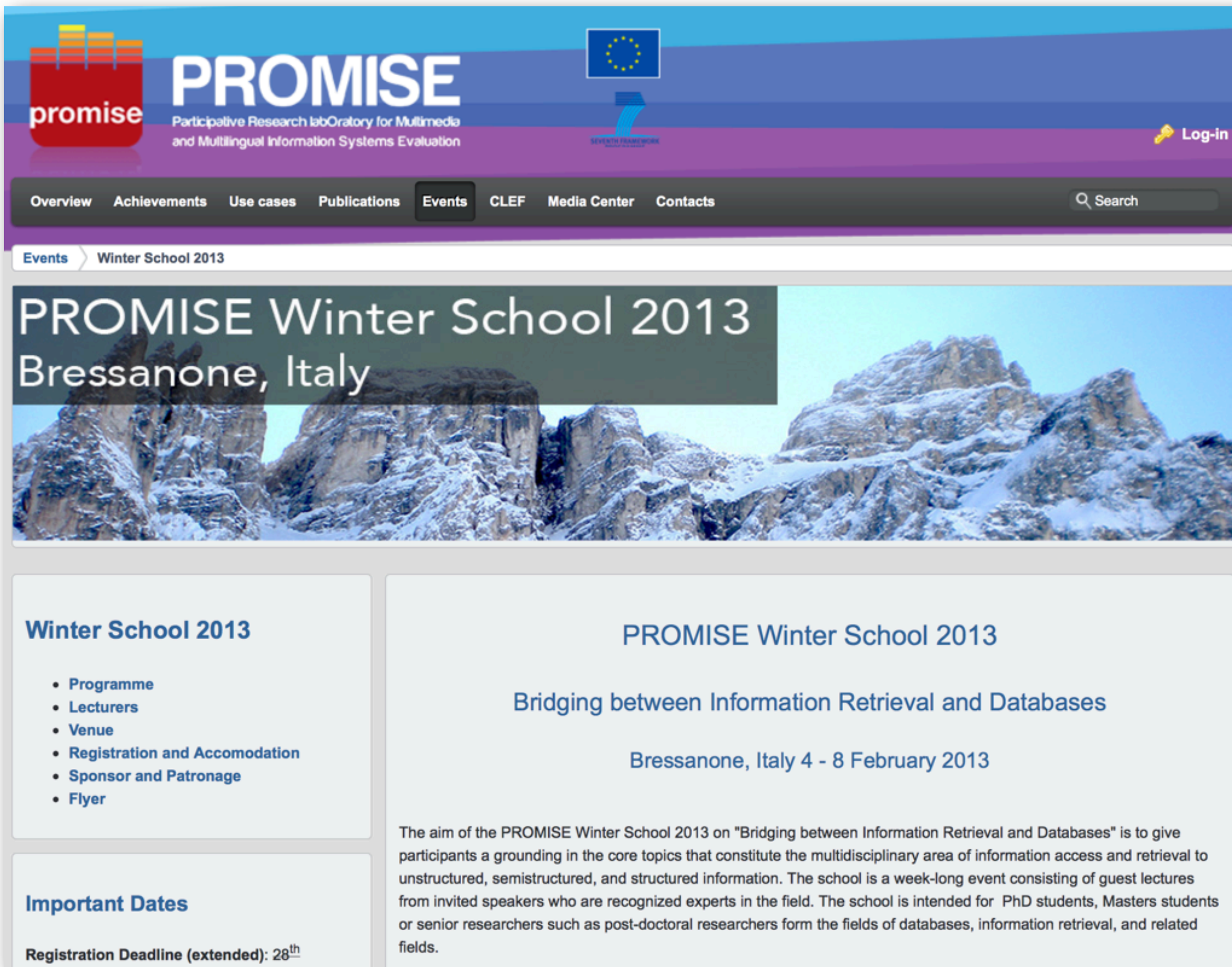
# In this part

- Incorporate document structure into the document language model
  - Represented as *document fields*

$$P(d|q) \propto P(q|d)P(d) = P(d)\prod_{t \in q} \underbrace{P(t|\theta_d)}_{\substack{\downarrow \\ \textbf{Document} \\ \textbf{language model}}}{}^{n(t,q)}$$

# Use case

## Web document retrieval



# Web document retrieval

## Unstructured representation

```
PROMISE Winter School 2013
Bridging between Information Retrieval and Databases
Bressanone, Italy 4 - 8 February 2013
The aim of the PROMISE Winter School 2013 on "Bridging between Information
Retrieval and Databases" is to give participants a grounding in the core
topics that constitute the multidisciplinary area of information access and
retrieval to unstructured, semistructured, and structured information. The
school is a week-long event consisting of guest lectures from invited
speakers who are recognized experts in the field. The school is intended for
PhD students, Masters students or senior researchers such as post-doctoral
researchers form the fields of databases, information retrieval, and related
fields.
[...]
```

# Web document retrieval

## HTML source

```
<html>
<head>
   <title>Winter School 2013</title>
   <meta name="keywords" content="PROMISE, school, PhD, IR, DB, [...]" />
   <meta name="description" content="PROMISE Winter School 2013, [...]" />
</head>
<body>
   <h1>PROMISE Winter School 2013</h1>
   <h2>Bridging between Information Retrieval and Databases</h2>
   <h3>Bressanone, Italy 4 - 8 February 2013</h3>
   <p>The aim of the PROMISE Winter School 2013 on "Bridging between
   Information Retrieval and Databases" is to give participants a grounding
   in the core topics that constitute the multidisciplinary area of
   information access and retrieval to unstructured, semistructured, and
   structured information. The school is a week-long event consisting of
   guest lectures from invited speakers who are recognized experts in the
   field. The school is intended for  PhD students, Masters students or
   senior researchers such as post-doctoral researchers form the fields of
   databases, information retrieval, and related fields. </p>
   [...]
</body>
</html>
```

# Web document retrieval

## Fielded representation based on HTML markup

| | |
|---|---|
| **title:** | Winter School 2013 |
| **meta:** | PROMISE, school, PhD, IR, DB, [...]<br>PROMISE Winter School 2013, [...] |
| **headings:** | PROMISE Winter School 2013<br>Bridging between Information Retrieval and Databases<br>Bressanone, Italy 4 - 8 February 2013 |
| **body:** | The aim of the PROMISE Winter School 2013 on "Bridging between Information Retrieval and Databases" is to give participants a grounding in the core topics that constitute the multidisciplinary area of information access and retrieval to unstructured, semistructured, and structured information. The school is a week-long event consisting of guest lectures from invited speakers who are recognized experts in the field. The school is intended for PhD students, Masters students or senior researchers such as post-doctoral researchers form the fields of databases, information retrieval, and related fields. |

# Fielded Language Models

[Ogilvie & Callan, SIGIR'03]

- 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**

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

# Field Language Model

$$P(t|\theta_{d_j}) = (1-\lambda_j)\underbrace{P(t|d_j)}_{\text{Empirical field model}} + \overbrace{\lambda_j}^{\text{Smoothing parameter}}\underbrace{P(t|C_j)}_{\text{Collection field model}}$$

**Smoothing parameter**

**Empirical field model**

Maximum likelihood estimates

**Collection field model**

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

# Fielded Language Models

## Parameter estimation

- Smoothing parameter
  - Dirichlet smoothing with avg. representation length
- Field weights
  - Heuristically (e.g., proportional to the length of text content in that field)
  - Empirically (using training queries)
    - Computationally intractable for more than a few fields

