# University of Twente

### Information Retrieval Modeling

Russian Summer School in Information Retrieval



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## PART 1 the basics

### Goal

- Gain basic knowledge of IR
- Intuitive understanding of difficulty of the problem
- Insight in consequences of modeling assumptions
- biased comparison of formal models

### **Overview**

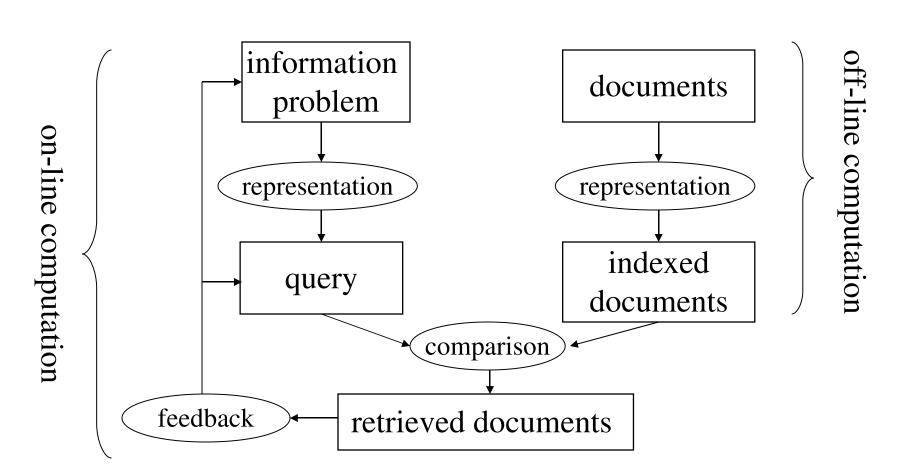
- Boolean retrieval
- 2. Vector space models
- 3. Probabilistic retrieval / Naive Bayes
- 4. Google's PageRank
- 5. The QUIZ

### **Course material**

 Djoerd Hiemstra, "Information Retrieval Models", In: Ayse Goker, John Davies, and Margaret Graham (eds.), Information Retrieval: Searching in the 21st Century, Wiley, 2009.

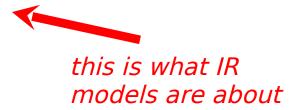


### **Information Retrieval**



- Index based on uncontrolled (free) terms (as opposed to controlled terms)
- Every word in a document is a potential index term
- Terms may be linked to specific XML elements in a text (title, abstract, preface, image caption, etc.)

- Different views on documents
  - External: data not necessarily contained in the document (metadata)
  - Logical: e.g. chapters, sections, abstract
  - Layout: e.g. two columns, A4 paper,
     Times
  - Content: the text



mostly...

- Automatic processing of natural language:
  - statistics (counting words)
  - stop list
  - morphological stemming
  - part-of-speech tagging
  - compound splitting
  - partial parsing: noun phrase extraction
  - other: use of thesaurus, named entity recognition, ...

this is what IR models are about

mostly...

- stop list
  - remove frequent words (the, and, for, etc.)
- stemmer
  - rewrite rules, rules of the thumb
  - sky skies ski skiing →ski
- compound words
  - word contains more than one morpheme
  - Fietsbandventiel  $\rightarrow$  fiets, band, ventiel
- phrases
  - separate words not good predictors: New York

### Being an IR model

apply big billi bodi boston brought creat decid docum dump electron employe format good govern hope industri join king live lot massachusett microsoft offic open parti peopl problem recognit revolut sauc save softwar standard state tea thumb worri

#### **Massachusetts dumps Microsoft Office**

**Massachusetts** The people who brought you the Boston tea party, have joined in another revolution against good King Billy's Office software. The state government has decided that all electronic documents saved and created by state employees have to use open formats.

Microsoft is clearly worried. A lot of people live in Massachusetts and that is a big thumbs up for open sauce. However, it is hoping to get around the problem by applying recognition from an industry standards body for recognition of its own formats as open standards.

