IN4325

Personalization in (web) search

Claudia Hauff (WIS, TU Delft)

Project interview questions

Your project in the course *context*.

You have used retrieval algorithm X in your project, can you tell me how it differs broadly from the vector space model?

You used relevance feedback in your project, could you use pseudo-relevance feedback as well?

You have used metrics X, Y and Z. How do they differ from each other?

Your project took place on domain X, could you apply a similar pipeline to domain Y? What would you change?

The big picture

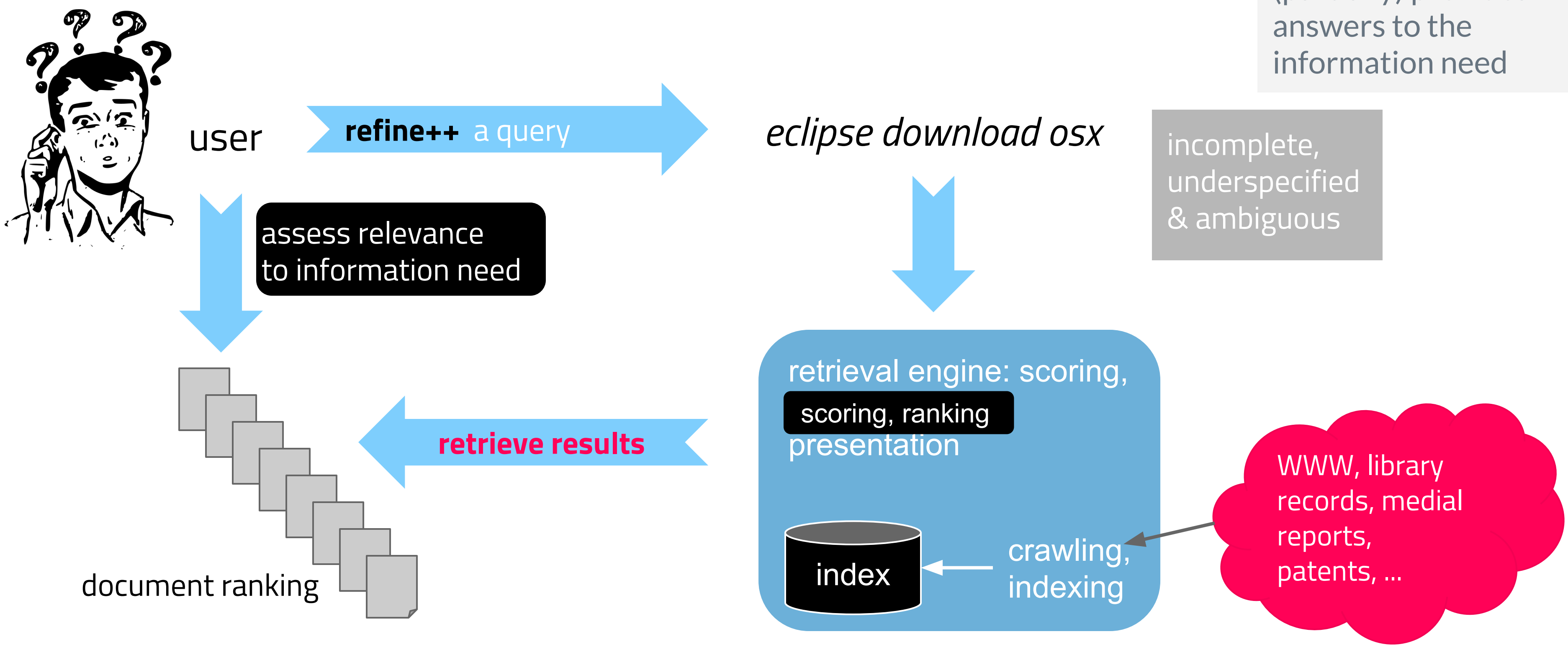
The essence of IR

Information need
Topic the user wants to know more about

Query
Translation of need into an input for the search engine

Relevance
A document is relevant if it (partially) provides answers to the information need

Information need: *Looks like I need Eclipse for this job. Where can I download the latest beta version for macOS Sierra?*



A hot topic for industry ...

"... The method comprises, at a computerized search engine system distinct from a client system: receiving a search request associated with a user from the client system, the search request having one or more search terms; obtaining a user profile corresponding to the user, where the user profile is generated based in part on the user's prior computing activities, comprising one or more of browsing, searching, and messaging; obtaining search results for the search request; generating a personalized snippet for at least one of the search results in accordance with the obtained user profile, the snippet comprising a text portion of the search result chosen based on at least one or more search terms and one or more terms of the obtained user profile; and transmitting the search results and personalized snippet to the client system for display." (ONE sentence)

patent retrieval

personalized search patent

About 17,600 results (**0.11** sec)

System and method for **personalized** snippet generation
TH Haveliwala, SD Kamvar - US **Patent** 9,805,116, 2017 - Google Patents
... No. 14/154,071, filed Jan. 13, 2014 which is a continuation of US **patent** application Ser. No ... FIG. 2 is a flow chart for a process for generating **personalized** snippets for a set of **search** results in accordance with some embodiments of the present invention. FIG ...
Cited by 16 Related articles All 4 versions Import into EndNote

System and Method for **Personalized Search** While Maintaining Searcher Privacy
PV Hayes - US **Patent** App. 15/183,619, 2017 - Google Patents
... 0012]. The present disclosure relates to a system and method for **personalized search** while maintaining ... of ResultRank, indicated and/or inferred searcher satisfaction with the relevance of **search** result abstracts ... The term Result Rank was introduced in US **patent** application Ser ...
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Adaptive Reading Level Assessment for **Personalized Search**
DJ Weiss, E Miltsakaki - US **Patent** App. 15/650,173, 2017 - freepatentsonline.com
... Title: Adaptive Reading Level Assessment for **Personalized Search**. Document Type and Number: United States **Patent** Application 20170372628 Kind Code: A1. Abstract: A system and associated methods are provided for generating ...
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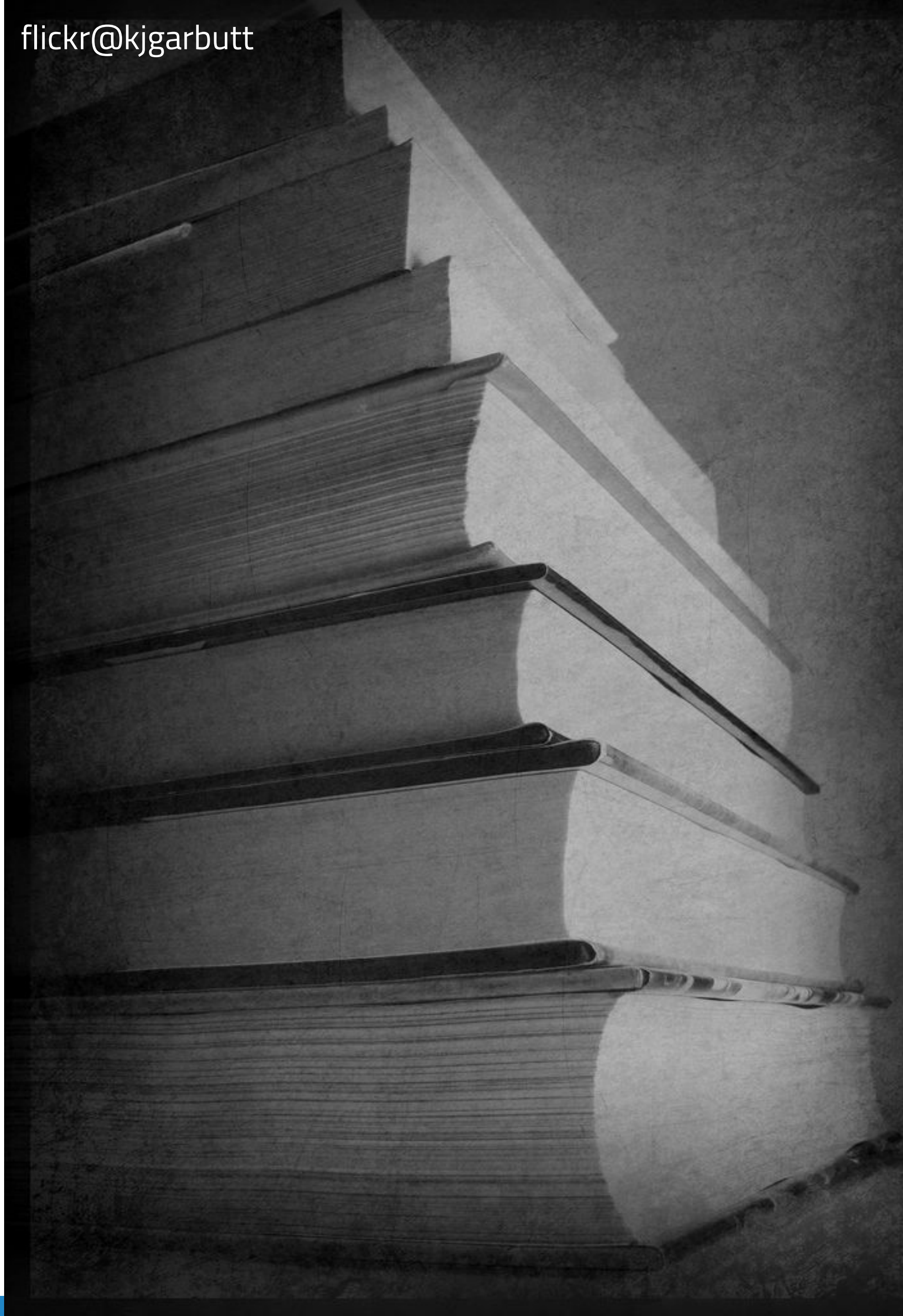
Personalized search result summary
BW Chang, SK Rakshit - US **Patent** 9,779,170, 2017 - Google Patents
... a **search** query, if the personalization system 120 identifies the **search** result as related to a **patent**, then the personalization system 120 selects the **patent** summary template 200 and displays the **personalized** summary for the **search** result using the **patent** summary template 200 ...
Cited by 1 Related articles All 4 versions Import into EndNote