# Example

$$q = \{\text{IR}, \text{winter}, \text{school}\}$$

$$\text{fields} = \{\text{title}, \text{meta}, \text{headings}, \text{body}\}$$

$$\mu = \{0.2, 0.1, 0.2, 0.5\}$$

$$P(q|\theta_d) = \underbrace{P(\text{``IR''}|\theta_d)} \cdot P(\text{``winter''}|\theta_d) \cdot P(\text{``school''}|\theta_d)$$

$$\begin{aligned}
P(\text{``IR''}|\theta_d) \quad &= \quad 0.2 \cdot P(\text{``IR''}|\theta_{d_{title}}) \\
&+ \quad 0.1 \cdot P(\text{``IR''}|\theta_{d_{meta}}) \\
&+ \quad 0.2 \cdot P(\text{``IR''}|\theta_{d_{headings}}) \\
&+ \quad 0.2 \cdot P(\text{``IR''}|\theta_{d_{body}})
\end{aligned}$$

# Use case

## Entity retrieval in RDF data

Create account Log in

Article Talk Read Edit View history Search

WIKIPEDIA
The Free Encyclopedia

- 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

# 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]

The Audi A4 automobile layout consists of a longitudinally oriented engine at the front, with transaxle-type transmissions mounted at the rear of the engine. The cars are front-wheel drive, or on some models, "quattro" all-wheel drive.

The A4 is available as a saloon/sedan and estate/wagon. The second (B6) and third generations (B7) of the A4 also had a convertible version, but the B8 version of the convertible became a variant of the Audi A5 instead as Audi got back into the compact executive coupé segment. The facebook fans of the Audi A4 page are more than 870,000.

**Contents** [show]

**Audi A4**

| | |
|---|---|
| **Manufacturer** | Audi |
| **Production** | 1994–present |
| **Assembly** | Ingolstadt, Germany<br>Changchun, China[1]<br>Tokyo, Japan (AMA; B5 only)<br>Jakarta, Indonesia (Garuda Mataram Motor; B5 & B8)<br>Solomonovo, Ukraine (Eurocar; B7 only)<br>Aurangabad, India |
| **Predecessor** | Audi 80 |
| **Class** | Compact executive car (globally) |

# Use case

## Entity retrieval in RDF data

**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<br>2001<br>2005<br>2008 |
| **rdf:type** | **dbpedia-owl:MeanOfTransportation**<br>**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** |

# Hierarchical Entity Model

[Neumayer et al., ECIR'12]

- 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
- 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

# 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<br>2001<br>2005<br>2008 |
| **Out-relations** | **rdf:type** | **dbpedia-owl:MeanOfTransportation**<br>**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** |

# Hierarchical Entity Model

[Neumayer et al., ECIR'12]

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

**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)

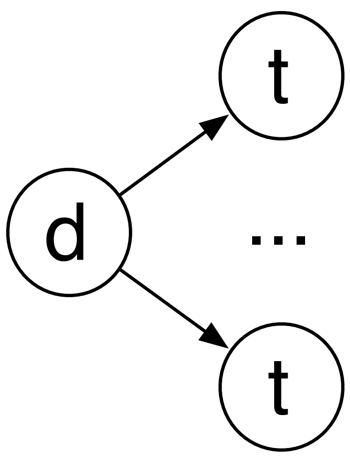
**Field generation**

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

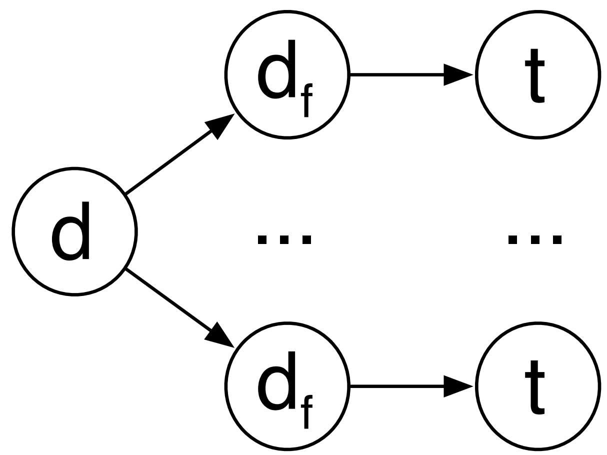
# Field generation

- Uniform
  - All fields of the same type are equally important
- Length
  - Proportional to field length (on the entity level)
- Average length
  - Proportional to field length (on the collection level)
- Popularity
  - Number of documents that have the given field

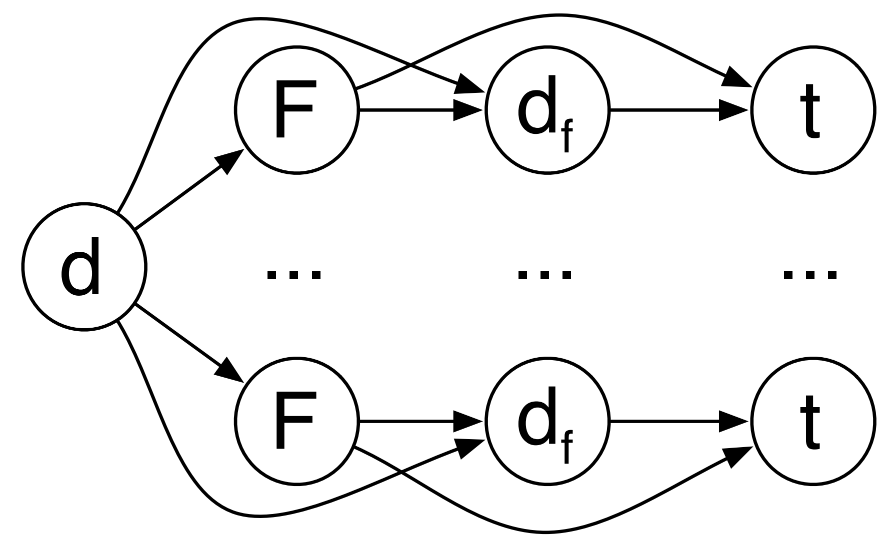
# Comparison of models




**Unstructured document model**




**Fielded document model**




**Hierarchical document model**

# Use case

## Finding movies in IMDB data


**The Transporter** (2002)  Top 5000

PG-13 92 min - Action | Crime | Thriller - 11 October 2002 (USA)

6.7

**Your rating:** -/10

Ratings: **6.7**/10 from 133,802 users Metascore: 51/100

Reviews: 428 user | 154 critic | 27 from Metacritic.com

This film is about a man whose job is to deliver packages without asking any questions. Complications arise when he breaks those rules.

