Document Priors

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Outline

Introduction to language modeling

Language modeling for information retrieval

Query-likelihood Retrieval Model

Smoothing

Priors

Linear Interpolation

Review

$$score(Q, D) = \prod_{i=1}^{n} (\lambda P(q_i|D) + (1 - \lambda) P(q_i|C))$$

- $P(q_i|D)$ = probability given to query term q_i by the document language model
- $P(q_i|C)$ = probability given to query term q_i by the collection language model

Linearly Interpolated Smoothing

Review

- Doc 1: haikus are easy
- Doc 2: but sometimes they don't make sense
- Doc 3: refrigerator
- Query: haikus make sense

$$score(Q, D) = \prod_{i=1}^{n} (\lambda P(q_i|D) + (1 - \lambda)P(q_i|C))$$

(source: threadless t-shirt)

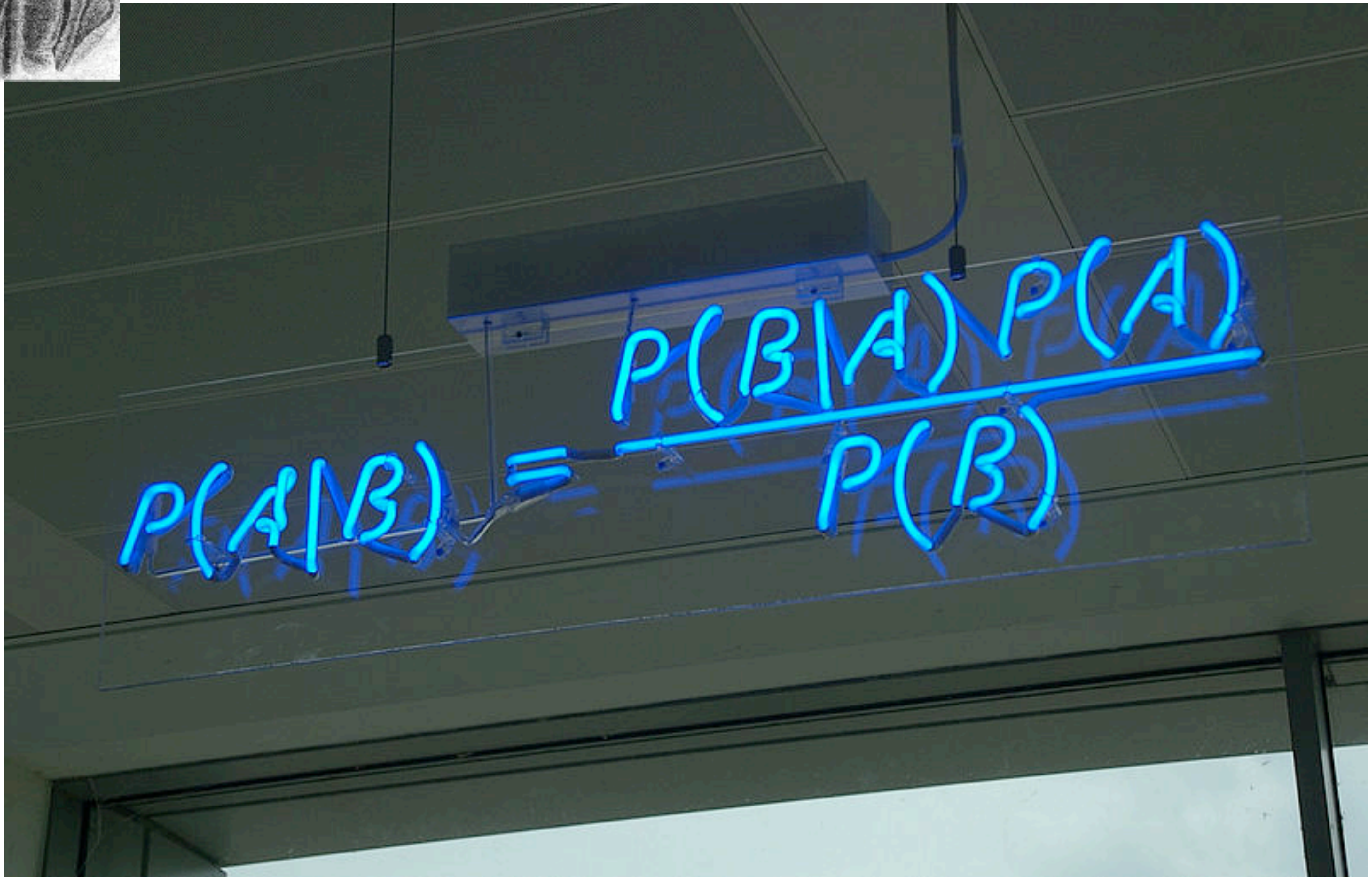
Let’s Take A Step Back

- The query likelihood model has a more theoretic motivation than I’ve portrayed so far