Methods, systems and techniques for **personalized search** query suggestions
S Zhu, CM Sze, H Su, H Wu, H Wu, J Gan... - US **Patent** App. 14 ..., 2017 - Google Patents
Connect public, paid and private **patent** data with Google Patents Public Datasets Methods, systems and techniques for **personalized search** query suggestions. Download PDF Info. Publication number US20170097939A1. Authority ...
All 2 versions Import into EndNote

Personalized search library based on continual concept correlation
S Mo, RH Wouhaybi, MA Mian, TM Kohlenberg... - US **Patent** ..., 2017 - Google Patents
... Download PDF Info. Publication number US9582572B2. Authority US Grant status Grant. **Patent** type. Prior art keywords content **personalized search** user concept Prior art date 2012-12-19 Legal status (The legal status is an assumption and is not a legal conclusion ...
Cited by 2 Related articles All 4 versions Import into EndNote

Topics

- Evaluation strategies
- Search strategies
- Privacy and software architectures
- HITS
- (Personalized) PageRank



Personalized search: evaluation scenarios

Search tailored to a user's interests.

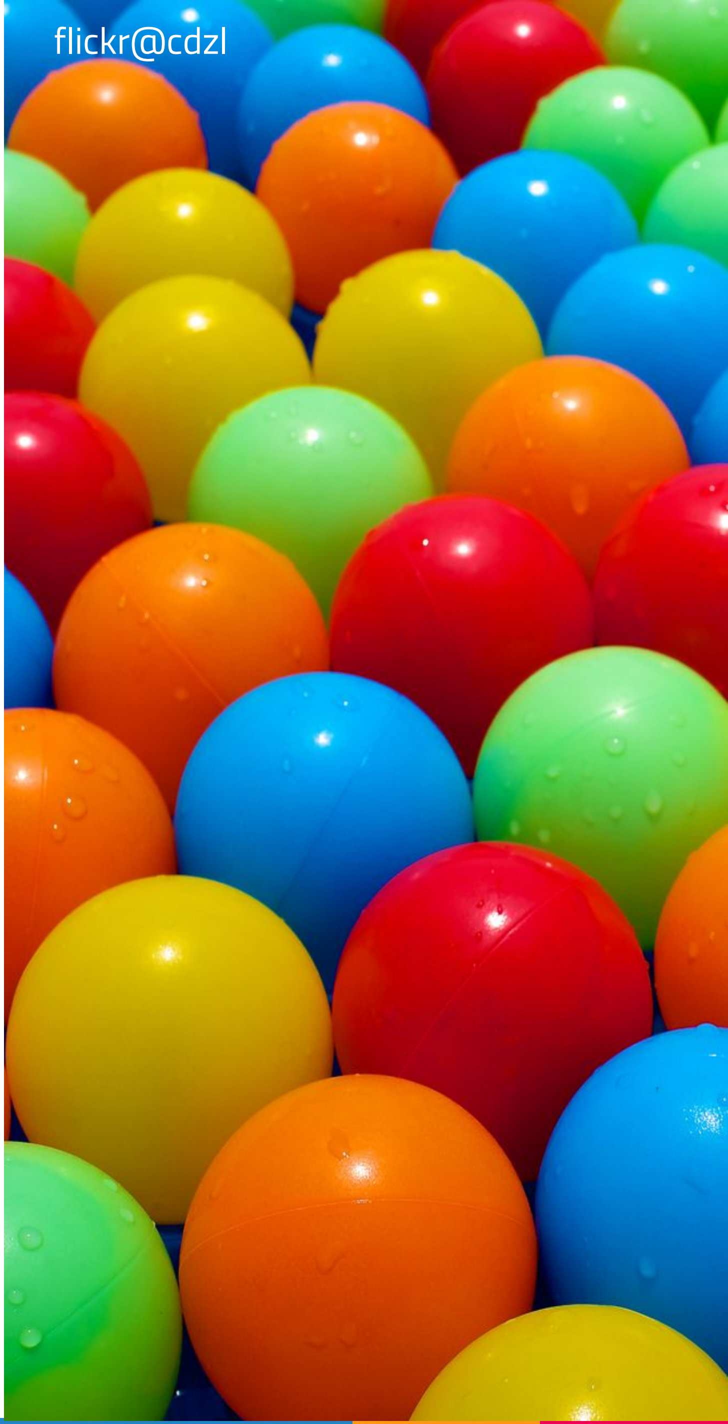
User evaluation

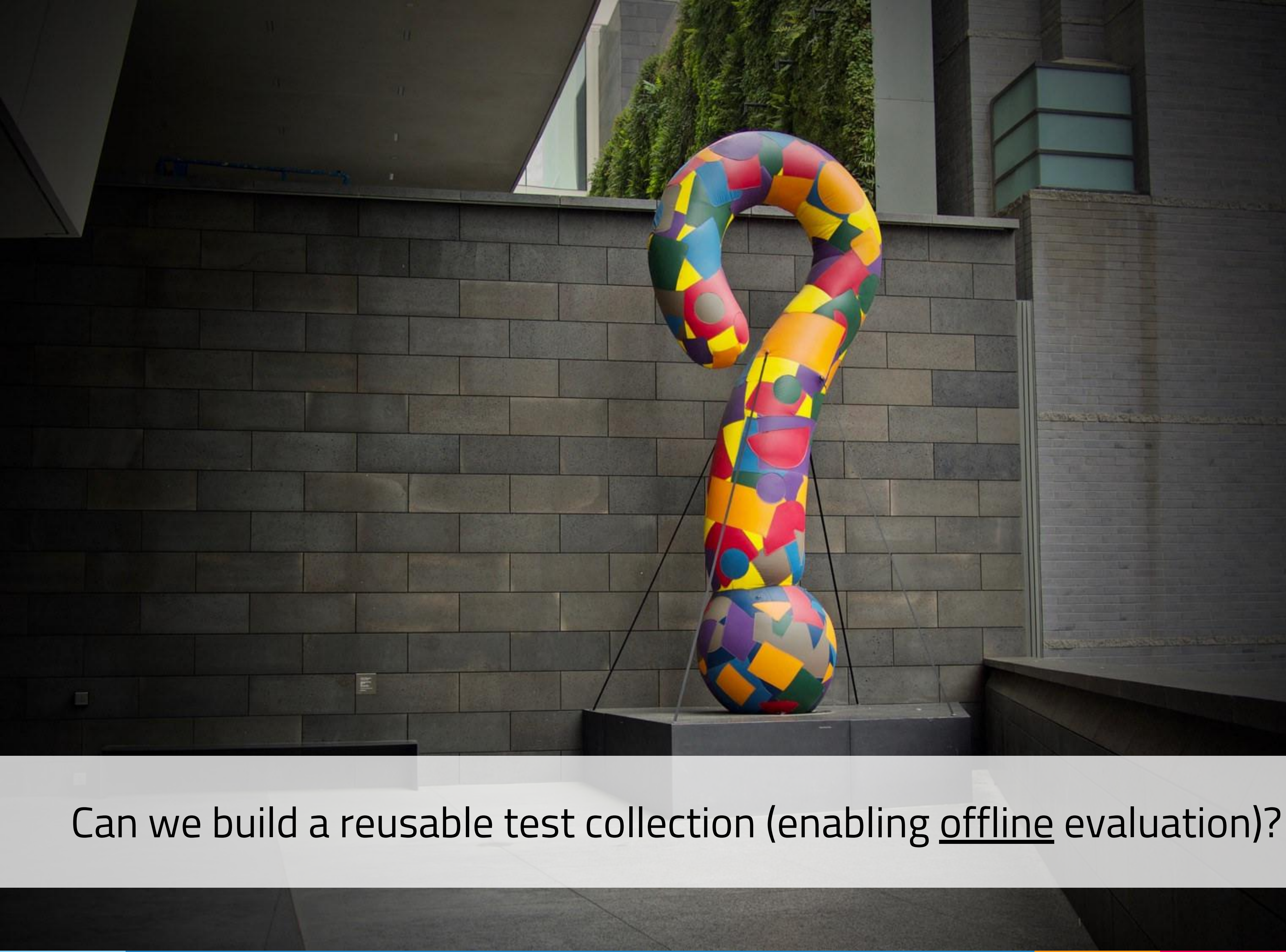
Participants use a **personalized search system** (online eval.) and compare the personalized and non-personalized SERP