**Directors:** Louis Leterrier, Corey Yuen

**Writers:** Luc Besson, Robert Mark Kamen

**Stars:** Jason Statham, Qi Shu and Matt Schulze | See full cast and crew

# Use case

## Finding movies in IMDB data

```xml
<title>The Transporter</title>
<year>2002</year>
<language>English</language>
<genre>Action</genre>
<genre>Crime</genre>
<genre>Thriller</genre>
<country>USA</country>
<actors>
   <actor>Jason Statham</actor>
   <actor>Matt Schulze</actor>
   <actor>François Berléand</actor>
   <actor>Ric Young</actor>
   <actress>Qi Shu/actress>
</actors>
<team>
   <director>Louis Leterrier</director>
   <director>Corey Yuen</director>
   <writer>Luc Besson</writer>
   <writer>Robert Mark Kamen</writer>
   <producer>Luc Besson</producer>
   <cinematographer>Pierre Morel</cinematographer>
</team>
```

# Probabilistic Retrieval Model for Semistructured data

**[Kim et al., ECIR'09]**

- Find which document field each query term may be associated with
- Extending **[Ogilvie & Callan, SIGIR'03]**

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

**Mapping probability**

Estimated for each query term

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

# PRMS

## 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

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

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

# PRMS

## Mapping example

Query: `meg ryan war`

| $d_j$ | $P(t\|d_j)$ |
|---|---|
| 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 |

# Part 2

Query structure

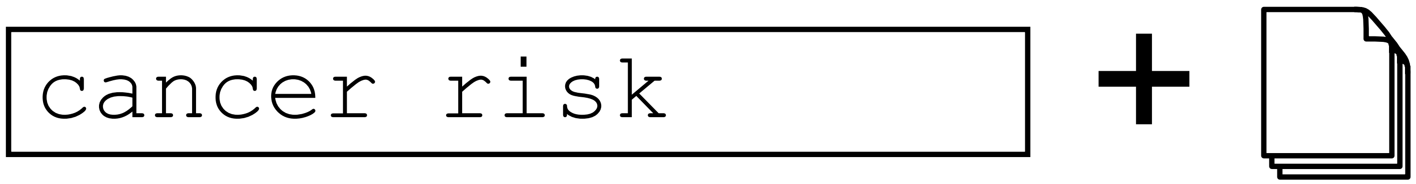
# Structured query representations

- Query may have a semistructured representation, i.e., multiple fields
- Examples
  - TREC Genomics track
    - (1) gene name, (2) set of symbols
  - TREC Enterprise track, document search task
    - (1) keyword query, (2) example documents
  - INEX Entity track
    - (1) keyword query, (2) target categories, (3) example entities
  - TREC Entity track
    - (1) keyword query, (2) input entity, (3) target type

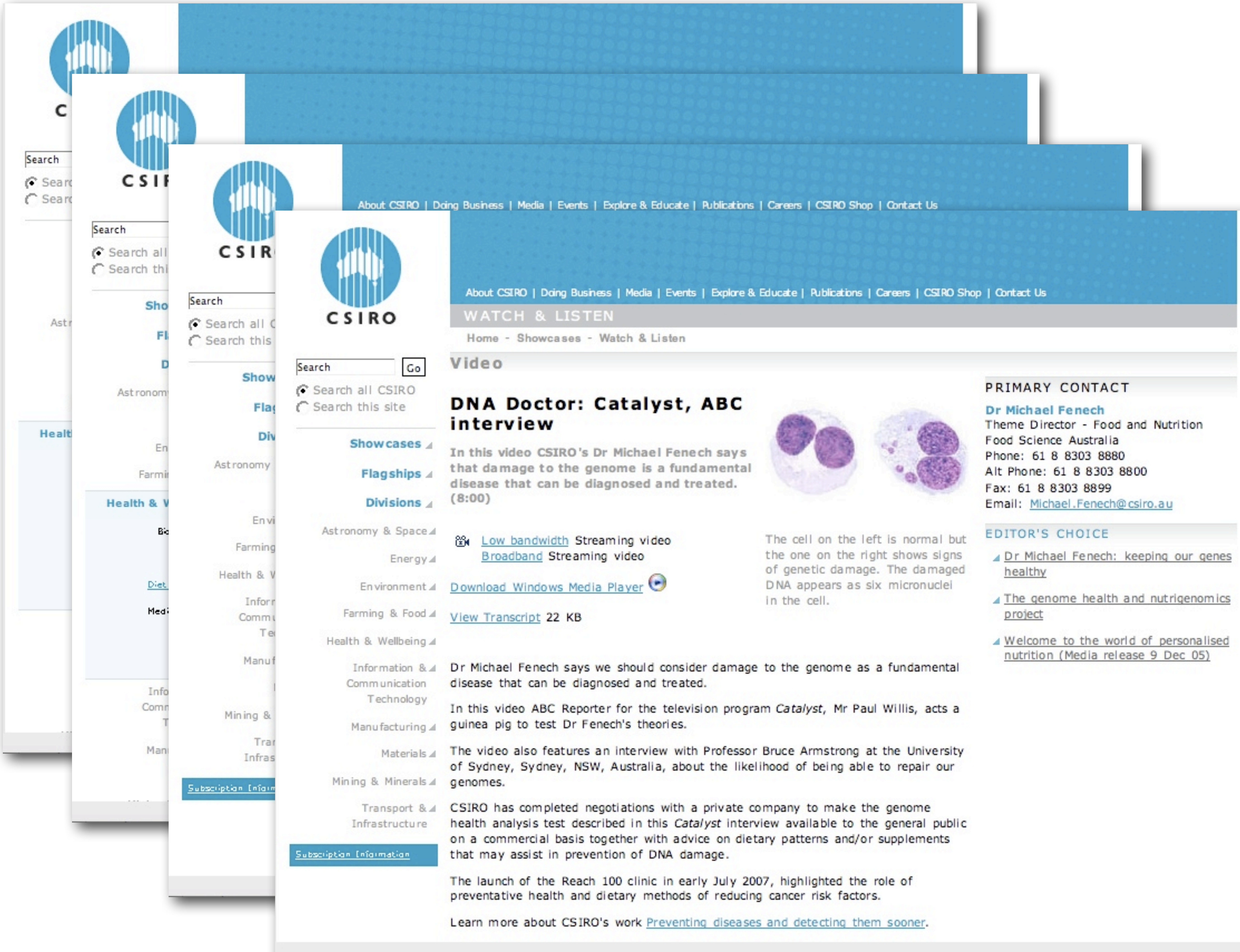
# Use case

## Enterprise document search (TREC 2007)

- Task: create an overview page on a given topic
  - Find documents that discuss the topic in detail




```
<topic>
  <num>CE-012</num>
  <query>cancer risk</query>
  <narr>
    Focus on genome damage and therefore cancer risk in humans.
  </narr>
  <page>CSIRO145-10349105</page>
  <page>CSIRO140-15970492</page>
  <page>CSIRO139-07037024</page>
  <page>CSIRO138-00801380</page>
</topic>
```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Video

## DNA Doctor: Catalyst, ABC interview

**In this video CSIRO's Dr Michael Fenech says that damage to the genome is a fundamental disease that can be diagnosed and treated. (8:00)**

Low bandwidth Streaming video
Broadband Streaming video

Download Windows Media Player

View Transcript 22 KB

The cell on the left is normal but the one on the right shows signs of genetic damage. The damaged DNA appears as six micronuclei in the cell.

Dr Michael Fenech says we should consider damage to the genome as a fundamental disease that can be diagnosed and treated.

In this video ABC Reporter for the television program *Catalyst*, Mr Paul Willis, acts a guinea pig to test Dr Fenech's theories.

The video also features an interview with Professor Bruce Armstrong at the University of Sydney, Sydney, NSW, Australia, about the likelihood of being able to repair our genomes.

CSIRO has completed negotiations with a private company to make the genome health analysis test described in this *Catalyst* interview available to the general public on a commercial basis together with advice on dietary patterns and/or supplements that may assist in prevention of DNA damage.