Bayes' Law

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)}$$

Bayes' Law



(source: wikipedia)

Bayes' Law Derivation

$$P(A,B) = P(A|B) \times P(B)$$

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$$P(A,B) = P(A,B)$$

$$P(A|B) \times P(B) = P(B|A) \times P(A)$$

$$\boxed{P(A|B) = \frac{P(B|A) \times P(A)}{P(B)}}$$

Bayes' Law Applied to Ranking

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

Bayes' Law Applied to Ranking

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

If we're scoring and ranking documents based on this formula, which number doesn't 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)

Document Prior

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

query-likelihood score
(you already know this)

document prior
(new concept)

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

Document Prior

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

query-likelihood score
(you already know this)

document prior
(this is a new concept)

- 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 <u>independent of the query</u>

Document Prior

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

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

Document Prior

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

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

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


THE
BEATLES
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Document Prior

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

- Not that difficult...

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

Document Prior

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Document Popularity

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

$$\frac{\text{\# of clicks on the document}}{\text{\# of clicks on any document}}$$

Document Popularity
most clicked urls - aol query-log (2006)

rank	URL	P(URL)	rank	URL	P(URL)
1	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

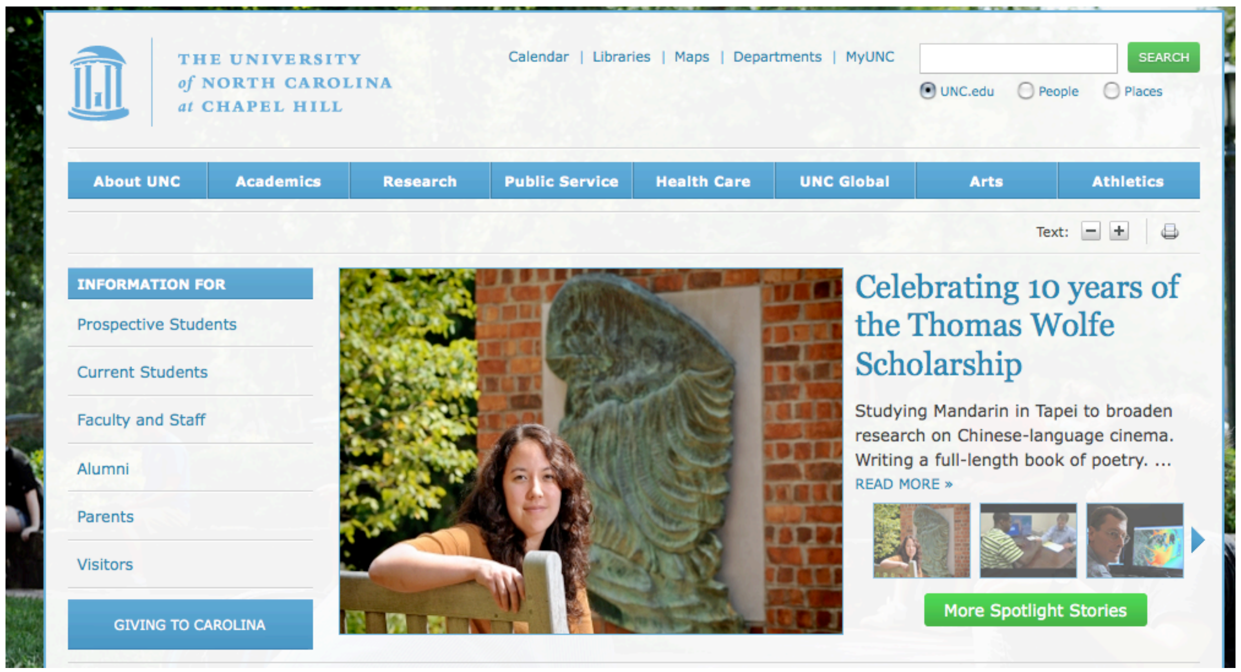
Document Popularity
least clicked urls - aol query-log (2006)

