COEN 169

Document Prior

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Outline

Introduction to language modeling

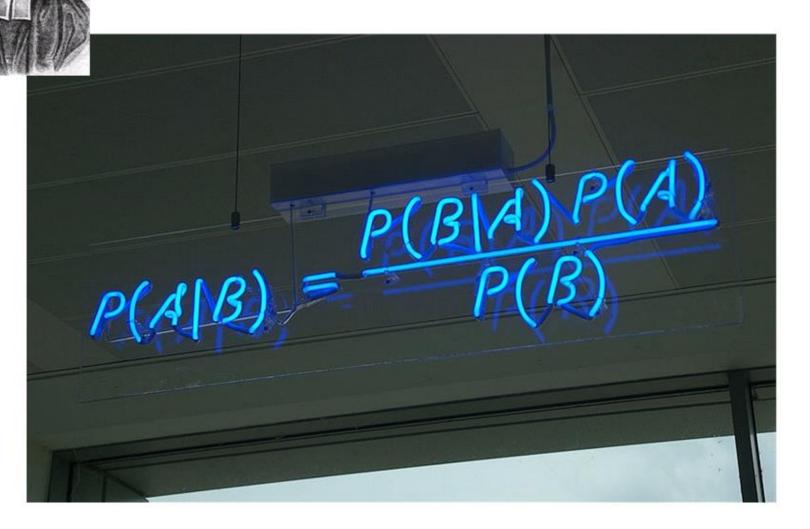
Language modeling for information retrieval

Query-likelihood Retrieval Model

Smoothing

Document priors

Bayes' Law



(source: wikipedia)

Bayes' Law Applied to Ranking

$$P(D|Q) = \frac{P(Q|D) \times P(D)}{P(Q)}$$

If we use this formula for ranking, which probability does not matter?

Query-likelihood Retrieval Model

- Dividing every document score by the same number doesn't change the ranking of documents ...
- So, we can ignore the denominator P(Q)

$$P(D|Q) = \frac{P(Q|D) \times P(D)}{P(Q)}$$

$$P(D|Q) \propto P(Q|D) \times P(D)$$

query-likelihood score (you already know this) document prior (new concept)

$$P(D|Q) \propto P(Q|D) \times P(D)$$

- The document prior, P(D), is the probability that the document is relevant to any query
- It is a document-specific probability
- It is a query-independent probability

$$P(D|Q) \propto P(Q|D) \times P(D)$$

- Unknowingly, so far we've assumed that P(D) is the same for all documents
- Under this assumption, the ranking is based only on the query-likelihood given the document language model
- Now, we will assume that P(D) is not uniform
- That is, some documents are more likely to be relevant independent of the query

$$P(D|Q) \propto P(Q|D) \times P(D)$$

- What is it?
- Anything that affects the likelihood that a document is relevant to any query
 - document popularity
 - document authority
 - amount of content (e.g., length)
 - topical cohesion
 - really, you decide ...

$$P(D|Q) \propto P(Q|D) \times P(D)$$

But, it is a probability, so in a collection of M documents...

$$\sum_{i=1}^{M} P(D_i) = ?$$

$$P(D|Q) \propto P(Q|D) \times P(D)$$

Not that difficult...

$$P(D_j) = \frac{score(D_j)}{\sum_{i=1}^{M} score(D_i)}$$

$$P(D|Q) \propto P(Q|D) \times P(D)$$

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- Given user-interaction data, we can determine the popularity of a document based on clicks
- Click-rate:

```
# of clicks on the document
```

of clicks on any document

most clicked urls - AOL query-log (2006)

rank	URL	P(URL)	rank	URL	P(URL)
I	http://www.google.com	0.0204	11	http://www.geocities.com	0.0022
2	http://www.myspace.com	0.0093	12	http://www.hotmail.com	0.0022
3	http://mail.yahoo.com	0.0090	13	http://www.ask.com	0.0021
4	http://en.wikipedia.org	0.0066	14	http://www.bizrate.com	0.0017
5	http://www.amazon.com	0.0056	15	http://www.tripadvisor.com	0.0017
6	http://www.mapquest.com	0.0054	16	http://www.msn.com	0.0017
7	http://www.imdb.com	0.0053	17	http://profile.myspace.com	0.0016
8	http://www.ebay.com	0.0044	18	http://www.craigslist.org	0.0015
9	http://www.yahoo.com	0.0030	19	http://disney.go.com	0.0015
10	http://www.bankofamerica.com	0.0027	20	http://cgi.ebay.com	0.0015

least clicked urls – AOL query-log (2006)

rank	URL	P(URL)	rank	URL	P(URL)
1501087	http://www.live4soccer.com	0.0000	1501097	http://www.toymod.com	0.0000
1501088	http://www.smalltowngallery.com	0.0000	1501098	http://www.aaabarcodes.com	0.0000
1501089	http://1239.8wmc5l.info	0.0000	1501099	http://www.stubaidirect.com	0.0000
1501090	http://silverjews.lyrics-online.net	0.0000	1501100	http://rtbknox.no-ip.biz	0.0000
1501091	http://www2.glenbrook.k12.il.us	0.0000	1501101	http://www.panontheweb.com	0.0000
1501092	http://www.palmerschools.org	0.0000	1501102	http://4395.bsxnf57.info	0.0000
1501093	1093 http:// www.rainbowridgefarmequestriancenter.com	0.0000	1501103	http://www.calco.com	0.0000
1501094	http://mncable.net	0.0000	1501104	http://www.sharpe.freshair.org	0.0000
1501095	http://www.modem-software.com	0.0000	1501105	http://www.opium.co.za	0.0000
1501096	http://www.clevelandrugby.com	0.0000	1501106	http://grediagnostic.ets.org	0.0000

http://www.scu.edu/

http://www.scu.edu/scunews/scutoday/news-views.cfm?c=13215

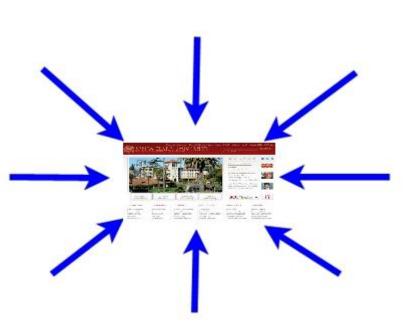




- URL depth
 - website entry-pages tend to be more popular than those that are deep within the domain
- Count the number of "/" in the URL

