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Information Retrieval

Quality Models

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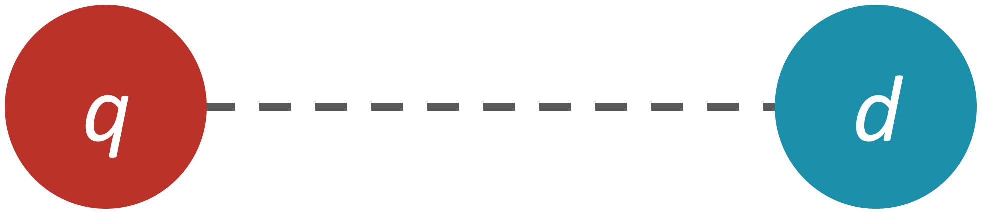
The ranking problem



$$f(q,d)$$

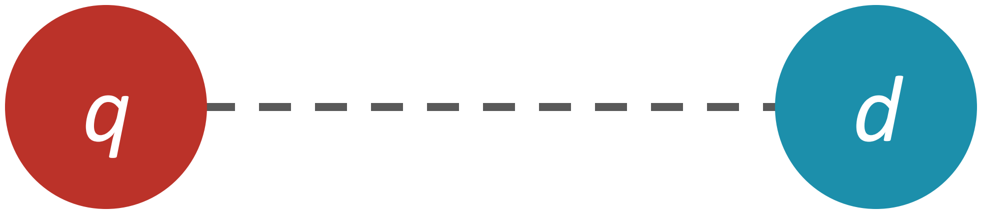
Query likelihood model

$$f(q,d) \approx P(q,d)$$
$$= P(q|d)P(d) \quad \text{Bayes' rule}$$

Two core components

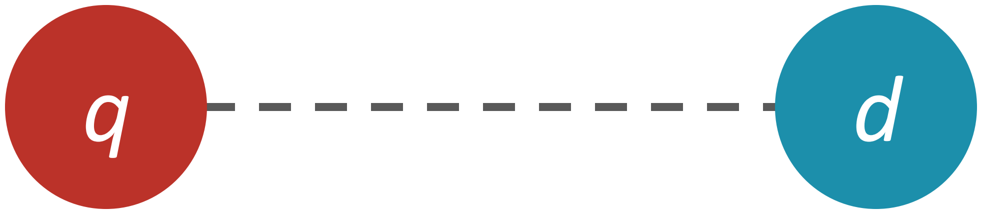
- $P(q|d)$: query likelihood
- $P(d)$: document prior

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 (Singhal et al., 1996)

- Full length in tokens

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 and depth (Kraaij et al., 2002)

- 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)

- Reasonable amount conveys factuality
- 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 a 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 random link from the current page

Repeat

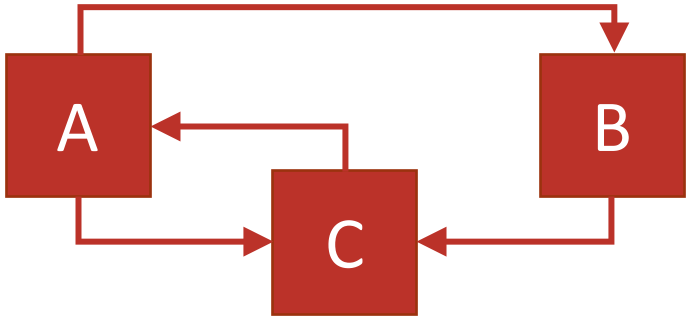
PageRank

PageRank of page u is the probability that the “random surfer” will be looking at u as $t \rightarrow \infty$

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

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

PageRank example ($\lambda = 0$)



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

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

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

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

Convergence check

Typical stopping criteria

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

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 that 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

