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Ranking Models

Quality Models

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The ranking problem

***f*(*q*, *d*)**

Inferring relevance

$$f(q,d) = P(d|q) = \frac{P(q|d)P(d)}{P(q)}$$

How does observing q affect the probability of d?

- $P(d|q)$: document posterior (**a posteriori** relevance)
- $P(d)$: document prior (**a priori** relevance)

The ranking problem

***f*(*q*, *d*)**

The ranking problem

***f*(*d*)**

Quality as prior relevance

High quality of the web document content increases the a priori probability of the document being relevant

- a.k.a. document prior

Quality factors should be combined in a way that directly improves the retrieval effectiveness

- e.g., nDCG or MAP

Document quality in web search

Web is decentralized and heterogeneous
- Different authority
- Different goals
- Different credibility
- Different publishing standards

Document quality in web search

Quality of a web page is determined by many factors
- Original, up-to-date content of genuine value
- Links to related resources
- Layout for easy reading and navigation

Continuous spectrum from high-quality pages to spam
- Most web documents are somewhere in between

Document quality in web search

“ *As pure web spam has decreased over time, attention has shifted instead to sites with shallow or low-quality content.*
- Matt Cutts, 2011

Document quality in web search

Document quality in search engines
- Promote high-quality content
- Demote low-quality content

Two broad sources of quality evidence
- On-document evidence
- Off-document evidence

On-document evidence

Verbosity

Readability

Cohesiveness

Navigability

Support

Verbosity

Document nominal length
- Full length in tokens (Singhal et al., 1996)

Document visible length (Zhu & Gauch, 2000)
- Content actually rendered

Document title length (Bendersky et al., 2011)
- Measures descriptiveness of page metadata

Readability

Average term length (Kanungo & Orr, 2009)
- Longer terms denote thoughtful selection

Stopwords ratio/coverage (Ntoulas et al., 2006)
- Correlated with informativeness

Fraction of table text (Bendersky et al., 2011)
- High fraction denotes poor readability

Cohesiveness

Entropy of the page content (Bendersky et al., 2011)
- Lower entropy denotes better focus

$$H(\theta_d) = -\sum_{t \in d} P(t|d) \log P(t|d)$$

Navigability

URL length (Kraaij et al., 2002)

URL depth (number of parts splitting by '/')
- Lower length and depth denote easier navigation

URL type (domain, subdomain, path, file)
- Homepages tend to be of type domain

Support

Fraction of anchor text (Ntoulas et al., 2006)
- Denote the amount of supporting information provided from external sources
- Excess denotes shallowness

Off-document evidence

On-document evidence provides valuable evidence about the quality of the document
- Also prone to manipulation by the document author

Off-document evidence isn't immune, but is less biased
- Hyperlink structure
- Click-through data

Link analysis

Links are a key component of the Web
- Important for navigation, but also for search

Two complementary sources of information

Example website
- "Example website": anchor text
- "http://example.com": destination link

Authority

Billions of web pages, more or less informative

- Links can be viewed as information about the popularity (authority?) of a web page

Inlink count could be used as simple measure

- Link analysis algorithms like PageRank provide more reliable ratings (less susceptible to link spam)

Random surfer model

Choose a random number r between 0 and 1

- If $r < \lambda$: go to a random page (avoid getting stuck)
- If $r \geq \lambda$: follow a link at random on the current page

Repeat

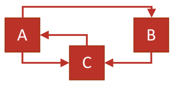
PageRank

PageRank of a page is the probability that the "random surfer" will be looking at that page as $t \to \infty$

$$PR^{(t+1)}(u) = \frac{\lambda}{n} + (1-\lambda) \sum_{v \in I_u} \frac{PR^{(t)}(v)}{|O_v|}$$