Questionnaires and **browser histories** are used to create user profiles

What if a revised personalization approach needs to be tested?

Issues: small number of participants and **potential bias** through self-selected test queries



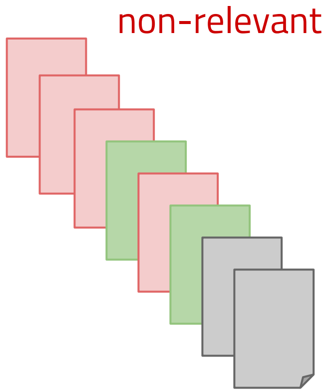


Can we build a reusable test collection (enabling <u>offline</u> evaluation)?

Click-log evaluation

Click-through data in query logs is used to **simulate** user experience in Web search

Assumption: users click on search results from top to bottom



Idea: if the user **clicks** on one or more documents and **skips over others**, those **clicked documents** are more relevant to her

Personalized retrieval is evaluated by **reranking** the result list; ideally those clicked results should appear at the top of the ranking → *click decisions become qrels*

advantages / disadvantages?

Click-log evaluation metrics

Rank scoring (RS):

1, if click on j given q;
0 otherwise

Rank of the page

$$R_q = \sum_j \frac{\delta(q, j)}{2^{(j-1)/(\alpha-1)}}$$

Expected utility of a ranked list for test query q

Rank scoring (RS) across all test queries:

$$R = 100 \frac{\sum_q R_q}{\sum_q R_q^{Max}}$$

Max. possible utility when all clicked pages appear at the top

https://dl.acm.org/citation.cfm?id=1242651

Click-log evaluation metrics

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$$R = 100 \frac{\sum_q R_q}{\sum_q R_q^{Max}}$$

Average rank (AR):

Rank of page p

$$AvgRank_q = \frac{1}{|\mathcal{P}_q|} \sum_{p \in \mathcal{P}_q} R(p)$$

clicked pages for q

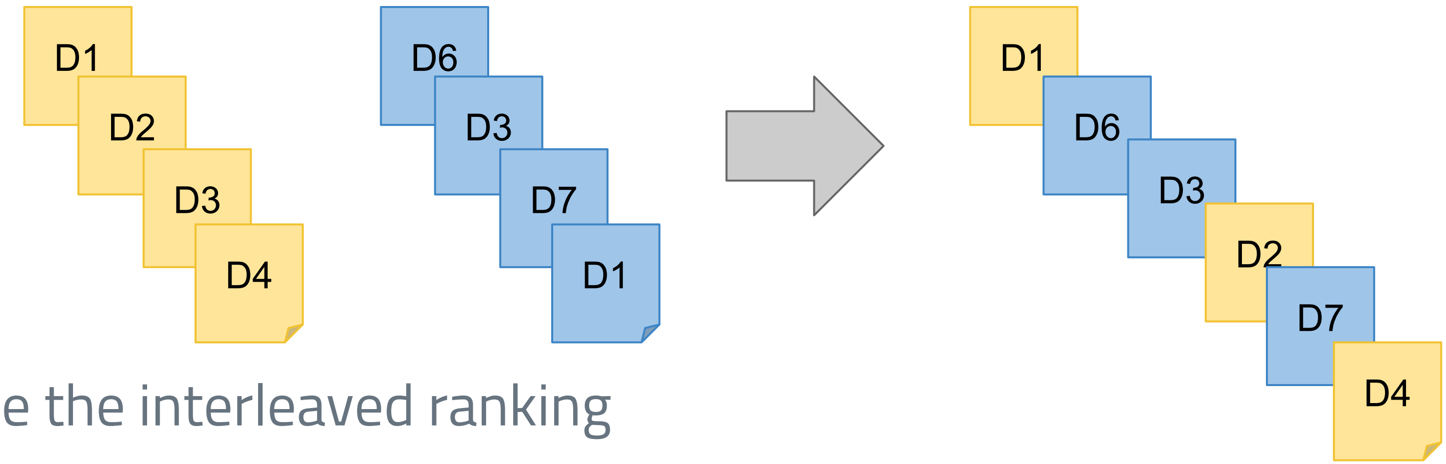
Average rank (AR) across all test queries:

$$AvgRank = \frac{1}{|\mathcal{Q}|} \sum_{q \in \mathcal{Q}} AvgRank_q$$

https://dl.acm.org/citation.cfm?id=1242651

Interleaved evaluation (common today)

Combines the ranked lists of two (or more) rankings by alternating between the result lists and ignoring duplicates



Users receive the interleaved ranking

Ranking that received most clicks over many queries is considered of higher quality. More sensitive than other approaches.

Requires a substantial amount of user data

Personalized search: strategies

click-based

profile-based

Search tailored to a user's interests.

Person-level reranking strategy

Intuition: given a user's query, web pages that the user clicked on in the past are more relevant to her than those rarely clicked

user

#clicks in the past

$$S^{P-click}(q,p,u) = \frac{|Clicks(q,p,u)|}{|Clicks(q,\bullet,u)| + \beta}$$

Score of page p given query q by user u

#clicks in the past on any page given q and u

Smoothing factor

Issue: reranking fails if the user never issued the query before; luckily users are prone to repeat searches over time ("**re-finding**" of Web pages constitutes a large part of Web search traffic).

https://dl.acm.org/citation.cfm?id=1242651

Slight detour

Re-finding

Definition: a user clicking a URL following a search, and then later clicking the same URL via <u>another</u> search

	Label	Query	Click
Monday	Q_1	*swine flu incidence*	
	C_{11}		healthmap.org/swineflu
	C_{12}		www.swine-flu-map-animation.com
	C_{13}		www.cdc.gov/H1N1Flu **
	Q_2	*swine flu deaths*	
	Q_3	*h1n1*	
	C_{31}		en.wikipedia.org/wiki/H1N1
	C_{32}		www.cdc.gov/H1N1Flu **
Tues.	Q_4	*h1n1*	
	C_{41}		www.cdc.gov/H1N1Flu **
	C_{42}		h1n1.nejm.org
Wed.	Q_5	*swine flu*	
	Q_6	*cdc swine flu*	
	C_{61}		www.cdc.gov/H1N1Flu **
Sat.	Q_7	*cdc swine flu*	
	C_{71}		www.cdc.gov/H1N1Flu **

One month of MSN log data ...

- **22%** of all of the queries sampled were instances of re-finding
- **30%** of all single-click queries were re-finding queries (5% for a multi-click query)
- **66%** of re-finding queries were also previous queries for a later re-finding
- **48%** of all re-finding instances occurred within a single session

https://dl.acm.org/citation.cfm?id=1718512

Person-level reranking based on user interests

Intuition: given a user's query, web pages that are covering topics of interest to the user (based on her history) are more likely to be relevant

$$S^{L-profile}(q,p,u) = \frac{c_l(u) \times c(p)}{\| c_l(u) \| \| c(p) \|}$$

Reranking based on user profile and document profile vector similarity

User profile: weighted vector of topic categories

Document profile: weighted vector of topic categories

How can we build c(u)/c(p)?

$$c_l(u) = \sum_{p \in \mathcal{P}(u)} P(p|u) w(p) c(p)$$

Pages visited in the past by u

Unpopularity of p across users

Click prob. of p

What issues does this profile have?