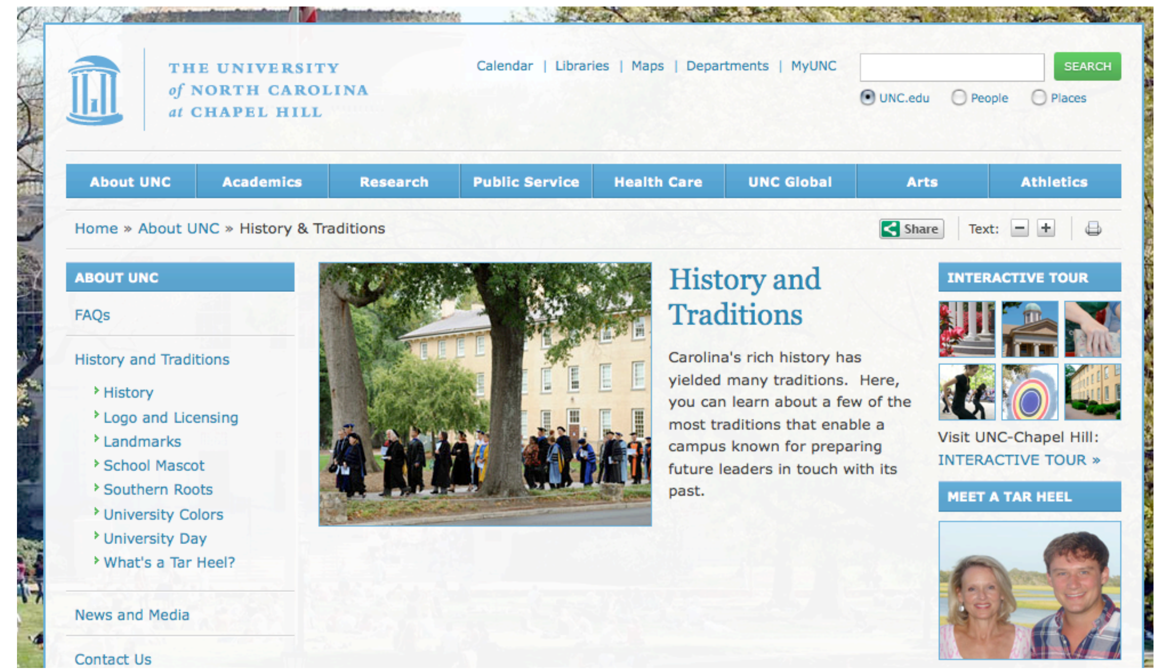
rank	URL	P(URL)	rank	URL	P(URL)
1501087	http://www.live4soccer.com	0.0000	1501097	http://www.toymod.com	0.0000
1501088	http://www.smalltowngallery.com	0.0000	1501098	http://www.aaabarcodes.com	0.0000
1501089	http://1239.8wmc5l.info	0.0000	1501099	http://www.stubaidirect.com	0.0000
1501090	http://silverjews.lyrics-online.net	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	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