### Being an IR model

bitterli central clear cloudi cloudier coast cold dai east easterli edg flurri forecast frost lead moder northeast part period persist plenti risk shower sleet snow south southern southwestern sunshin todai weather wind wintri

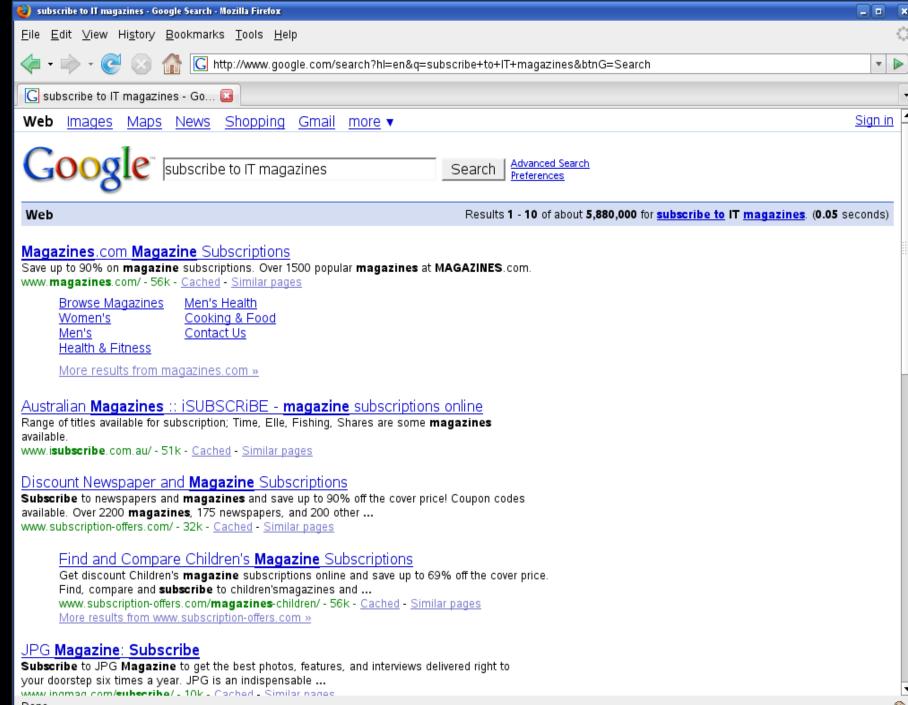
#### **Today's weather forecast**

Clear periods leading to a moderate frost in many parts away from the east coast. The northeast will be cloudier, as will the far south, here the risk of a few snow flurries. The bitterly cold easterly wind persisting.

Plenty of sunshine around, but rather cloudy in northeast, here some wintry showers. The south also rather cloudy, perhaps sleet or snow edging into southwestern and central southern parts later in day.

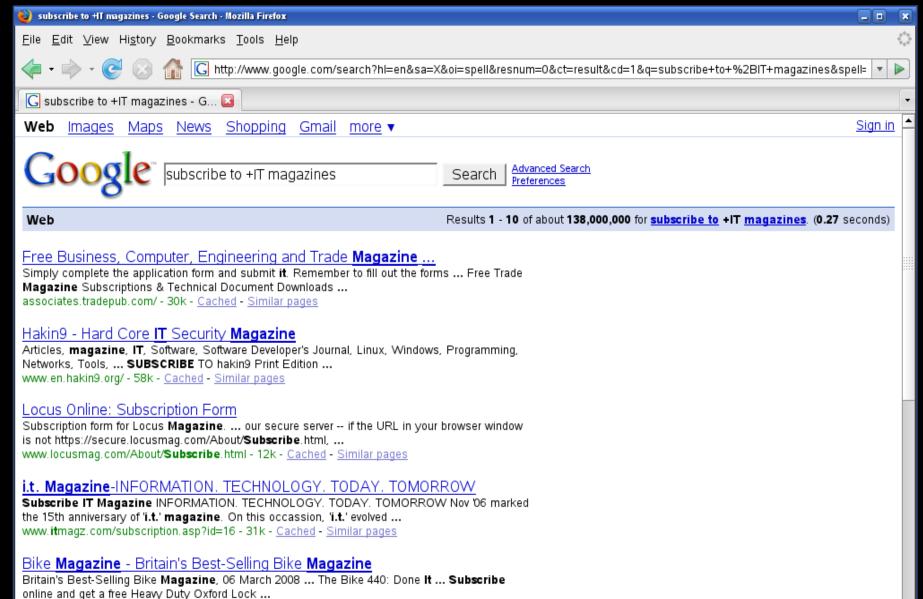
- Advantages:
  - fully automatic indexing (saves time and money)
  - less standardisation (tailored to variation in information need of different users)
  - can still be combined (?) with aspects of controlled approach (thesaurus, metadata)