- I_u: inlinks of page u
- O_v: outlinks of page v

PageRank example ($\lambda = 0$)



$$PR^{(t+1)}(A) = \frac{PR^{(t)}(C)}{1}$$

$$PR^{(t+1)}(B) = \frac{PR^{(t)}(A)}{2}$$

$$PR^{(t+1)}(C) = \frac{PR^{(t)}(A)}{2} + \frac{PR^{(t)}(B)}{1}$$

	$PR^{(t)}(A)$	$PR^{(t)}(B)$	$PR^{(t)}(C)$
$t = 0$	0.33	0.33	0.33
$t = 1$	0.33	0.17	0.50
$t = 2$	0.50	0.17	0.33
$t = 3$	0.33	0.25	0.42
…			
$t = \infty$	0.40	0.20	0.40

Convergence check

Typical stopping criteria

- $\left\|\overrightarrow{PR}^{(t)} - \overrightarrow{PR}^{(t-1)}\right\| / n < \epsilon$

Setting ϵ

- Small ϵ: slow convergence, accurate PR
- Large ϵ: fast convergence, inaccurate PR

Click-through rate

Global click likelihood

$$CTR(d) = \frac{\sum_{q \in L} 1_{K_q}(d)}{\sum_{q \in L} 1_{R_q}(d)}$$

- $q \in L$: a query in the log
- K_q: documents clicked for q
- R_q: documents displayed for q

What is web spam?

Spamming = any deliberate action solely in order to boost a web page's position in search engine results, incommensurate with page's real value

- Spam = web pages that are the result of spamming

Approximately 10-15% of web pages are spam

- High premium to appear on the first page of results

Web spam taxonomy

Boosting techniques

- Aim at scoring high for topicality / authoritativeness

Hiding techniques

- Aim at hiding the use of boosting

Boosting techniques

Term spamming

- Inflate content to appear relevant to many queries

Link spamming

- Creating link structures that boost authority

Term spamming

Repetition

- Repeat one or a few specific terms (e.g., free, cheap)
- Goal is to subvert tf-idf ranking schemes

Dumping

- Add a large number of unrelated terms
- Goal is to match a variety of queries

Term spamming

Weaving

- Randomly stick spam terms along legitimate content

Phrase stitching

- Glue together sentences from different sources

Link spamming

Spammer's inaccessible pages

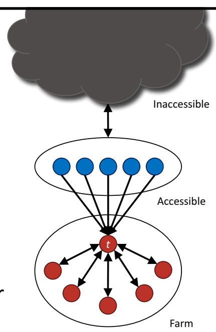
- Most of the Web

Spammer's accessible pages

- e.g., blog comments pages

Spammer's own pages

- Completely controlled by spammer



Link farms

Spammer's goal
- Maximize the authority of target page t

Spammer's approach
- Get many links from accessible pages to page t
- Construct "link farm" to get multiplier effect

Hiding techniques

Content hiding
- Use same color for text and page background

Cloaking
- Return different page to crawlers and browsers

Detecting spam

Term spamming
- Analyze text using statistical classifiers
- Also useful: near duplicate detection

Link spamming
- Trust propagation (ham pages link to ham pages)
- Open research area

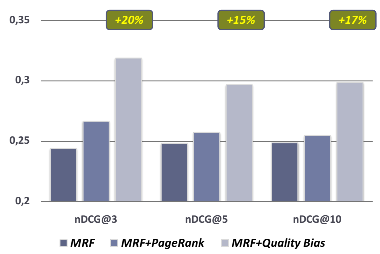
How to combine relevance and quality?

Quality as a static score

Query-independent scoring
- Typically computed offline

Precomputed scores leveraged in multiple ways
- As a multiplier in vector space models
- As a prior in probabilistic models
- As a feature in feature-based models

How effective is it?



Summary

Document quality can be heterogeneous
- Quality models can help distinguish between documents with similar relevance scores
- Also useful for queries that explicitly seek for high-quality content (authority, readability)
- Lots of signals, high potential for integration

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