Document Popularity

http://www.unc.edu

http://www.unc.edu/about/history-traditions

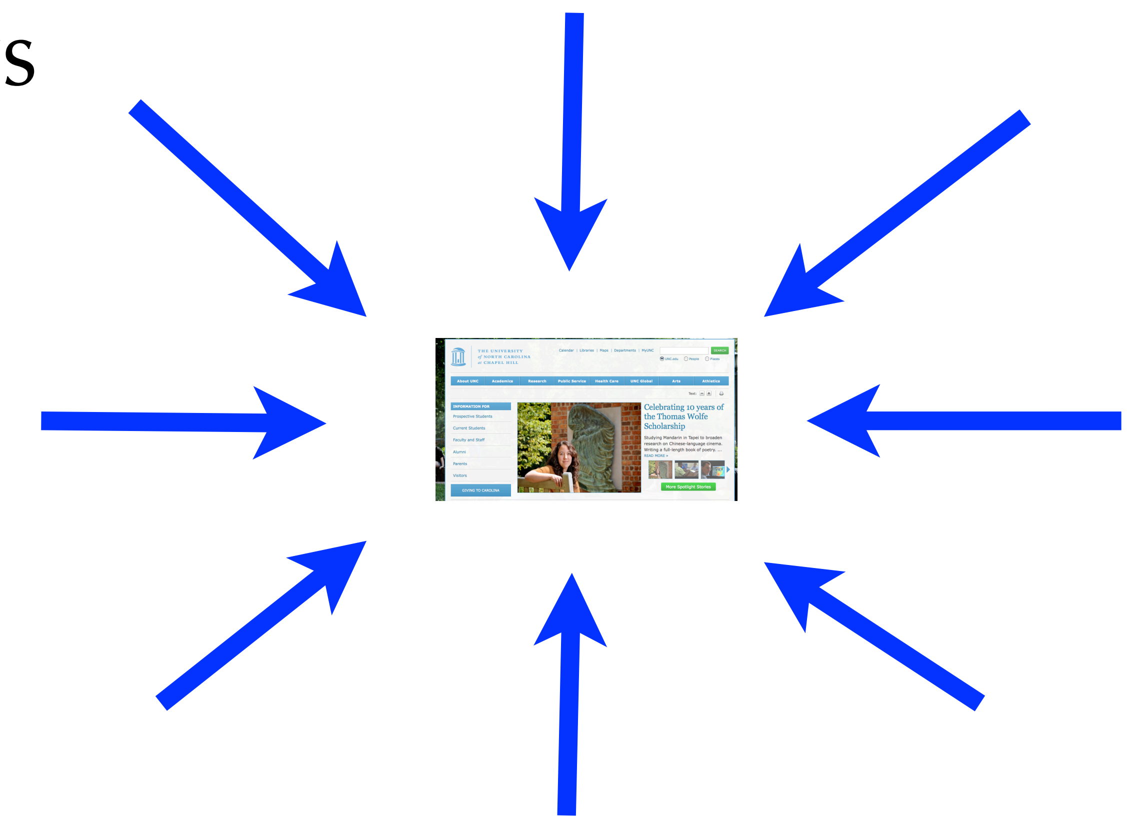




- URL depth
  - website entry-pages tend to be more popular than those that are deep within the domain
- Count the number of "/" in the URL