- Main disadvantage: the (professional) user looses his/her control over the system...
  - because of 'ranking' instead of 'exact matching', the user does not *understand* why the system does what it does
  - assumptions of stop lists, stemmers, etc. do not hold universally:
    - e.g. the query "last will": are "last" or "will" stop words? should it retrieve "last would"?



Done

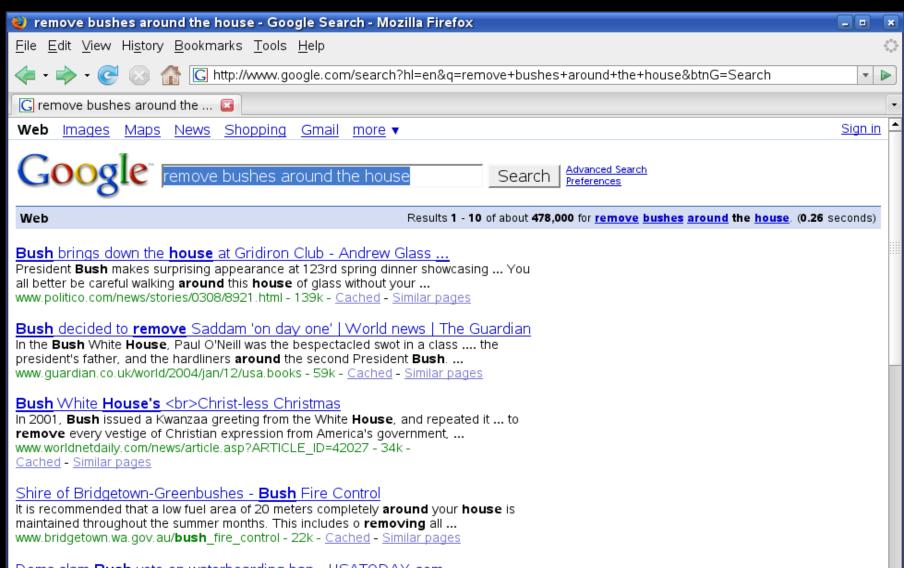
4



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To subscribe to Manufacturing & Logistics IT Magazine, simply complete the form below. We can only send copies of the magazine to people who have completed ... www.logisticsit.com/subscribe.aspx - 42k - Cached - Similar pages



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**Bush** said such tactics have helped foil terrorist plots. His critics likened some methods to torture and said they sullied America's reputation **around** the ... www.usatoday.com/news/washington/2008-03-08-**bush**address\_N.htm - 54k - Cached - Similar pages

#### Doctors remove 5 polyps from Bush's colon - CNN.com

http://www.politico.com/news/stories/0308/8921.html



#### Protect yourself against home burglary

**Remove bushes** and shrubs from **around the house**, especially under windows and next to doors. Keep your yard free of overgrowth. ... www.statefarm.com/learning/be\_safe/home/burglary/burglary.asp - 18k - Cached - Similar pages

#### How To Remove Bushes | eHow.com

How to **Remove Bushes**. Removing unsightly or just unwanted shrubbery and bushes ... Dig a trench **around** the stump. Throw the soil away from the stump to show ... www.ehow.com/how 2090247 remove-bushes.html - 63k - Cached - Similar pages