Short- and long-term profiles

Fact: short-term user profiles tend to be more useful to improve search in the current session

$$S^{S-profile}(q,p,u) = \frac{c_q(u) \times c(p)}{\| c_q(u) \| \| c(p) \|}$$

Scoring **only** dependent on the **clicks of the current** search session

Short- and long-term profiles can be combined:

$$S^{LS\text{-}profile}(q,p,u) = \theta \times S^{S\text{-}profile}(q,p,u) + (1-\theta) S^{L\text{-}profile}(q,p,u)$$

Group-level re-ranking

Intuition: a single user may only have a relatively sparse user profile, we can benefit from combining her profile with that of similar users

Set of nearest user profile neighbours

similarity between two user profiles

$$S^{G-click}(q,p,u) = \frac{\sum_{u_s \in S_u(u)} Sim(u_s,u) \times |Clicks(q,p,u_s)|}{\beta + \sum_{u_s \in S_u(u)} |Clicks(q,\bullet,u_s)|}$$

Intuition: the more similar a user profile x to the current user, the more important the clicks of x are to the current user

https://dl.acm.org/citation.cfm?id=1242651

Dataset

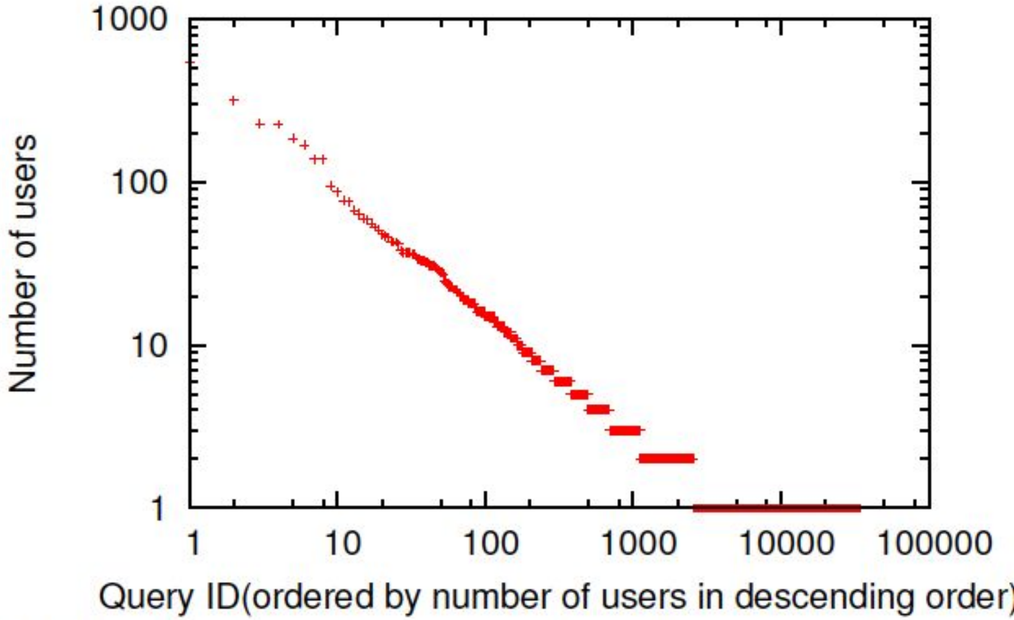
12 days of MSN log data (2006) with 10K users randomly sampled from it

11 days to **train**, **1** day to **test**

The 3% most popular distinct queries are issued by 47% of users

46% of all queries in the test set also appear in training

Item	ALL	Training	Test
#days	12	11	1
#users	10,000	10,000	1,792
#queries	55,937	51,334	4,639
#distinct queries	34,203	31,777	3,465
#Clicks	93,566	85,642	7,924
#Clicks/#queries	1.6727	1.6683	1.7081
#sessions	49,839	45,981	3,865



https://dl.acm.org/citation.cfm?id=1242651

Fusing the rankings

1) Retrieve the top N search results for query Q from a search engine (result list $R1$) [*personalization switched off]

2) Compute the personalized score for each document in $R1$ and **rerank** by it (result list $R2$)

3) Combine the rankings $R1$ and $R2$ through **Borda count** (generalization of majority vote), yielding the personalized result list R

R1	**R2**
D1 (4p)	**D3** (4p)
D2 (3p)	**D4** (3p)
D3 (2p)	D2 (2p)
D4 (1p)	D1 (1p)

Personalization strategies evaluated

R.S. = Rank scoring (higher is better)
A.R. = Average rank (smaller is better)

Queries for which reranking may help. WEB does not produce optimal ranking.

method	all		not-optimal	
	R.S.	A.R.	R.S.	A.R.
WEB	69.4669	3.9240	47.2623	7.7879
P-Click	**70.4350**	**3.7338**	**49.0051**	**7.3380**
L-Profile	66.7378	4.5466	45.8485	8.3861
S-Profile	66.7822	4.4244	45.1679	8.3222
LS-Profile	68.5958	4.1322	46.6518	8.0445
G-Click	70.4168	3.7361	48.9728	7.3433

- **Click-based personalization** outperforms the WEB baseline
- **Profile-based personalization** degrades on average (large performance deviation across queries)

https://dl.acm.org/citation.cfm?id=1242651

Query click variation

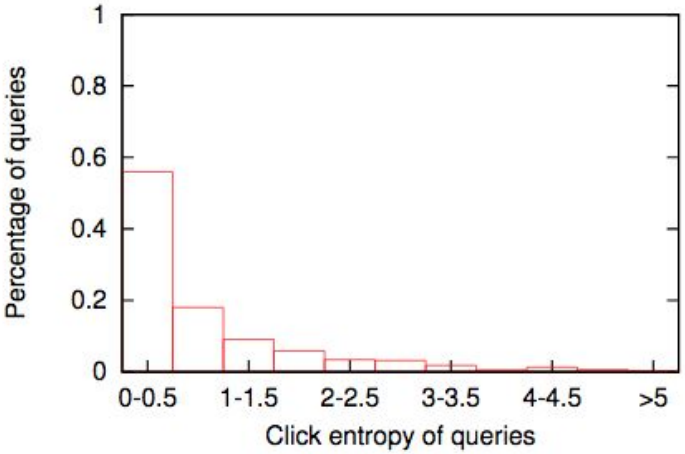
Click entropy captures how uniform or divergent the clicks following a specific query are:

$$CE(q) = \sum_{p \in \mathcal{P}(q)} -P(p|q) \log_2 P(q|p)$$

Pages clicked for query q

%of clicks on p for all clicks by users issuing q

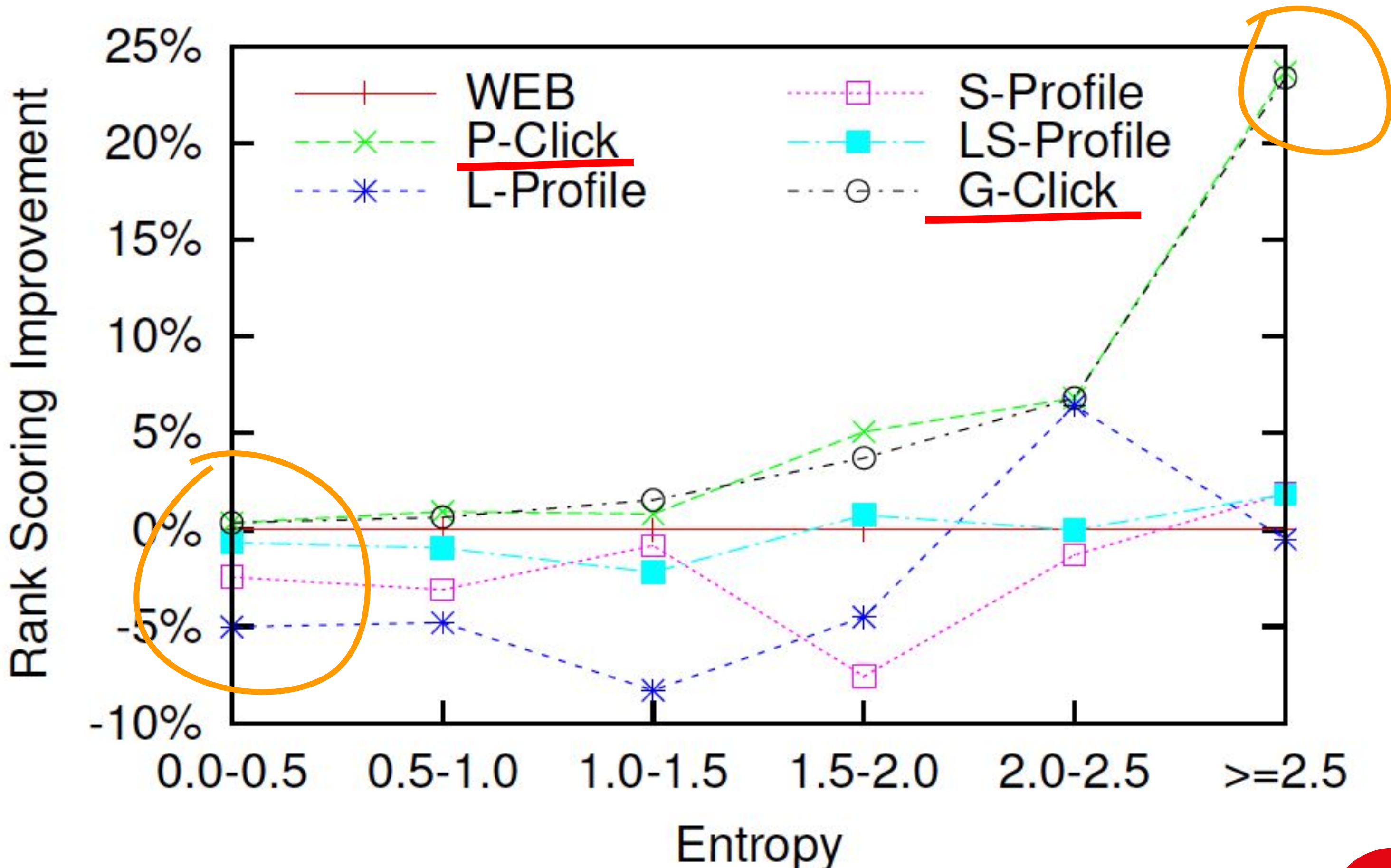
When is the entropy zero?
When is it largest?