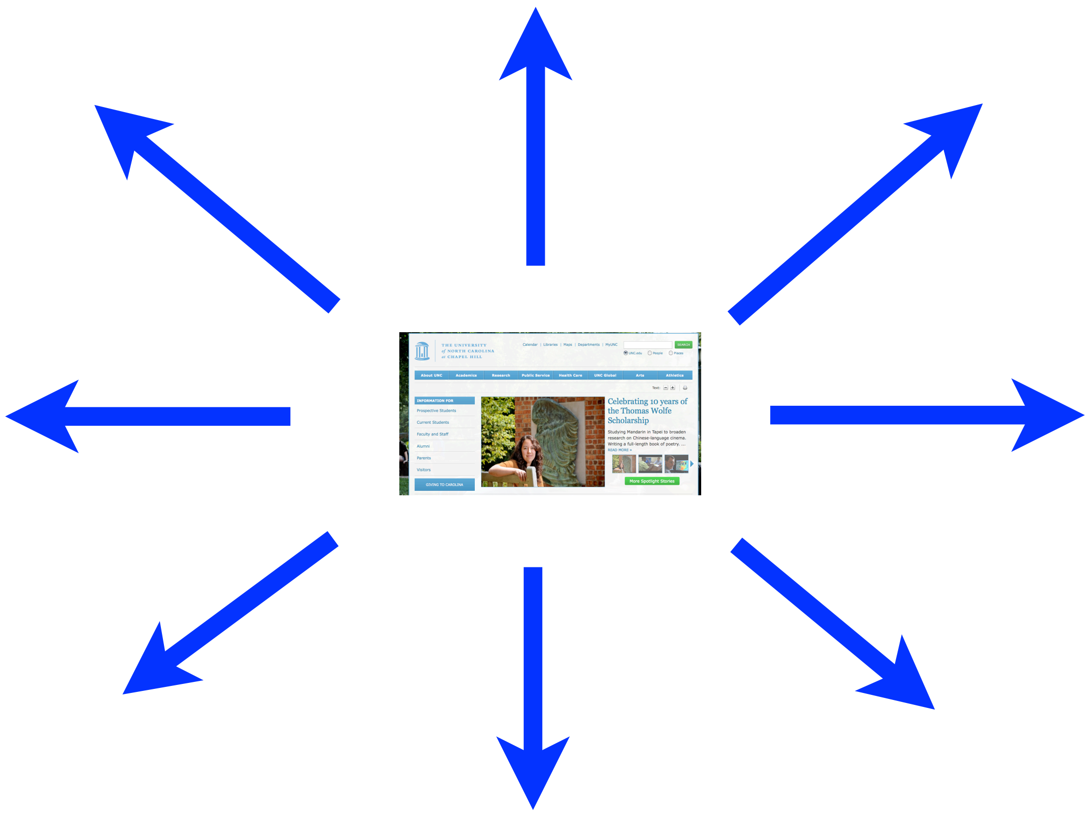
Document Authority

- 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 <u>other</u> 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