#### How To Remove Shrubbery LeHow.com

This can be especially trying for new homeowners of an older **house**: You love ... How to **Remove Bushes** By: eHow Home & Garden Editor Rating: N/A Category: ... www.ehow.com/how 2192674 remove-old-shrubbery.html - 65k - Cached - Similar pages

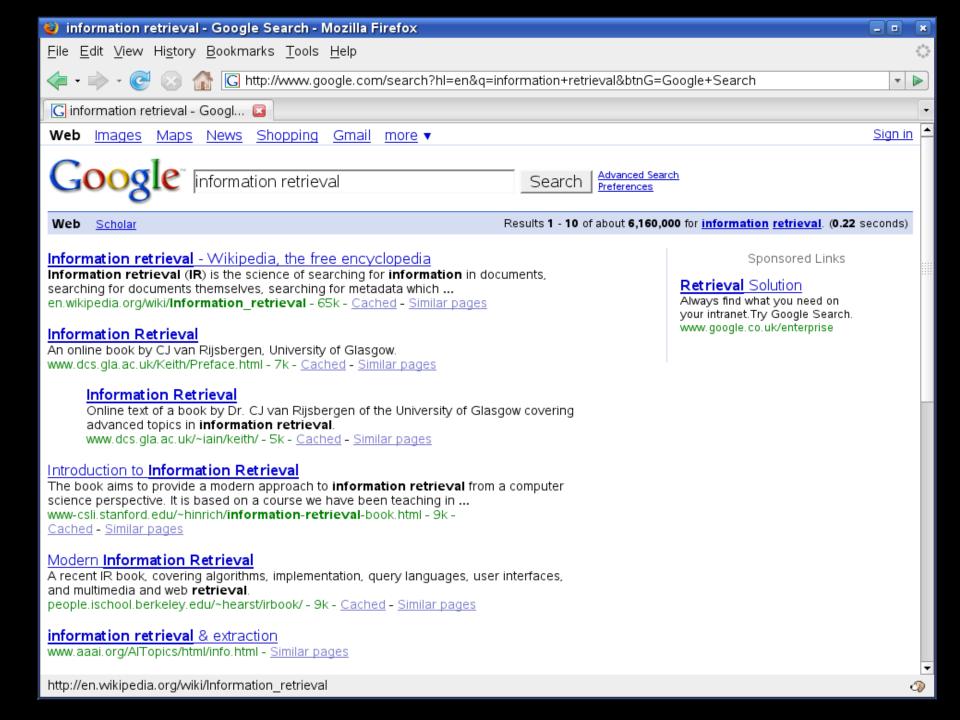
#### Home Safety

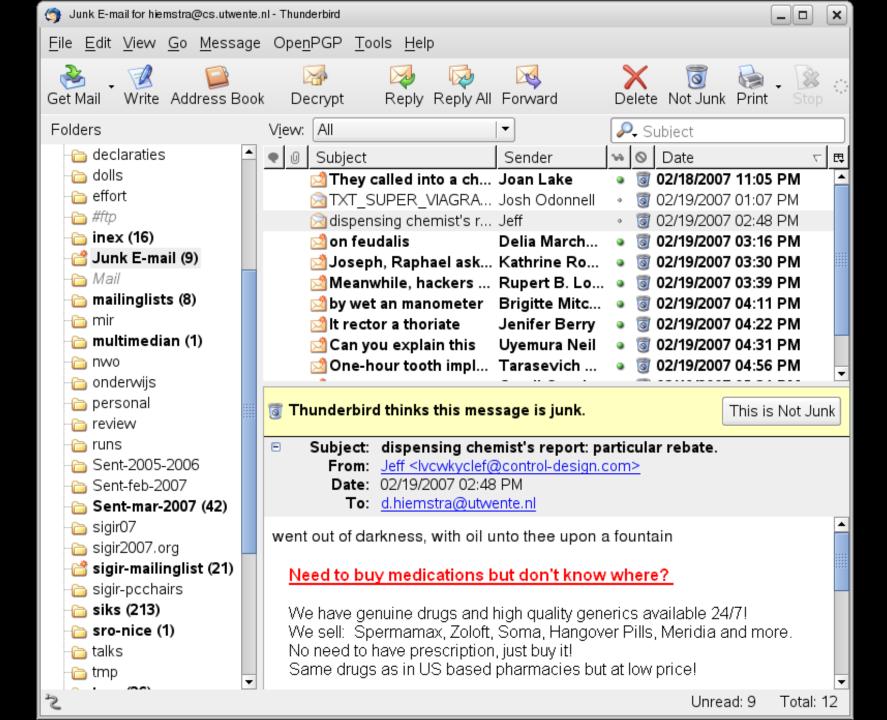
**Remove bushes** and shrubs from **around the house**, especially under windows and next to doors. Install a security alarm system with a loud alarm and/or ... www.adasheriff.org/Safety/houseRob.asp - 17k - Cached - Similar pages