(b) Queries with query times>5

https://dl.acm.org/citation.cfm?id=1242651

Evaluation across click entropies



Personalization hurts queries with low entropy.

What now?

- Why was no significance test performed?
- What do you expect the reranking effectiveness to be on repeated queries?
- What do you expect from users with more/less search activity in the training days?
- What kind of features could a click entropy classifier have?

	Click entropy	
	All	Low RE
Query length (words)	0.20	0.16
Query length (chars)	-0.04	0.03
URL fragment	-0.36	0.03
Location mentioned	-0.03	-0.04
Advanced query	-0.01	-0.02
# of query suggestions	0.12	0.15
# of times issued	0.00	-0.01
# of distinct users	-0.01	0.00
Avg. # of results	0.03	-0.02
% issued during work	-0.10	-0.04
Query clarity	0.02	-0.02
Category entropy	-0.01	0.01
# of distinct categories	0.01	-0.02
# of URLs in ODP	0.09	0.05
Top level domain entropy	0.02	0.04
# of distinct hosts	0.19	0.17
Click entropy	1.00	1.00
Potential at 10	0.87	0.86
Result entropy (RE)	0.53	-0.04
Avg. clicks per user	0.73	0.69
Avg. click position	0.90	0.86
Avg. seconds to click	0.03	0.05

Linear correlation coefficient between query features and click entropy for all 44K queries (All) and for queries with low result entropy (Low RE).

URL fragment in query

https://dl.acm.org/citation.cfm?id=1390364

Personalized search: privacy & software architectures

Tension

Personalized search requires the collection of information about users (the more the better)

Privacy preservation requires us to reveal as little as possible to the search provider

- Collected information reveals a lot about a user's private life
- **How can we preserve privacy in personalized search?**

https://dl.acm.org/citation.cfm?id=1273222

Formally

User identifying information (IP address, user ID)

Text description of information need N (related queries, viewed results …)

$$P(U) = \{ID(U, i), TEXT(N, i))\}$$

personal information of user U (needed for personalized search)

$$where\ i = 1, .., k$$

k search activities

Who should *P(U)* be revealed to?

Only a "trusted" party (e.g. a search engine company with clear privacy protection rules) or some "untrusted" parties (e.g. a third party with access to the Web search log) as well?

Level 1: pseudo identity

AOL debacle ...

$ID(U)$ is replaced by pseudo identity $IDP(U)$

$IDP(U)$ contains less personally identifiable information than $ID(U)$

Content of user profile information remains intact

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TECHNOLOGY

A Face Is Exposed for AOL Searcher No. 4417749

By MICHAEL BARBARO and TOM ZELLER Jr. AUG. 9, 2006

Buried in a list of 20 million Web search queries collected by AOL and recently released on the Internet is user No. 4417749. The number was assigned by the company to protect the searcher's anonymity, but it was not much of a shield.

No. 4417749 conducted hundreds of searches over a three-month period on topics ranging from "numb fingers" to "60 single men" to "dog that urinates on everything."

And search by search, click by click, the identity of AOL user No. 4417749 became easier to discern. There are queries for "landscapers in Lilburn, Ga," several people with the last name Arnold and "homes sold in shadow lake subdivision gwinnett county georgia."

It did not take much investigating to follow that data trail to Thelma Arnold, a 62-year-old widow who lives in Lilburn, Ga., frequently researches her friends' medical ailments and loves her three dogs. "Those are my searches," she said, after a reporter read part of the list to her.

Level 1: pseudo identity

AOL debacle ...

ID(U) is replaced by pseudo identity *IDP(U)*

IDP(U) contains less personally identifiable information than *ID(U)*

Content of user profile information remains intact

Level 2: group identity

A group of users share a single identity *ID(U)*

The description of user information needs *TEXT(N,i)* is aggregated at the group level

To enable effective personalized search, group members should share interests

Implementable through a proxy or implicitly through `TrackMeNot`

Level 1: pseudo identity

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Level 3: No identity

The user identity *ID(U)* is not available to the search engine

The information need descriptions *TEXT(N,i)* cannot be aggregated on the search engine side

To enable personalized search, client-side personalization is necessary.

Level 1: pseudo identity

AOL debacle ...

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Level 3: No identity

The user identity *ID(U)* is not available to the search engine

The information need descriptions *TEXT(N,i)* cannot be aggregated on the search engine side

To enable personalized search, client-side personalization is necessary.

Level 4: No personal information

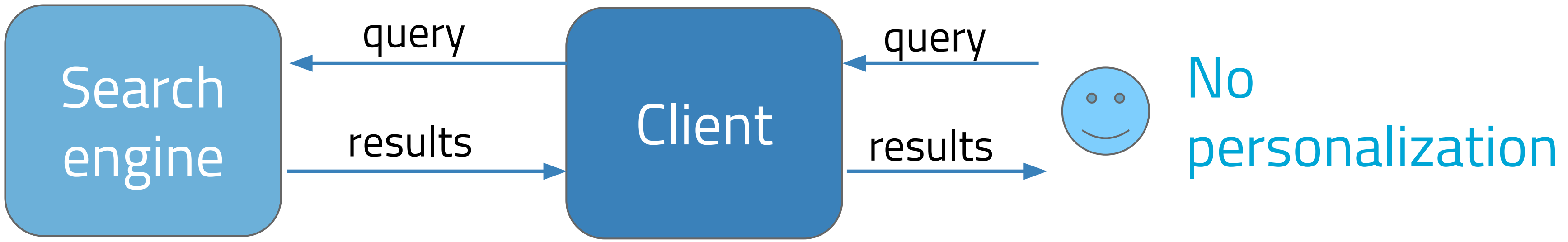
Neither the user identity *ID(U)* nor the description of information needs *TEXT(N)* are available to the search engine