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Topical Focus

- 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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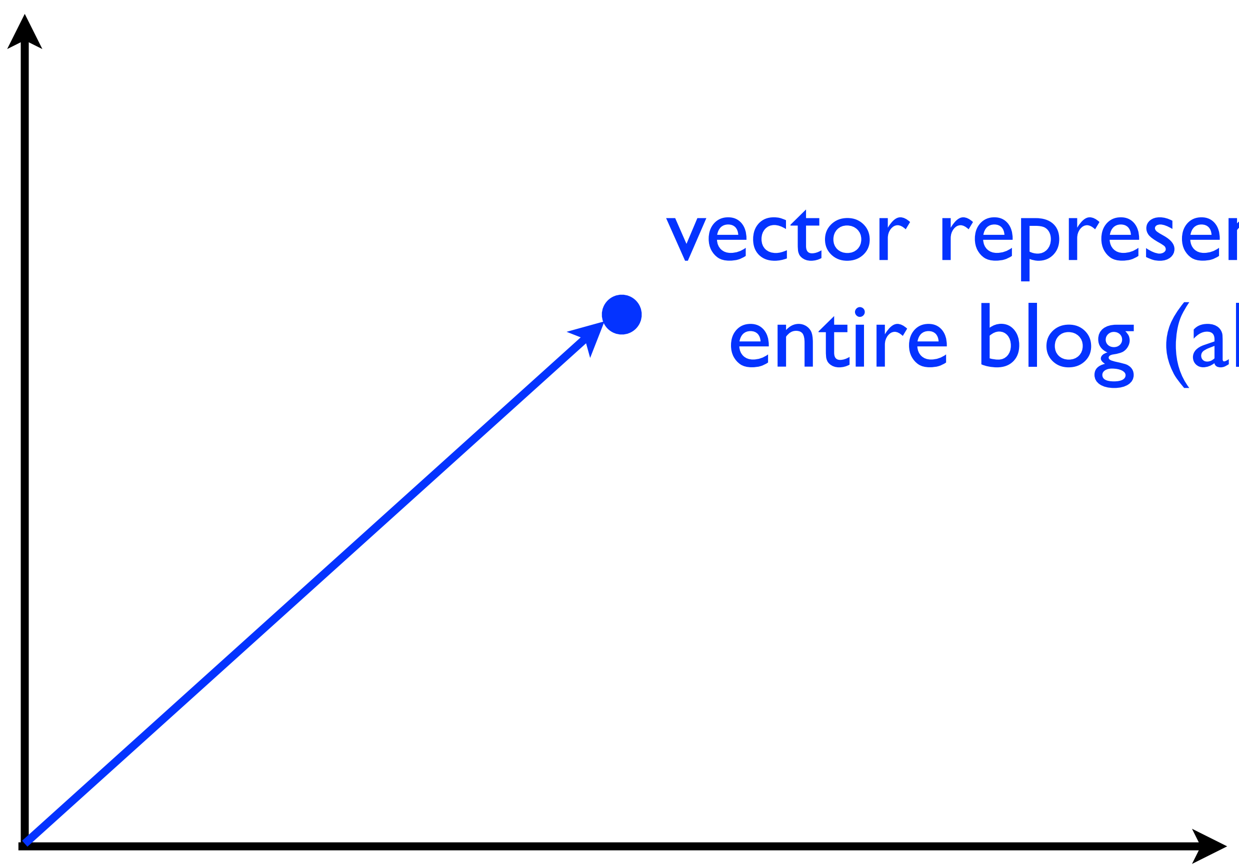
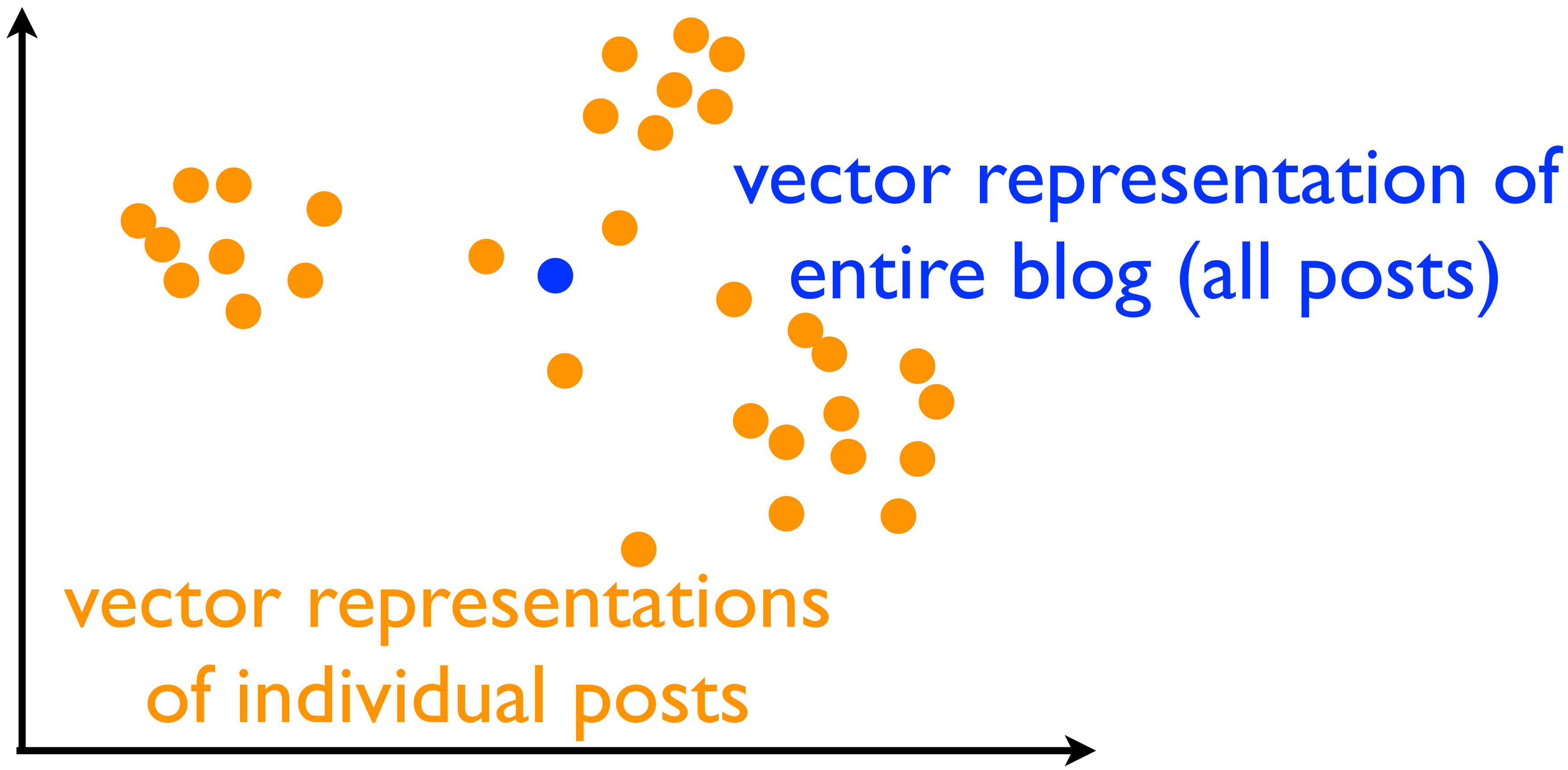


Topical Focus

- How might we do this? (HINT: vector space model)
- Compute <u>average</u> cosine similarity between the posts and the entire blog