#### Home Security - Safeguard Your Yard

Done







### **Models of information retrieval**

- A model:
  - abstracts away from the real world
  - uses a branch of mathematics
  - possibly: uses a metaphor for searching



### Short history of IR modelling

Boolean model (±1950)

Document similarity (±1957)

Vector space model (±1970)

Probabilistic retrieval (±1976)

• Language models (±1998)

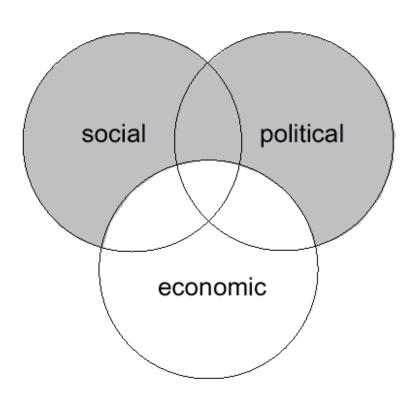
Google PageRank (±1998)

### The Boolean model (±1950)

- Exact matching: data retrieval (instead of information retrieval)
  - A term "specifies" a set of documents
  - Boolean logic to combine terms / document sets
  - AND, OR and NOT: intersection, union, and difference

### The Boolean model (±1950)

Venn diagrams



(social OR political)
NOT economic



## Statistical similarity between documents (±1957)

The principle of <u>similarity</u>

"The more two representations agree in given elements and their distribution, the higher would be the probability of their representing similar information"

(Luhn 1957)

## Statistical similarity between documents (±1957)

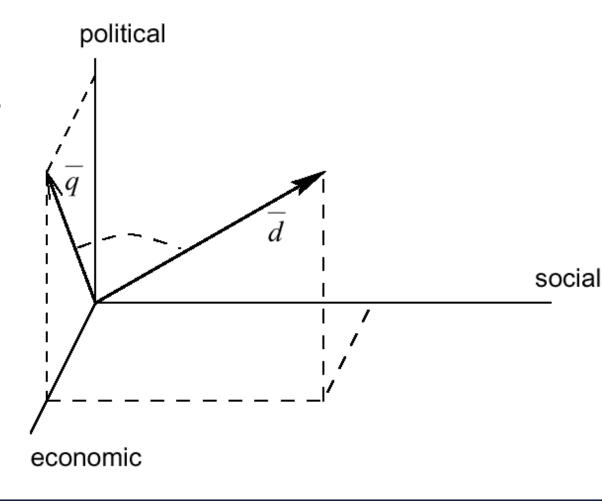
- Vector product
  - Binary components (the product measures the number of shared terms)
  - or.. Weighted components

$$score(q,d) = \sum_{k \in \text{ matching terms}} q_k \cdot d_k$$

### Intermezzo: Term weights??

- tf.idf term weighting schemes
  - a family of hundreds (thousands) of algorithms to assign weights that reflect the importance of a term in a document
  - tf = term frequency: the number of times a term occurs in a document
  - -idf = inverse document frequency: usually the logarithm of  $\frac{N}{dt}$ , where df = document frequency: the number of documents that contains the term, and N is the number of documents

- Documents and queries are vectors in a highdimensional space
- Geometric measures (distances, angles)