The launch of the Reach 100 clinic in early July 2007, highlighted the role of preventative health and dietary methods of reducing cancer risk factors.

Learn more about CSIRO's work Preventing diseases and detecting them sooner.

PRIMARY CONTACT

Dr Michael Fenech
Theme Director - Food and Nutrition
Food Science Australia
Phone: 61 8 8303 8880
Alt Phone: 61 8 8303 8800
Fax: 61 8 8303 8899
Email: Michael.Fenech@csiro.au

EDITOR'S CHOICE

- Dr Michael Fenech: keeping our genes healthy
- The genome health and nutrigenomics project
- Welcome to the world of personalised nutrition (Media release 9 Dec 05)

# Query modeling

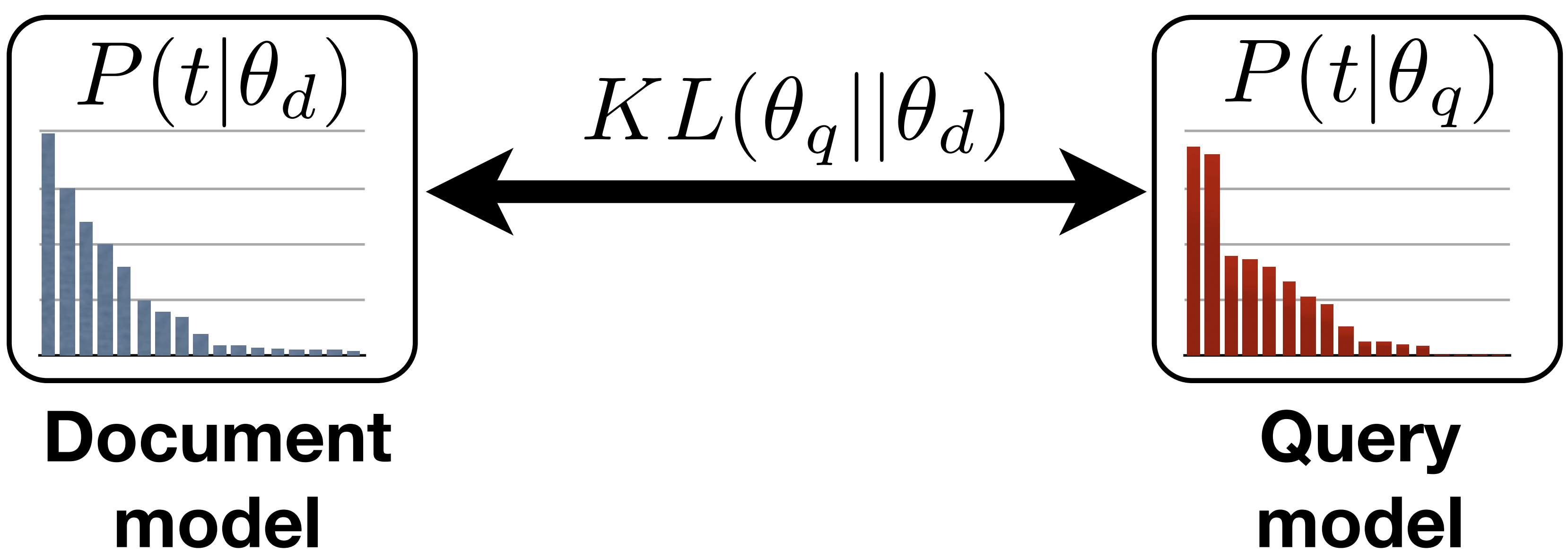
- Aims
  - Expand the original query with additional terms
  - Assign the probability mass non-uniformly

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

$$\log P(d|q) \propto \log P(d) + \sum_{t \in q} \overbrace{P(t|\theta_q)}^{\text{Query model}} \log P(t|\theta_d)$$

# Retrieval model

- Maximizing the query log-likelihood provides the same ranking as minimising KL-divergence
  - Assuming uniform document priors



# Estimating the query model

- Baseline maximum-likelihood

$$P(t|\theta_q) = P(t|q) = \frac{n(t,q)}{|q|}$$

- Query expansion using relevance models **[Lavrenko & Croft, SIGIR'01]**

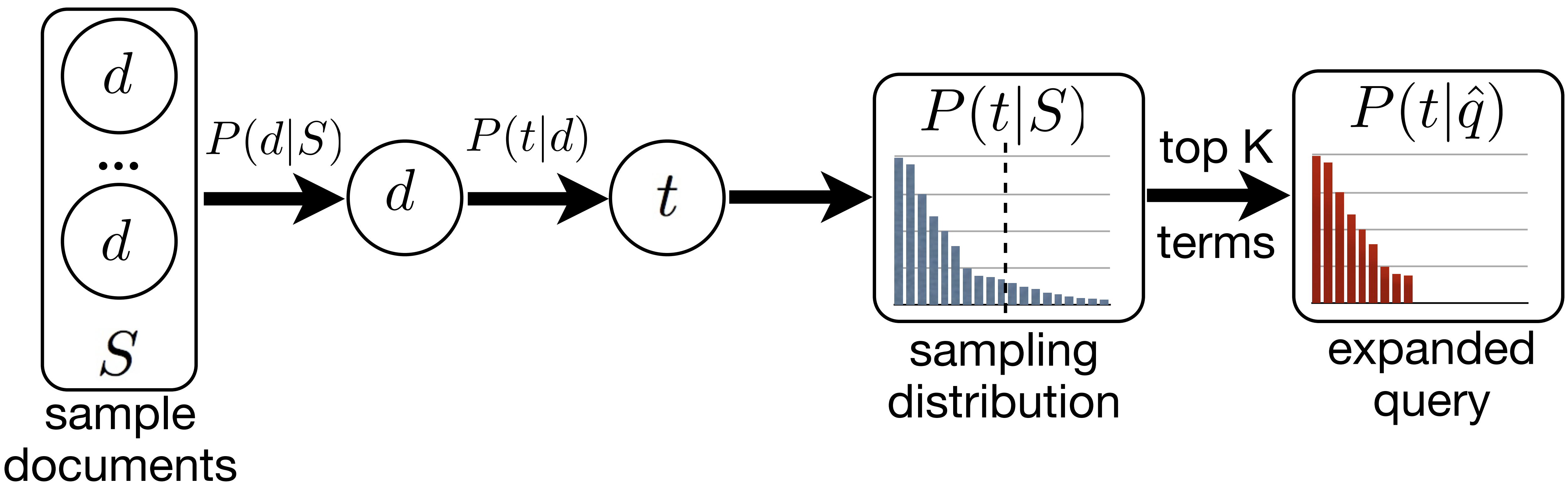
$$P(t|\theta_q) = (1-\lambda)\underbrace{P(t|\hat{q})}_{} + \lambda P(t|q)$$

**Expanded query model**
Based on term co-occurrence statistics

$$P(t|\hat{q}) \approx \frac{P(t, q_1, \ldots, q_k)}{\sum_{t'} P(t', q_1, \ldots, q_k)}$$