Ultimate privacy

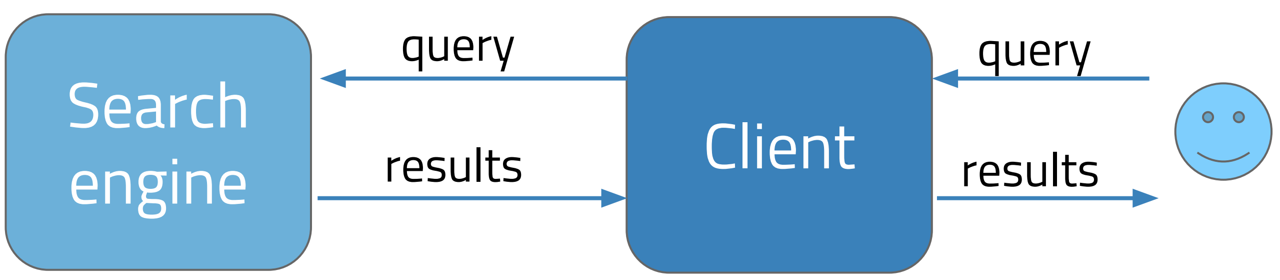
Hard to guarantee in practice (cryptography, laws, ...) without a private search engine

https://dl.acm.org/citation.cfm?id=1273222

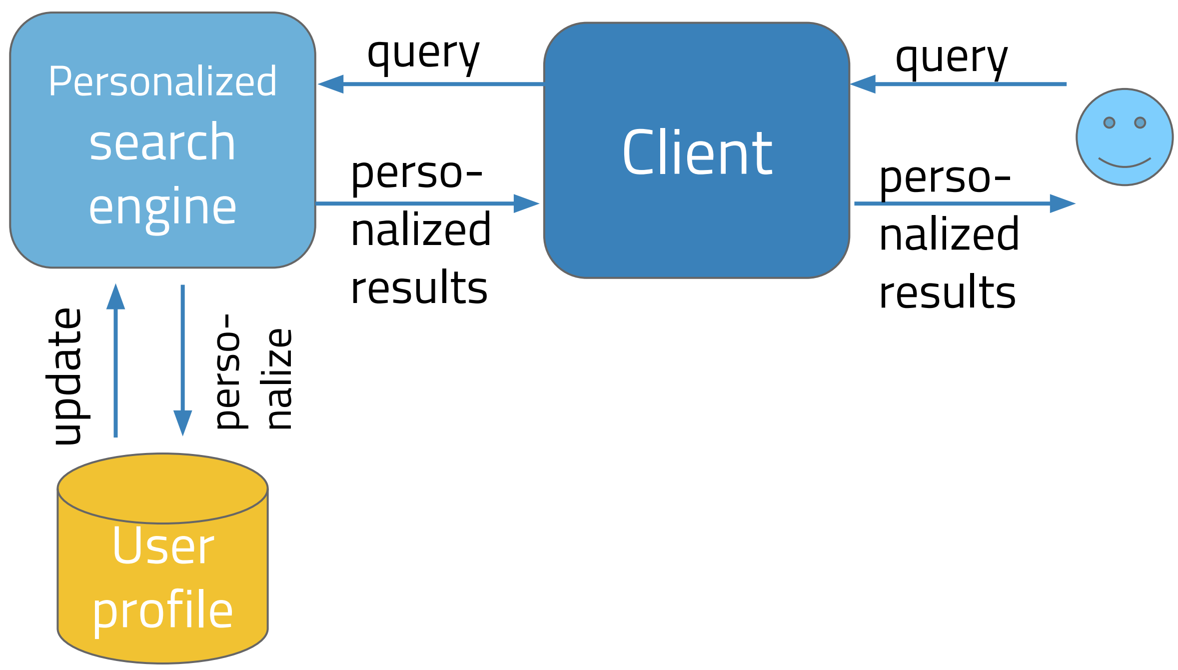
Software architectures



Software architectures



No personalization



Server-side personalization

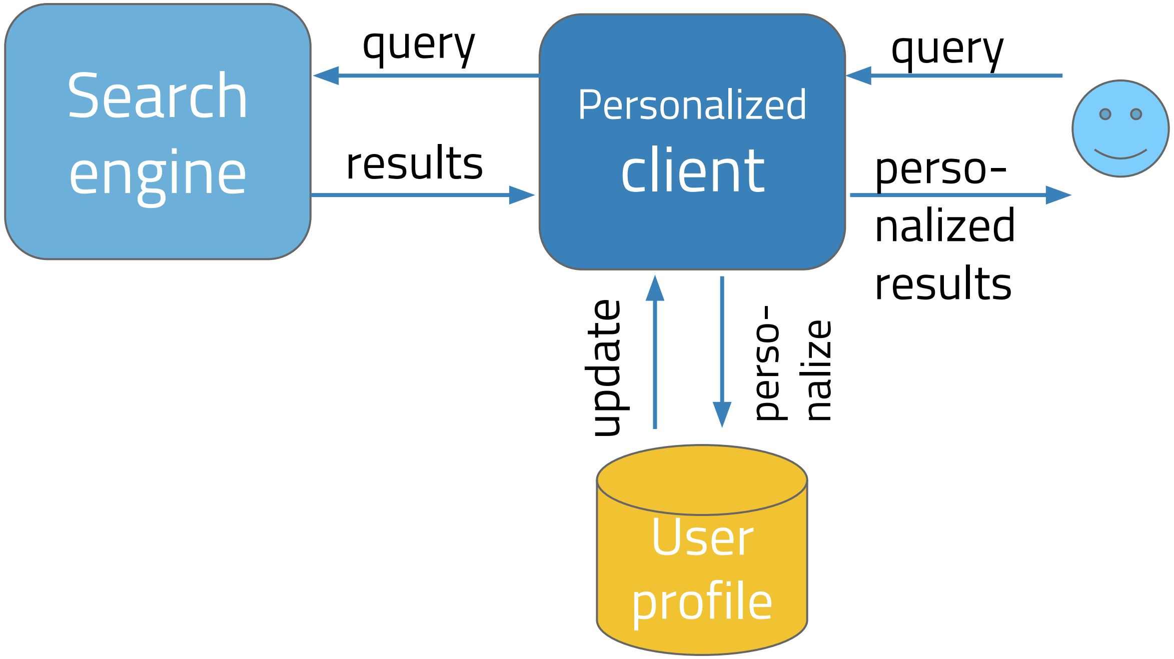
- $P(U)$ on the server
- Full power of personalized algs., client unchanged
- Level 1 privacy, with proxy level 2; levels 3/4 impossible

https://dl.acm.org/citation.cfm?id=1273222

Software architectures

Client-side personalization

- Reranking based on $P(U)$ or automatic query expansion
- Allows more than search activities into the profile
- Some knowledge is only available on the server
- Usage of an anonymous network enables privacy level 3

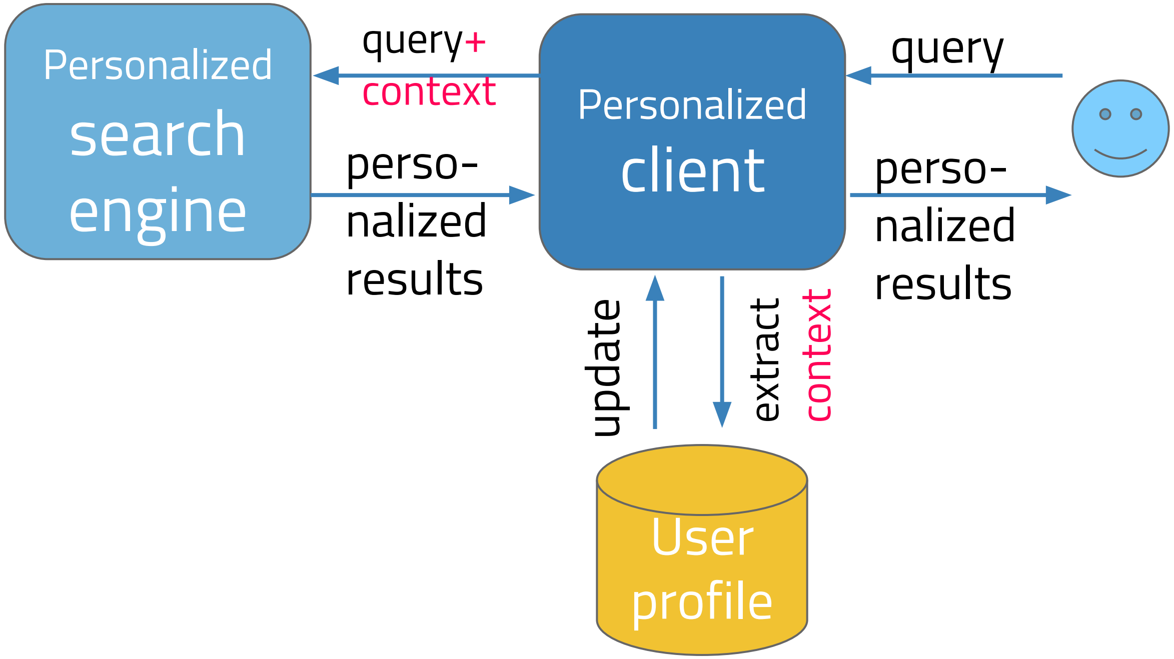


https://dl.acm.org/citation.cfm?id=1273222

Software architectures

Client-server collaborative personalization

- Compromise: enables the use of the search engine's resources to personalize while not storing $P(U)$
- Context example: query expansion terms, topic weights, …