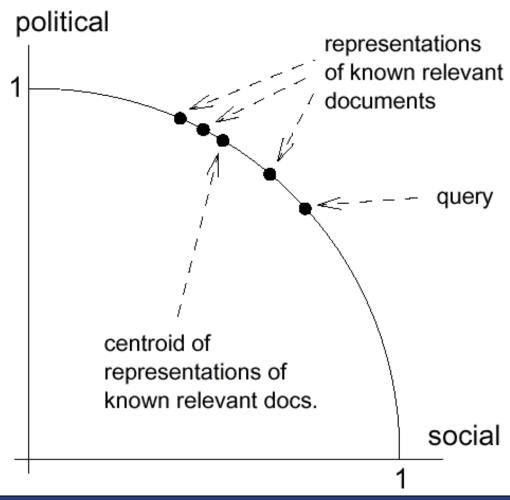
- Cosine of an angle:
  - close to 1 if angle is small
  - 0 if vectors are orthogonal

$$\cos(\vec{d}, \vec{q}) = \frac{\sum_{k=1}^{m} d_k \cdot q_k}{\sqrt{\sum_{k=1}^{m} (d_k)^2 \cdot \sum_{k=1}^{m} (q_k)^2}}$$

$$\cos(\vec{d}, \vec{q}) = \sum_{k=1}^{m} n(d_k) \cdot n(q_k), \qquad n(v_i) = \frac{v_i}{\sqrt{\sum_{k=1}^{m} (v_k)^2}}$$

- Measuring the angle is like normalising the vectors to length 1.
- Relevance feedback: move query on the sphere at length 1.

(Rocchio 1971)



- PRO: Nice metaphor, easily explained;
   Mathematically sound: geometry;
   Great for relevance feedback
- CON: Need term weighting (tf.idf);
   Hard to model structured queries
   (Salton & McGill 1983)

### **Probability ranking (±1976)**

• The probability ranking principle

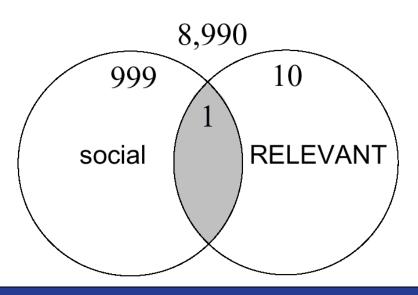
"If a reference retrieval system's response to each request is a ranking of the documents in the collections in order of decreasing probability of usefulness to the user (...) then the overall effectiveness will be the best that is obtainable on the basis of the data.

(Robertson 1977)

### Probabilistic retrieval (±1976)

 Probability of getting (retrieving) a relevant document from the set of documents indexed by "social".

(Robertson & Sparck-Jones 1976)



r = 1 (number of relevant docs containing "social")

R = 11 (number of relevant docs)

n = 1000 (number of docs containing "social")

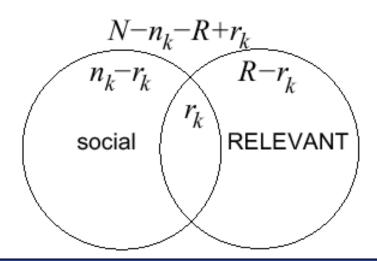
N = 10000 (total number of docs)

### Probabilistic retrieval (±1976)

- Bayes' rule
- Conditional independence

$$P(L \mid D) = \frac{P(D \mid L)P(L)}{P(D)}$$

$$P(D \mid L) = \prod_{k} P(D_{k} \mid L)$$



$$P(D_{k}=1 | L=1) = \frac{r_{k}}{R}$$

$$P(D_{k}=1 | L=0) = \frac{n_{k}-r_{k}}{N-R}$$

$$P(D_{k}=0 | L=1) = \frac{R-r_{k}}{R}$$

$$P(D_{k}=0 | L=0) = \frac{N-n_{k}-R+r_{k}}{N-R}$$

### Probabilistic retrieval (±1976)

- PRO: does not need term weighting
- CON: within document statistics (tf's) do not play a role
  - Need results from relevance feedback

### Language models (±1998)

- Let's assume we point blindly, one at a time, at 3 words in a document.
- What is the probability that I, by accident, pointed at the words "Russian", "Summer" and "School"?
- Compute the probability, and use it to rank the documents.