# Sampling from examples

[Balog et al., SIGIR'08]




$$P(t|S) = \sum_{d \in S} \underbrace{P(t|d)}_{\text{Term importance}} \underbrace{P(d|S)}_{\text{Document importance}}$$

$$P(t|\hat{q}) = \frac{P(t|S)}{\sum_{t' \in K} P(t'|S)}$$

# Sampling from examples

## Importance of a sample document

- Uniform $P(d|S) = 1/|S|$
  - All sample document are equally important
- Query-biased $P(d|S) \propto P(d|q)$
  - Proportional to the document's relevance to the (original) query
- Inverse query-biased $P(d|S) \propto 1 - P(d|q)$
  - Reward documents that bring in new aspects (not covered by the original query)

# Sampling from examples

## Estimating term importance

- Maximum-likelihood estimate

$$P(t|d) = \frac{n(t,d)}{|d|}$$

- Smoothed estimate

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

- Ranking function by **[Ponte, 2000]**

$$P(t|d) = s(t)/\sum_{t'} s(t') \qquad s(t) = \log \frac{P(t|d)}{P(t|C)}$$

# Use case

## Entity retrieval in Wikipedia (INEX 2007-09)

- Given a query, return a ranked list of entities
  - Entities are represented by their Wikipedia page
- Entity search
  - Topic definition includes target categories
- List search
  - Topic definition includes example entities

# *Titanic* (1997 film)

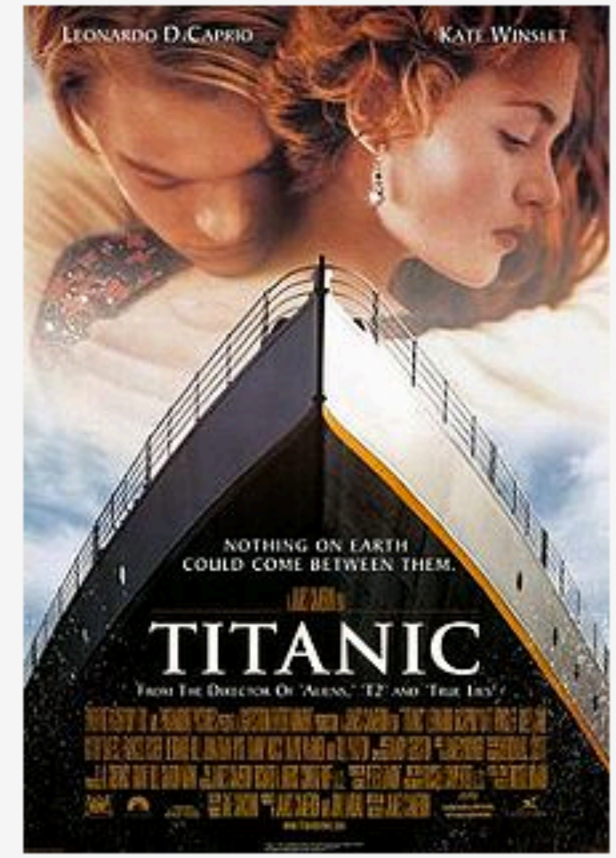
From Wikipedia, the free encyclopedia

***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

# Example query

```xml
<title>Movies with eight or more Academy Awards</title>
<categories>
     <category id="45168">best picture oscar</category>
     <category id="14316">british films</category>
     <category id="2534">american films</category>
</categories>
```

# Using categories for retrieval

- As a separate document field
- Filtering
- Similarity between target and entity categories
  - Set similarity metrics
  - Content-based (concatenating category contents)
  - Lexical similarity of category names

# Also related to categories

- Category expansion
  - Based on category structure
  - Using lexical similarity of category names
  - Ontology-base expansion
- Generalisation
  - Automatic category assignment

# Modeling terms and categories

[Balog et al., TOIS'11]

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

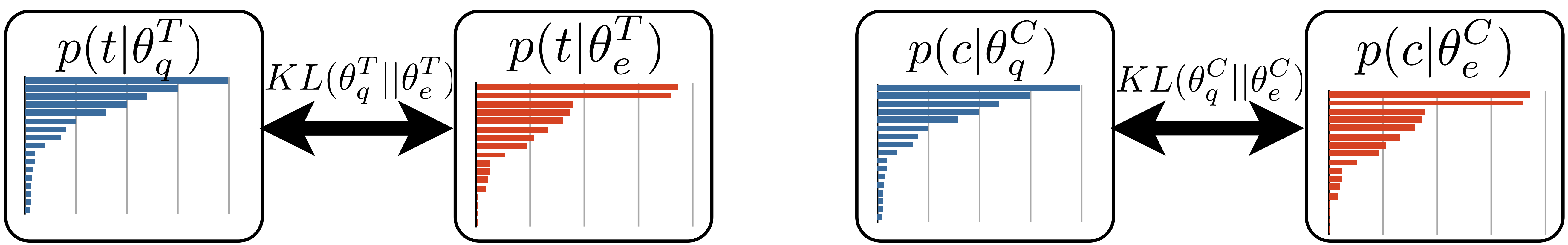
$$P(q|e) = (1-\lambda)P(\theta_q^T|\theta_e^T) + \lambda P(\theta_q^C|\theta_e^C)$$