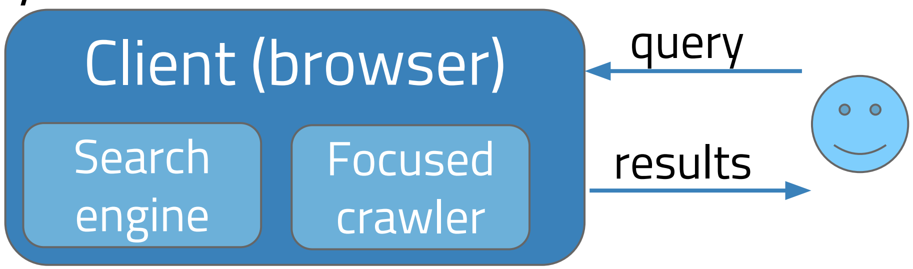


Software architectures

Private search

- Search engine self-contained in the browser; level 4 privacy
- No third party logging queries, clicks, page visits
- Useful for sensitive searches (medical conditions, etc.)
- Three stages:
  1. Focused crawler activated (can take a day)
  2. Index creation (`JScene` prototype: ~10h for 1M tweets)
  3. User interacts with the in-browser search engine

- Degree of privacy determined by breadth of crawl; time vs. privacy tradeoff



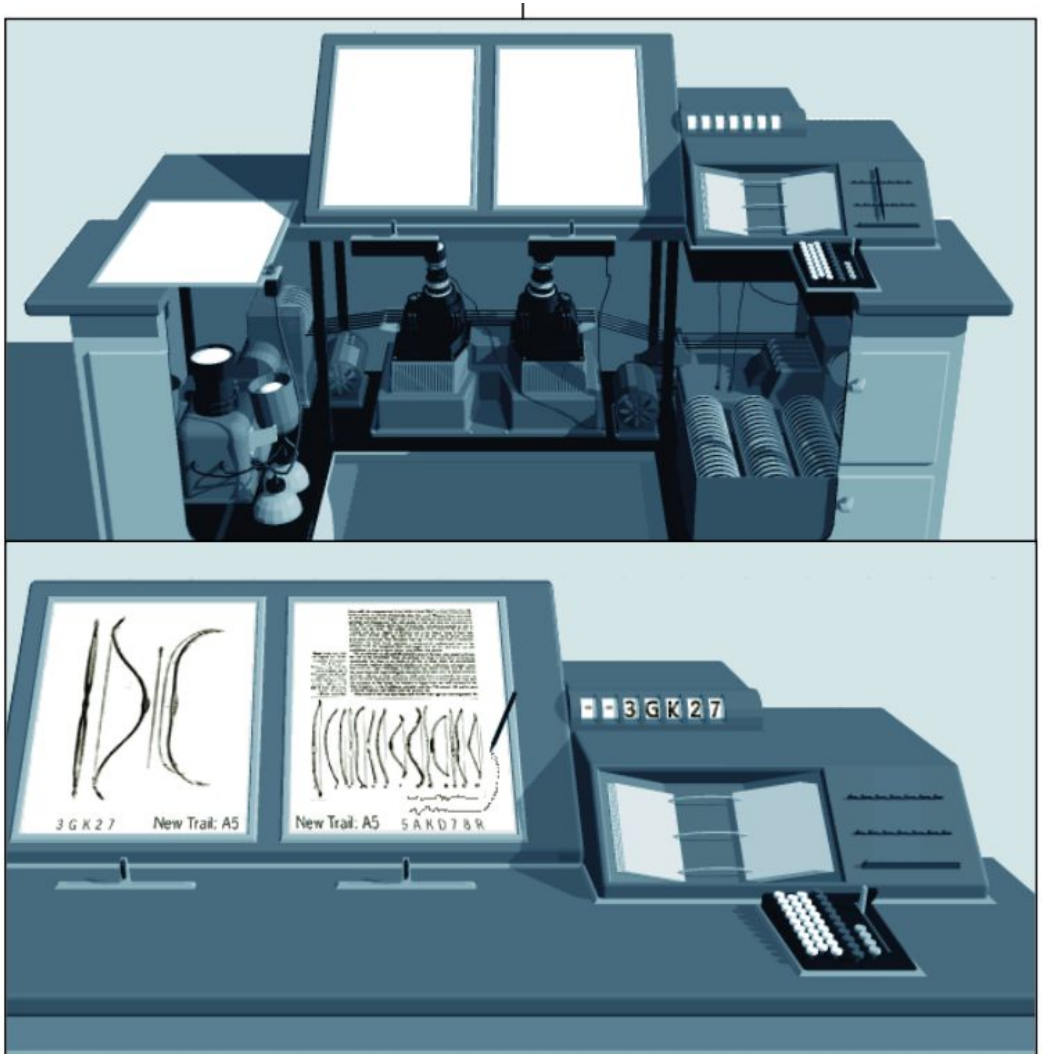
Towards personalised PageRank

https://dl.acm.org/citation.cfm?id=227186

Slight detour

The web

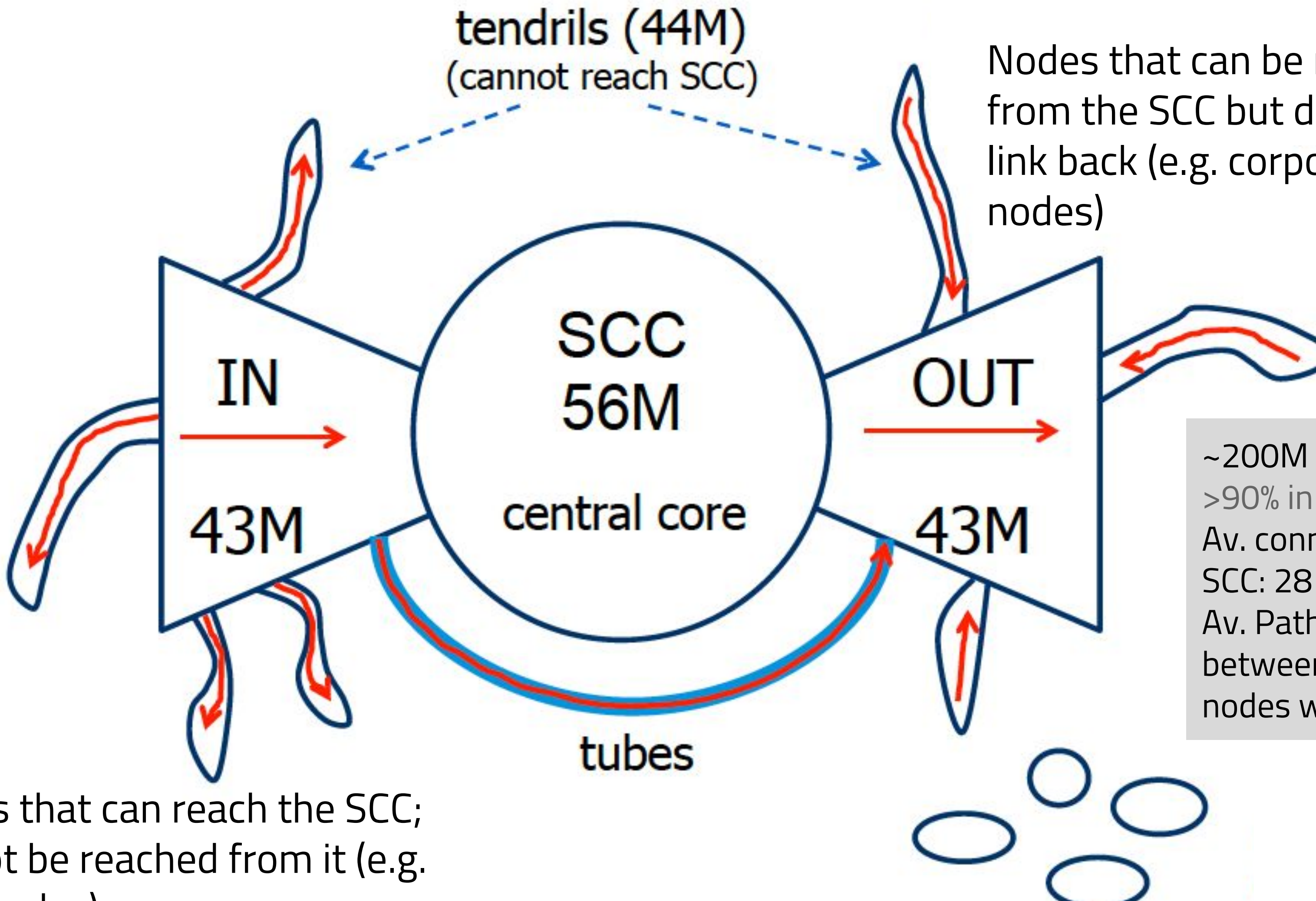
Vannevar Bush (1947)



“When the user is building a trail, he names it, inserts the name in his code book, and taps it out on his keyboard. Before him are the two items to be joined, projected onto adjacent viewing positions. At the bottom of each there are a number of blank code spaces, and a pointer is set to indicate one of these on each item. The user taps a single key, and the items are permanently joined.”