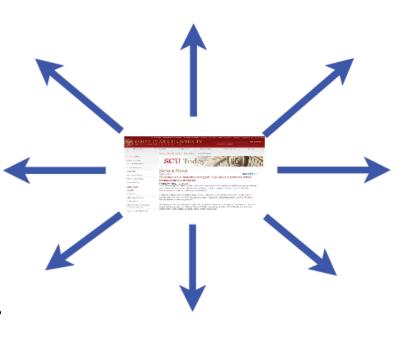
Document Authority

- Number of "endorsements"
- scientific search:number of citations in other papers
- web search: number of incoming hyperlinks
- blog search: number user-generated comments
- twitter search: number of followers
- review search:
 number of times someone found the review useful



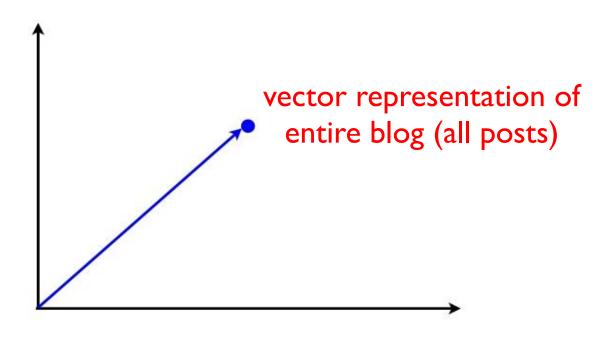
Document Authority

- "HUB" score
 - scientific search: number citations of other papers
 - web search: number of outgoing hyperlinks
 - blog search: number of links to other bloggers
 - twitter search: number of people followed by author
 - review search: number of reviews written by the reviewer

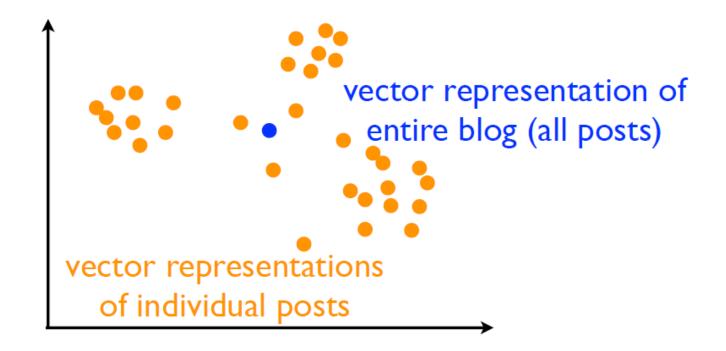


- Example: blog retrieval
- Objective: favor blogs that focus on a coherent, recurring topic
- How might we do this? (HINT: vector space model)

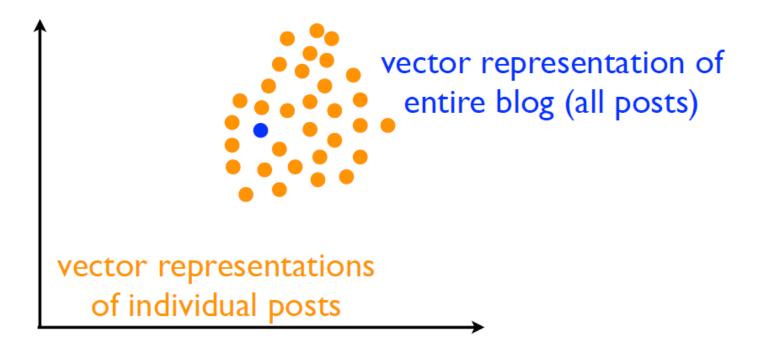
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- Compute average cosine similarity between the posts and the entire blog



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$$P(D|Q) \propto P(Q|D) \times P(D)$$

- What is it?
- Anything you want.
 - document popularity
 - document authority
 - amount of content (e.g., length)
 - topical focus
 - really, you decide

Remember Smoothing?

- When estimating probabilities, we tend to ...
 - Over-estimate the probability of observed outcomes
 - Under-estimate the probability of unobserved outcomes
- The goal of smoothing is to ...
 - Decrease the probability of observed outcomes
 - Increase the probability of unobserved outcomes
- Smoothing P(D) is very important!

Example: Click-Rate

of click
$$P(D|Q) \propto P(Q|D) \times P(D)$$

of clicks on the document # of clicks on any document

- Do we really want to always give documents that have never been clicked a score of zero?
- How could we smooth this probability?

Example: Click-Rate

$$P(D|Q) \propto P(Q|D) \times P(D)$$

of clicks on the document # of clicks on any document

- Do we really want to always give documents that have never been clicked a score of zero?
- Add-one smoothing!

(# of clicks on the document) + I

(# of clicks on any document) + (# of documents)

Review

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Smoothing

Priors