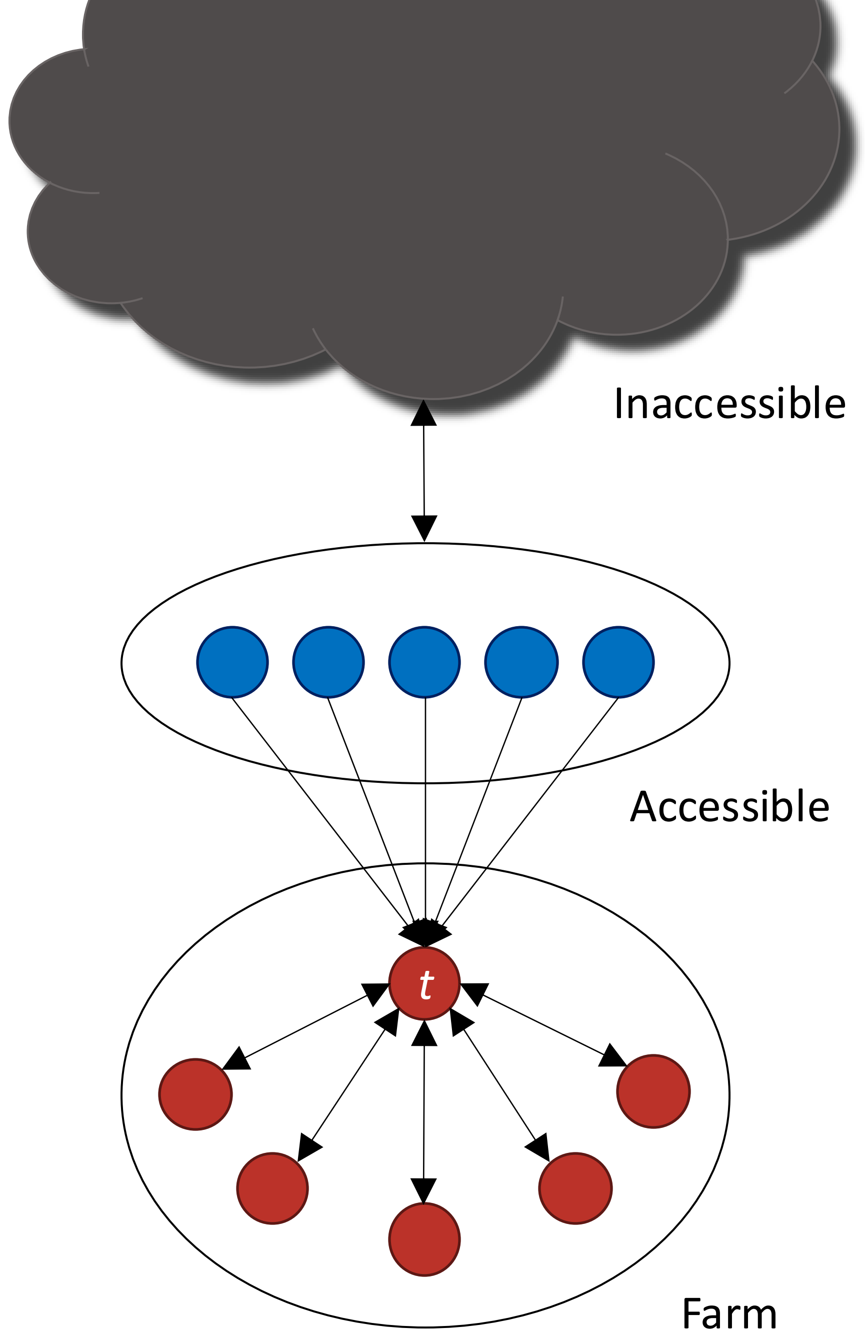
- Most of the Web

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

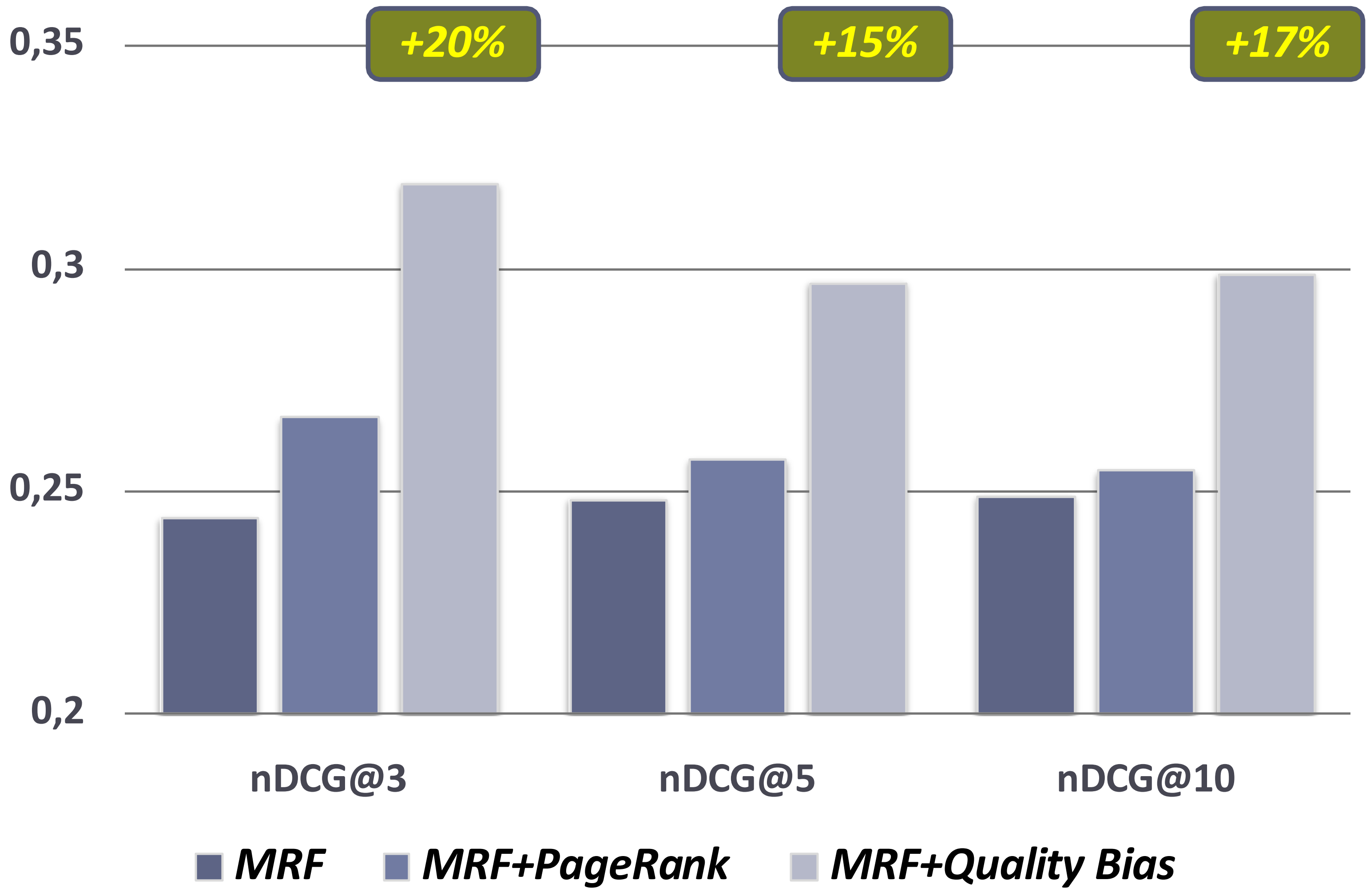
Query-independent scoring

- 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?
(Bendersky et al., 2011)



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)
- And to combat adversarial behavior (spam, fakes)

References

Quality-biased ranking of web documents

Bendersky et al., WSDM 2011

The importance of prior probabilities for entry page search

Kraaij et al., SIGIR 2002

The PageRank citation ranking: bringing order to the Web

Page and Brin, Tech report 1999

References

Relevance weighting for query independent evidence

Craswell et al., SIGIR 2005

Adversarial web search

Castillo and Davison, FnTIR 2011

Fake news detection on social media

Shu et al., SIGKDD Expl. 2017

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Coming next...

Feedback Models

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