(Hiemstra 1998)

### Language models (±1998)

• Given a query  $T_1, T_2, ..., T_n$ , rank the documents according to the following probability measure:

$$P(T_1, T_2, ..., T_n | D) = \prod_{i=1}^{n} ((1 - \lambda_i) P(T_i) + \lambda_i P(T_i | D))$$

 Linear combination of document model and background model

 $\lambda_i$ : probability of document model

1-  $\lambda_i$ : probability of background model

 $P(T_i | D)$ : document model

 $P(T_i)$ : background model

## Language models (±1998)

- Probability theory / hidden Markov model theory
- Successfully applied to speech recognition, and:
  - optical character recognition, part-of-speech tagging, stochastic grammars, spelling correction, machine translation, etc.

# Google PageRank (±1998)

- Suppose a million monkeys browse the web by randomly following links
- At any time, what percentage of the monkeys do we expect to look at page D?
- Compute the probability, and use it to rank the documents that contain all query terms (Brin & Page 1998)

### Google PageRank (±1998)

 Given a document D, the documents page rank at step n is:

$$P_n(D) = (1 - \lambda) P_0(D) + \lambda \left( \sum_{\substack{I \text{ linking to D}}} P_{n-1}(I) P(D \mid I) \right)$$

where

 $P(D \mid I)$ : probability that the monkey reaches page D through page I = 1 / months (= 1 / months of I)

 $\lambda$ : probability that the follows a link

1- $\lambda$ : probability that the monkey types a url

- In the Boolean model: how many different sets of documents can be specified with 3 query terms?
  - a) 8
  - b) 9
  - c) 256
  - d) unlimited

- In the vector space model: Given 2 documents D1 and D2. Suppose the similarity between D1 and D2 is 0.08, what will be the similarity between D2 and D1? (i.e. if we interchange the contents of the documents)
  - a) smaller than 0.08
  - b) equal: 0.08
  - c) bigger than 0.08
  - d) it depends on the document's contents

- In the probabilistic model: suppose we query for twente, and D1 has more occurrences of twente than D2, which document will be ranked first?
  - a) D1 will be ranked before D2
  - b) D2 will be ranked before D1
  - c) it depends on the model's implementation
  - d) it depends on the lengths of D1 and D2

- In the language model: let's assume document D consisting of 100 words in total, contains 4 times the word "IR", what is P(T="IR"|D)? (ignoring the background model)
  - a) smaller than 4/100 = 0.04
  - b) equal to 4/100 = 0.04
  - c) bigger than 4/100 = 0.04
  - d) it depends of the *tf.idf* weights

- In the probabilistic model: two documents might get the same score. How many different scores do we expect to get if we enter 3 query terms?
  - a) 8
  - b) 9
  - c) 256
  - d) unlimited

- <u>tf.idf</u> weighting: suppose we add some documents to the collection. Do the weights of terms in other document change?
  - a) no
  - b) yes, it affects the tf's of other documents
  - c) yes, it affects the *idf'* s of other documents
  - d) yes, it affects the *tf'*s and the *idf'*s of other documents

- In the vector space model using tf.idf: Suppose we use the cosine similarity (or normalize vectors to unit length). Again we add documents to the collection. Do the weights of terms in other document change?
  - a) no, other documents are unaffected
  - b) yes, the same weights as in Question 8
  - c) yes, all weights in the database change
  - d) yes, more weights change, but not all

- In the language model: suppose we use a linear combination of a do-cument model and a collection model. What happens if we take  $\lambda=1$ ?
  - a) all docucments get probability > 0
  - b) documents that contain at least one query term get probability > 0
  - c) only documents that contain all query terms get probability > 0
  - d) the system returns a randomly ranked list

#### Conclusion

- Email filtering?
- Navigational Web Queries?
- Informational Queries?
- New cool idea

- Naive Bayes
- PageRank

- Language
   Models
- ?

### References

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