Topical Focus

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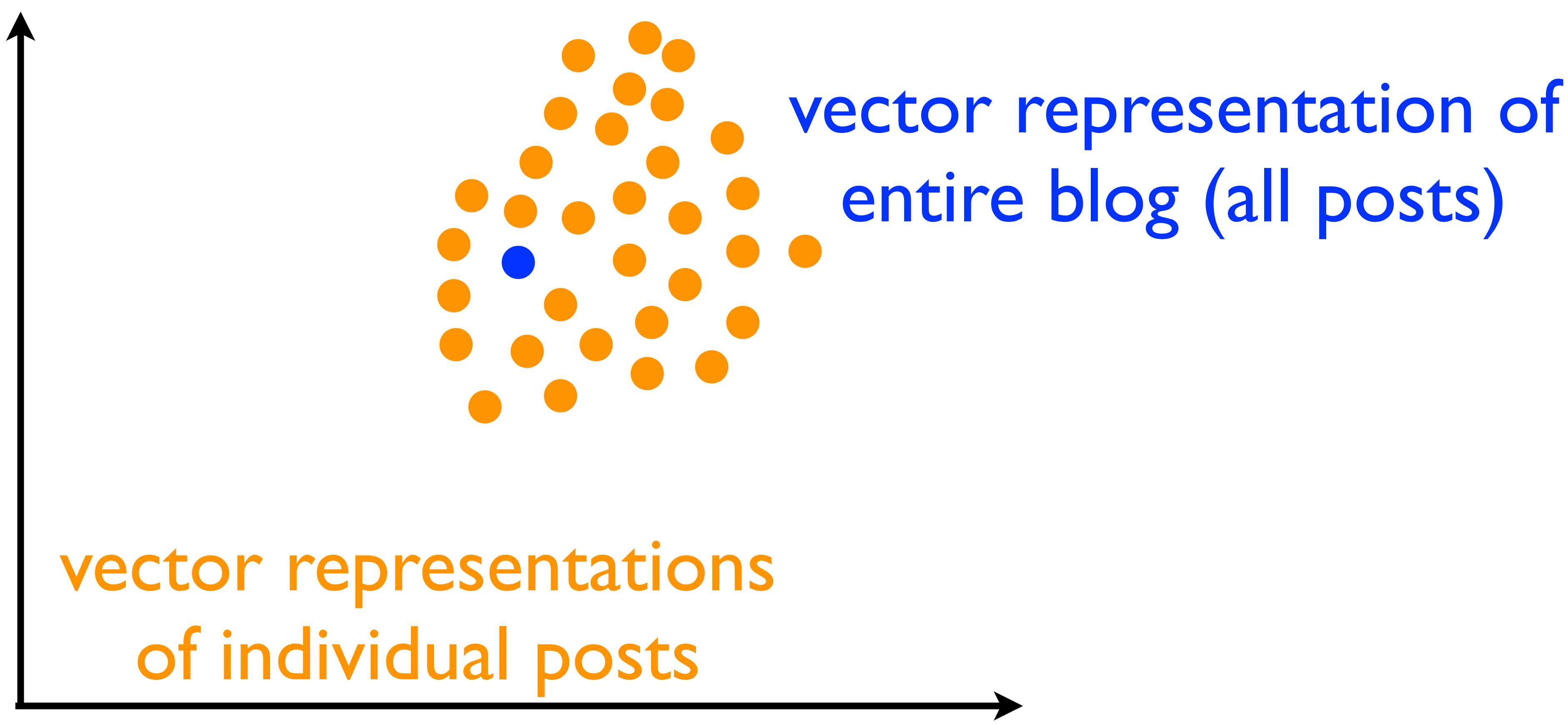

Document Prior

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

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

What document priors would you use?

Remember Smoothing?

- YOU: Are there mountain lions around here?
- YOUR FRIEND: Nope.
- YOU: How can you be so sure?
- YOUR FRIEND: Because I've been hiking here five times before and have never seen one.
- MOUNTAIN LION: You should have learned about smoothing by taking INLS 509. Yum!



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

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

$$P(D) = \frac{\text{\# of clicks on the document}}{\text{\# of clicks on any document}}$$

- 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

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

$$P(D) = \frac{\text{\# of clicks on the document}}{\text{\# of clicks on any document}}$$

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

$$\frac{(\text{\# of clicks on the document}) + 1}{(\text{\# of clicks on any document}) + (\text{\# of documents})}$$

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