**Term-based representation**

Query model | Entity model

**Category-based representation**

Query model | Entity model



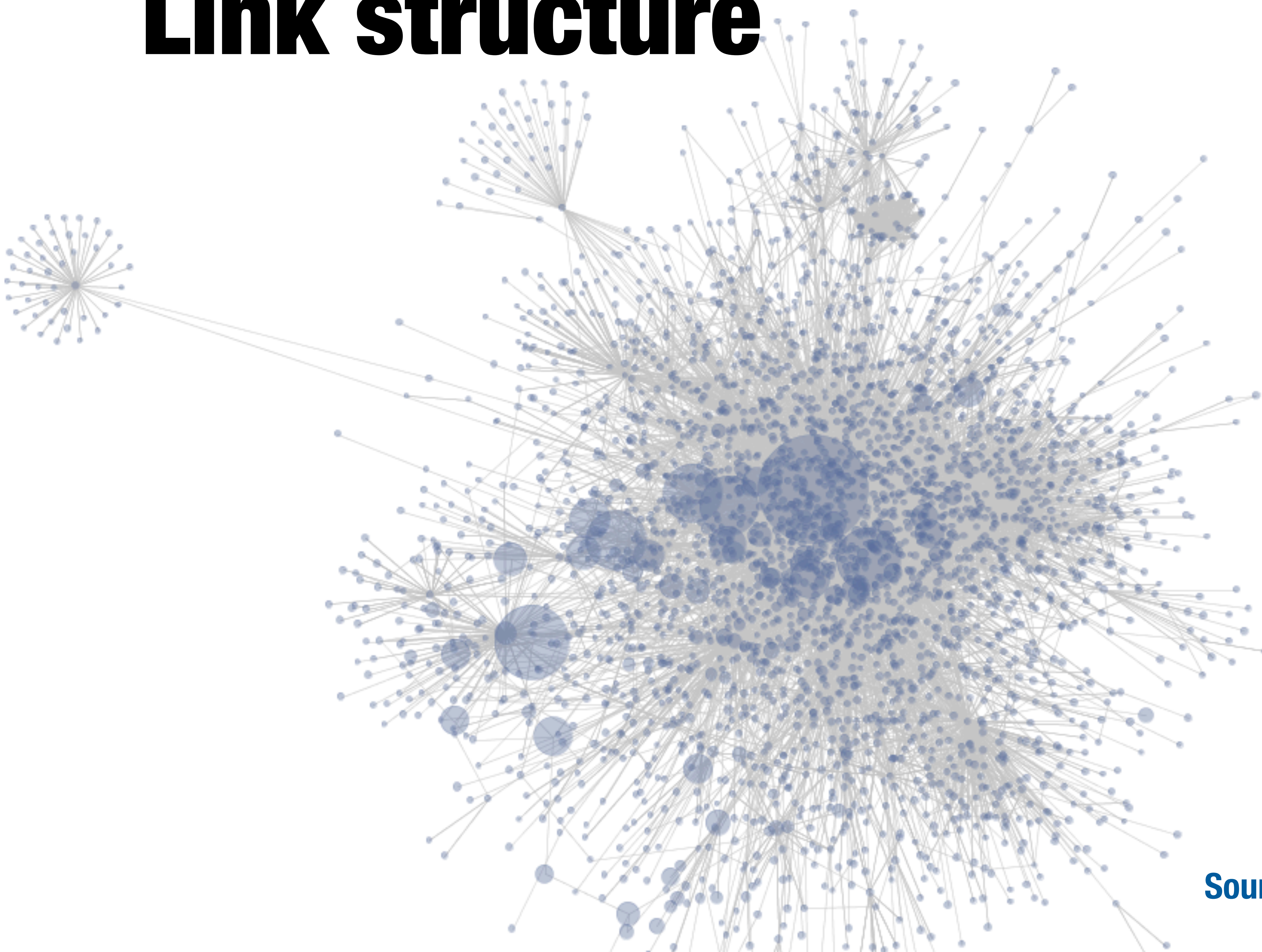
# Part 3

Contextual structures

# Other types of structure

- Link structure
- Linguistic structure
- Social structures

# Link structure



Source: Wikipedia

# Link structure

- Aim
  - High number of inlinks from pages relevant to the topic and not many incoming links from other pages
- Retrieve an initial set of documents, then rerank

$$P(d|q) \propto P(q|d)\underbrace{P(d)}$$

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

# Document link degree

[Kamps & Koolen, ECIR'08]

**Local indegree**
Number of incoming links from within the top ranked documents retrieved for *q*

$$P(d) \propto 1 + \frac{\overbrace{I_{local}(d)}}{1 + \underbrace{I_{global}(d)}}$$

**Global indegree**
Number of incoming links from the entire collection

# Relevance propagation

[Tsikrika et al., INEX'06]

- Model a user (random surfer) that after seeing the initial set of results
  - Selects one document and reads its description
  - Follows links connecting entities and reads the descriptions of related entities
  - Repeats it *N* times

$$P_0(d) = P(q|d)$$

$$P_i(d) = \underbrace{P(q|d)}_{\text{The probability of staying at the node equals to its relevance to the query}} P_{i-1}(d) + \sum_{\underbrace{d' \to d}_{\text{Outgoing links from } d' \text{ to } d}} (1 - P(q|d')) \underbrace{P(d'|d)}_{\text{Transition probabilities set to uniform}} P_{i-1}(d')$$

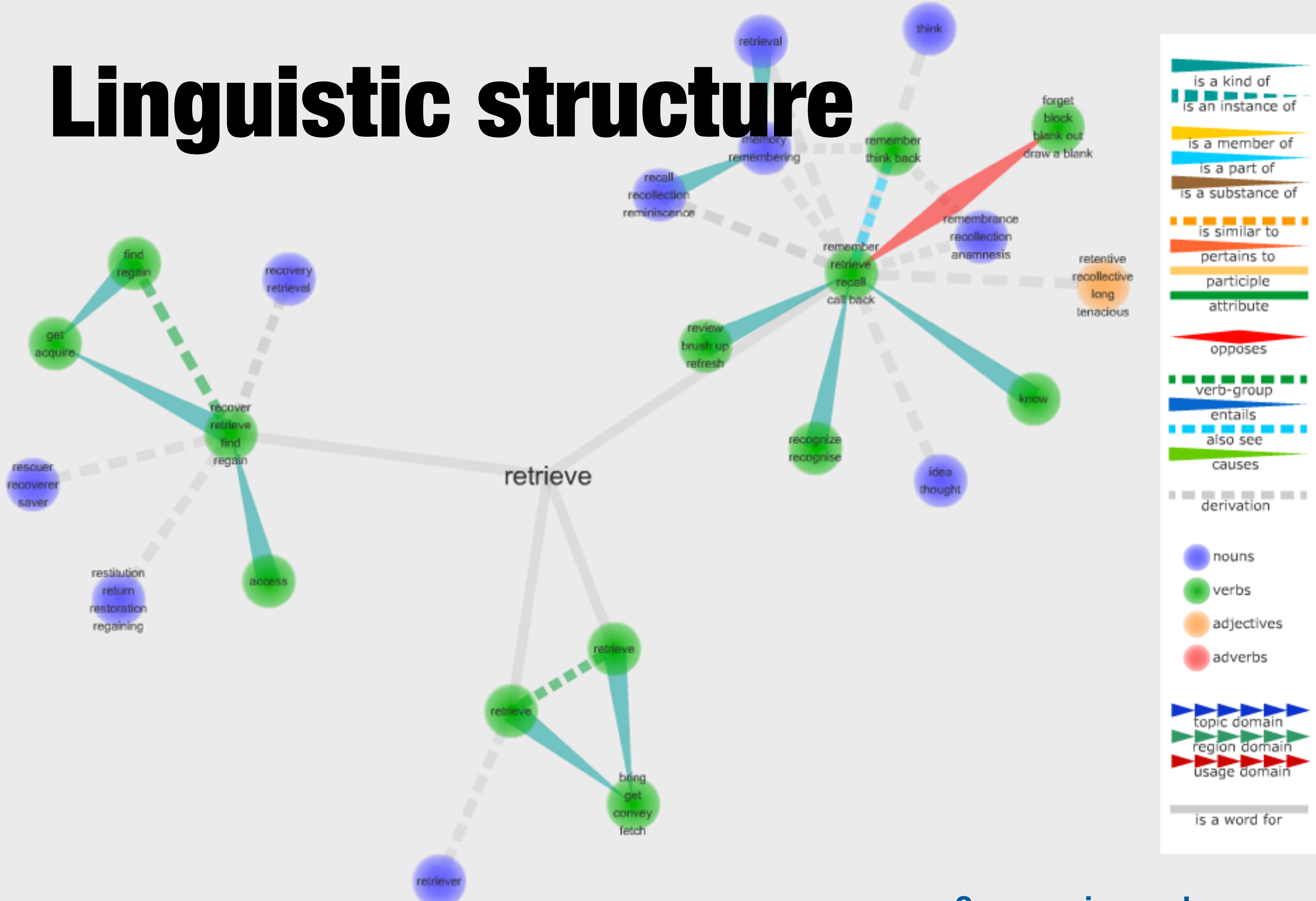
# Relevance propagation

**[Tsikrika et al., INEX'06]**

- Weighted sum of probabilities at different steps

$$P(d) \propto \mu_0 P_0(d) + (1 - \mu_0) \sum_{i=1}^{N} \mu_i P_i(d)$$

# Linguistic structure




Source: wisuwords.com

# Translation Model

**[Berger & Lafferty, SIGIR'99]**

$$P(q|d) = \prod_{t \in q} \Big( \sum_{w \in V} \underbrace{P(t|w)}_{} P(w|\theta_d) \Big)^{n(t,q)}$$

**Translation model**
Probability that word *w* can
"semantically translated" to word $q_i$

- Obtaining the translation model
  - Exploiting WordNet word co-occurrences **[Cao et al., SIGIR'05]**

# Use case

## Expert finding

- Given a keyword query, return a ranked list of people who are experts on the given topic
- Content-based methods can return the most knowledgeable persons
- However, when it comes to contacting an expert, social and physical proximity matters

# Expert profile

```
<person>
  <anr>710326</anr>
  <name>Toine M. Bogers</name>
  <name>Toine Bogers</name>
  <name>A. M. Bogers</name>
  <job>PhD student</job>
  <faculty>Faculty of Humanities</faculty>
  <department>Department of Communication and Information Sciences</department>
  <room>Room D 348</room>
  <address>P.O. Box 90153, NL-5000 LE Tilburg, The Netherlands</address>
  <tel>+31 13 466 245</tel>
  <fax>+31 13 466 289</fax>
  <homepage>http://ilk.uvt.nl/~toine</homepage>
  <email>A.M.Bogers@uvt.nl</email>

  <publications>
    <publication arno-id="1212">
      <title>Design and Implementation of a University-wide
        Expert Search Engine</title>
      <author>R. Liebregts and T. Bogers</author>
      <year>2009</year>
      <booktitle>Proceedings of the 31st European Conference on Information
Retrieval</booktitle>
    </publication>
    [...]
  </publications>
  [...]
</person>
```

# User-oriented model for EF

[Smirnova & Balog, ECIR'11]

$$S(e|u,q) = (1-\lambda)\underbrace{K(e|u,q)}_{\text{Knowledge gain}} + \lambda\underbrace{T(e|u)}_{\text{Contact time}}$$

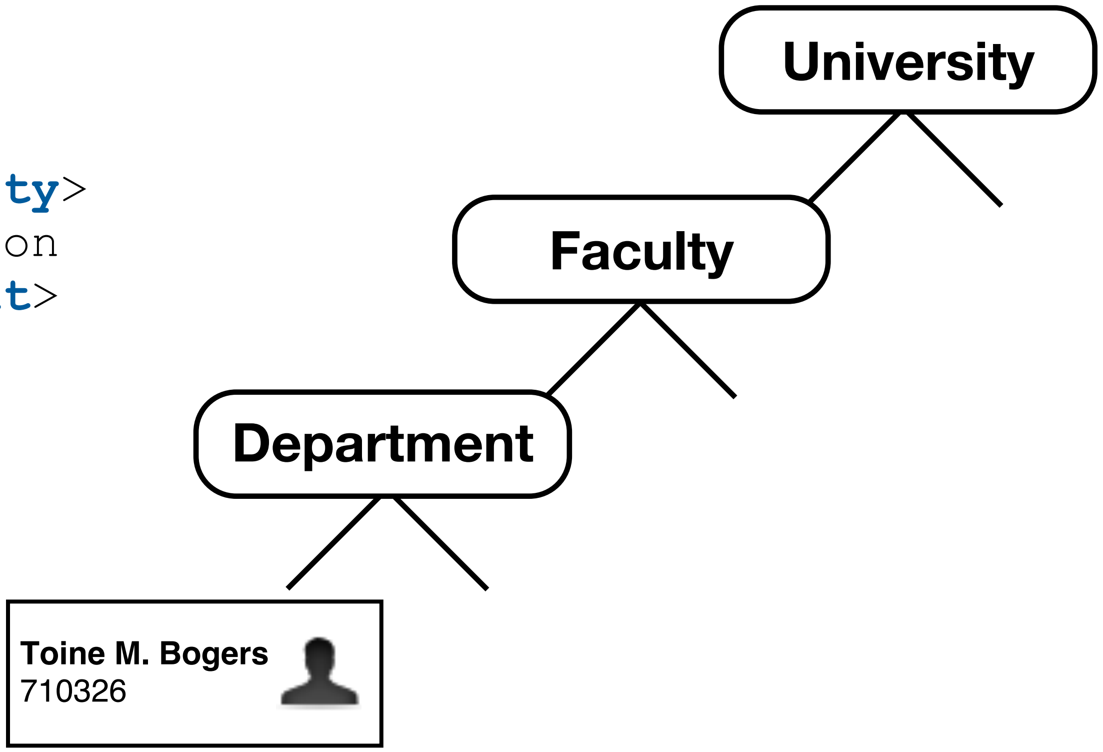
**Knowledge gain**
Difference between the knowledge of the expert and that of the user on the query topic

**Contact time**
Distance between the user and the expert in a social graph

# Social structures

## Organisational hierarchy

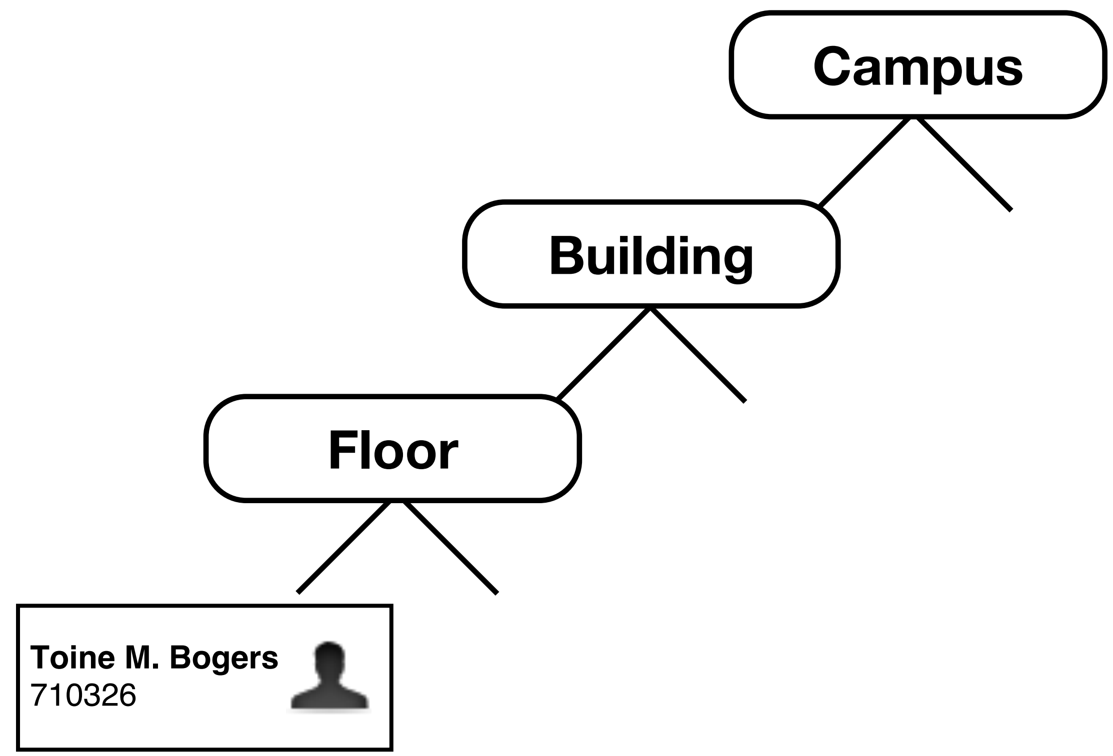
```
<person>
  <anr>710326</anr>
  <name>Toine M. Bogers</name>
  [...]
  <faculty>Faculty of Humanities</faculty>
  <department>Department of Communication
    and Information Sciences</department>
  [...]
</person>
```



# Social structures

## Geographical information

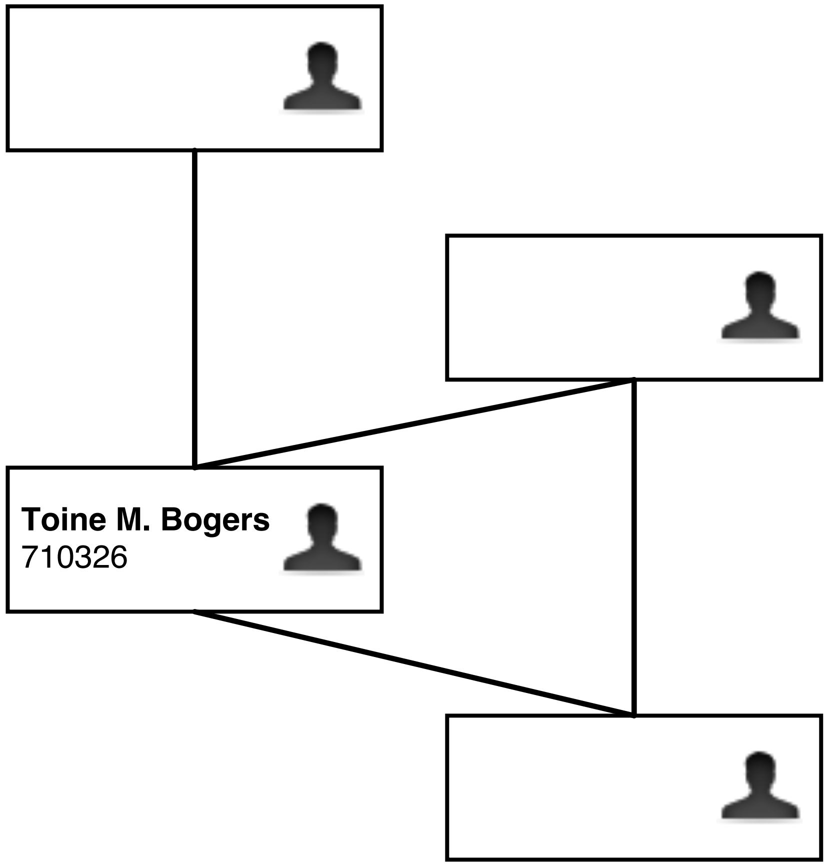
```
<person>
  <anr>710326</anr>
  <name>Toine M. Bogers</name>
  [...]
  <room>Room D 348</room>
  [...]
</person>
```

# Social structures

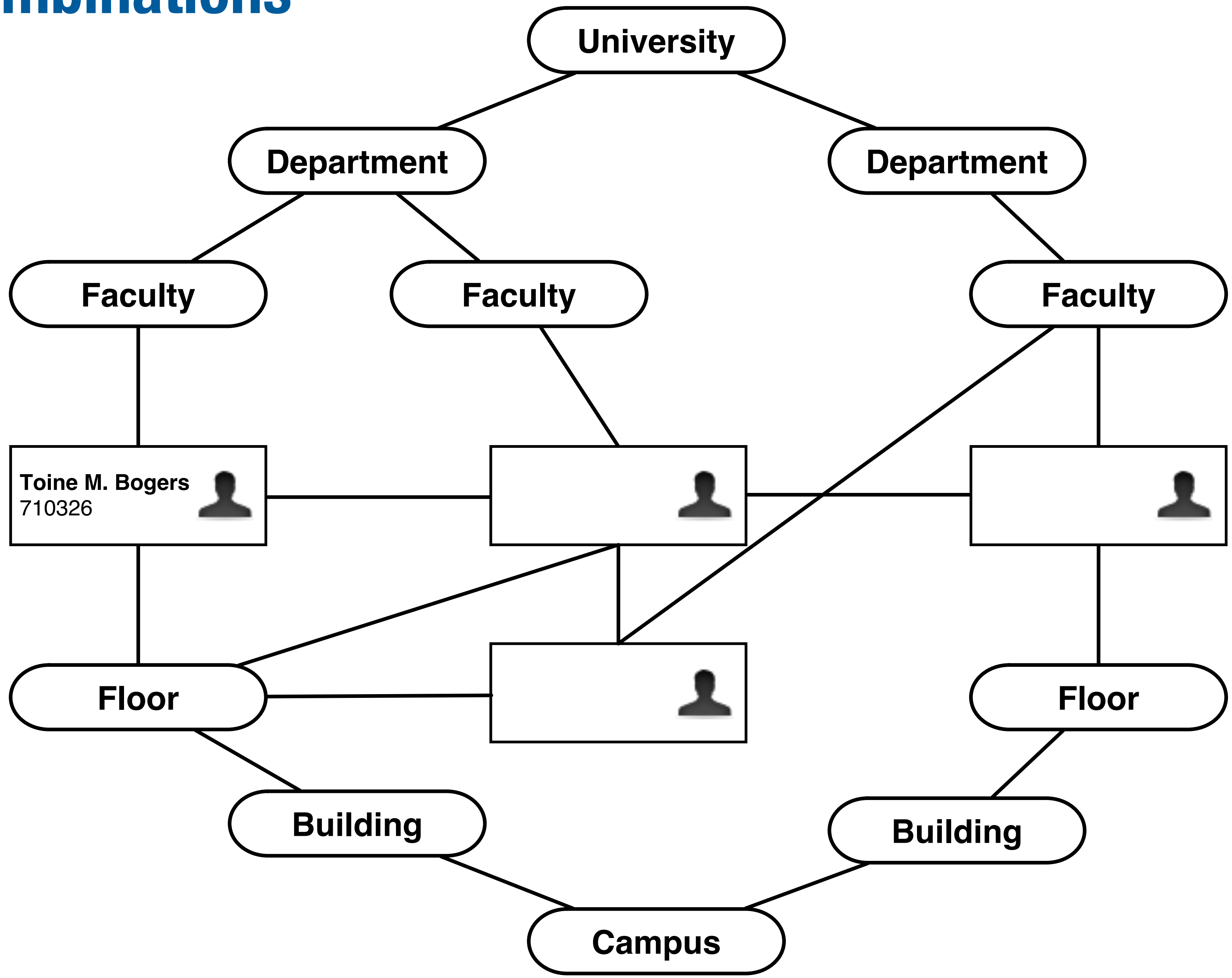
## Co-authorship


```
<person>
  <anr>710326</anr>
  <name>Toine M. Bogers</name>
  [...]
  <publications>
    <publication arno-id="1212">
      <title>
        Design and Implementation of a
        University-wide Expert Search Engine
      </title>
      <author>
        R. Liebregts and T. Bogers
      </author>
      <year>2009</year>
      <booktitle>
        Proceedings of the 31st European
        Conference on Information Retrieval
      </booktitle>
    </publication>
    [...]
  </publications>
  [...]
</person>
```

# Social structures

## Combinations



# Summary

- Different types of structure
  - Document structure
  - Query structure
  - Contextual structures
- Probabilistic IR and statistical Language Models yield a principled framework for representing and exploiting these structures

# Questions?

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