Slight detour

The structure of the web



Nodes that can be reached from the SCC but do not link back (e.g. corporate nodes)

~200M nodes
>90% in a single WCC
Av. connected dist. SCC: 28
Av. Path length: 16 between any two nodes with a path

Nodes that can reach the SCC; cannot be reached from it (e.g. new nodes)

https://dl.acm.org/citation.cfm?id=346290

“In a sense the web is much like a **complicated organism**, in which the local structure at a **microscopic scale** looks very regular like a biological cell, but the **global structure** exhibits interesting morphological structure (<u>body</u> and <u>limbs</u>) that are not obviously evident in the local structure.”

https://dl.acm.org/citation.cfm?id=324140

>9,000 citations

HITS: Hyperlink-Induced Topic Search

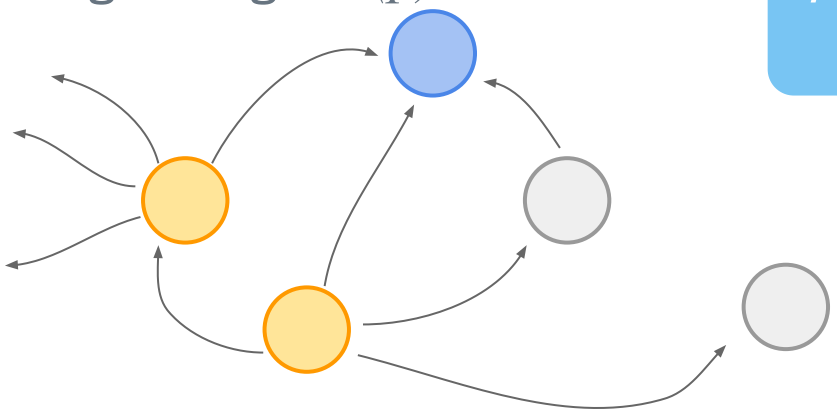
Intuition: two broad types of useful web pages for ad-hoc search queries

- **Authoritative pages**: pages containing a lot of relevant content (e.g. Wikipedia page); high weight $a(p)$

- **Hub pages**: pages containing a large number of useful hyperlinks pointing to pages with relevant content; high weight $h(p)$

A page pointed to by many **hubs**.

A page pointed to by many **authorities.**

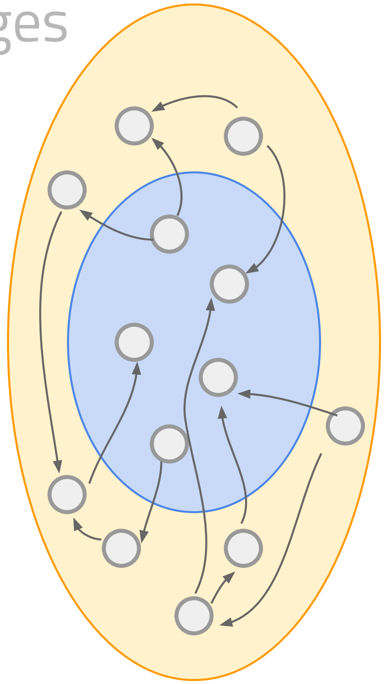


https://dl.acm.org/citation.cfm?id=324140

Do you see an issue?

HITS: Hyperlink-Induced Topic Search

1. **Root set (RS)**: retrieve the top N results for a given keyword query
2. **Base set (BS)**: expand RS by including all pages that link to pages in RS or are linked-to by pages in RS
3. Clean hyperlink structure (link removal between pages belonging to the same web site)
4. **Initialize** all hub/authority weights to 1.0
5. **Iteratively update** hub/authority weights and normalize



$$a(p) = \sum_{q \to p} h(q)$$

Authority weight increases if good hubs point to p.

$$h(p) = \sum_{p \to q} a(q)$$

Hub weight increases if p points to good authorities.

http://ilpubs.stanford.edu:8090/422/

>10,000 citations

PageRank

Which retrieval models can we easily adapt to include PageRank?

A **topic independent** approach to page importance, computed **once** per crawl

Every document of the corpus is assigned an **importance score**

Today, just one of hundreds/thousands of features in a modern web search engine.

PageRank takes the importance of the page where the link originates from into account (intuition: one link from `google.com` is better than 100 links from unpopular blogs)

"To test the utility of PageRank for search, we built a web search engine called Google."

Paper rejected from SIGIR 1998, accepted at WWW 1998.

http://ilpubs.stanford.edu:8090/422/

PageRank

Each page distributes importance through its out-links

Simple PageRank, iteratively defined:

Problem: pages that are sinks. PageRank mass vanishes.

$$PageRank_{i+1}(v) = \underbrace{\sum_{u \to v}}_{\text{all nodes linking to } v} \frac{PageRank_i(u)}{N_u}$$

eventual convergence

A page with many out-links has little influence on one particular page.

out-degree of node u

http://ilpubs.stanford.edu:8090/422/

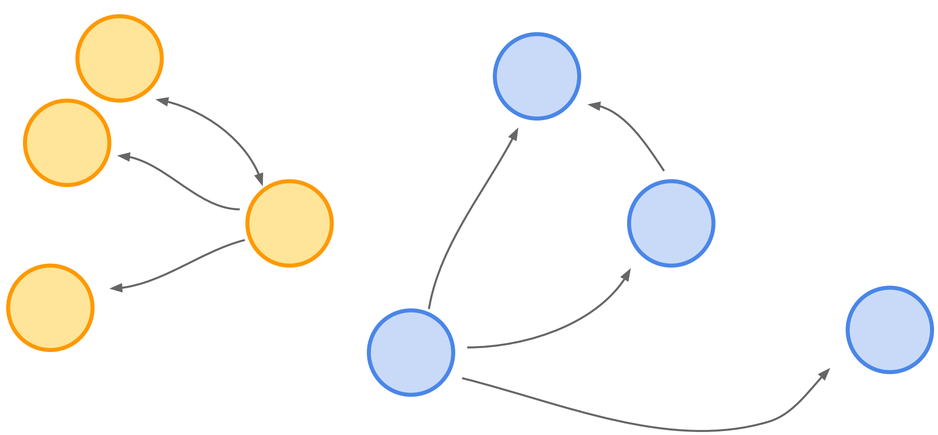
PageRank

Each page distributes importance through its out-links

PageRank, iteratively defined with a decay/damping factor:

$$PageRank_{i+1}(v) = p \sum_{u \to v} \frac{PageRank_i(u)}{N_u} + (1-p)$$

Probability that the random surfer "teleports" instead of following an outlink.



PageRank applications

Search: re-rank the top retrieved documents of a content retrieval technique according to the pages' PageRank score

Search: filter out pages with low PageRank scores

Personalized PageRank: instead of random teleporting, <u>bias</u> the teleport locations

PageRank as future **inlink count predictor**: re-order crawling list accordingly (crawl better pages first)

http://ilpubs.stanford.edu:8090/750/1/2003-29.pdf

~2,000 citations

Personalized PageRank

Desired: **query-time information** should be able to influence the PageRank score while still requiring **minimal computation**

Idea: compute offline a **set of PageRank scores** per document, each biased towards a topic (here: 16 ODP topics)

Slight detour

DMOZ

From Wikipedia, the free encyclopedia

DMOZ (from *directory.mozilla.org*, an earlier domain name) was a multilingual open-content directory of World Wide Web links. The site and community who maintained it were also known as the **Open Directory Project** (**ODP**). It was owned by AOL (now a part of Verizon's Oath Inc.) but constructed and maintained by a community of volunteer editors.

DMOZ used a hierarchical ontology scheme for organizing site listings. Listings on a similar topic were grouped into categories which then included smaller categories.

DMOZ closed on March 17, 2017 because AOL no longer wished to support the project.[2][3] The website became a single landing page on that day, with links to a static archive of DMOZ, and to the DMOZ discussion forum, where plans to rebrand and relaunch the directory are being discussed.[3]

As of September 2017, a non-editable mirror remained available at dmoztools.net,[4] and it was announced that while the DMOZ URL would not return, a successor version of the directory named **Curlie** would be provided.[5][6]

DMOZ

DMOZ/ODP Wikipedia entry

http://ilpubs.stanford.edu:8090/750/1/2003-29.pdf

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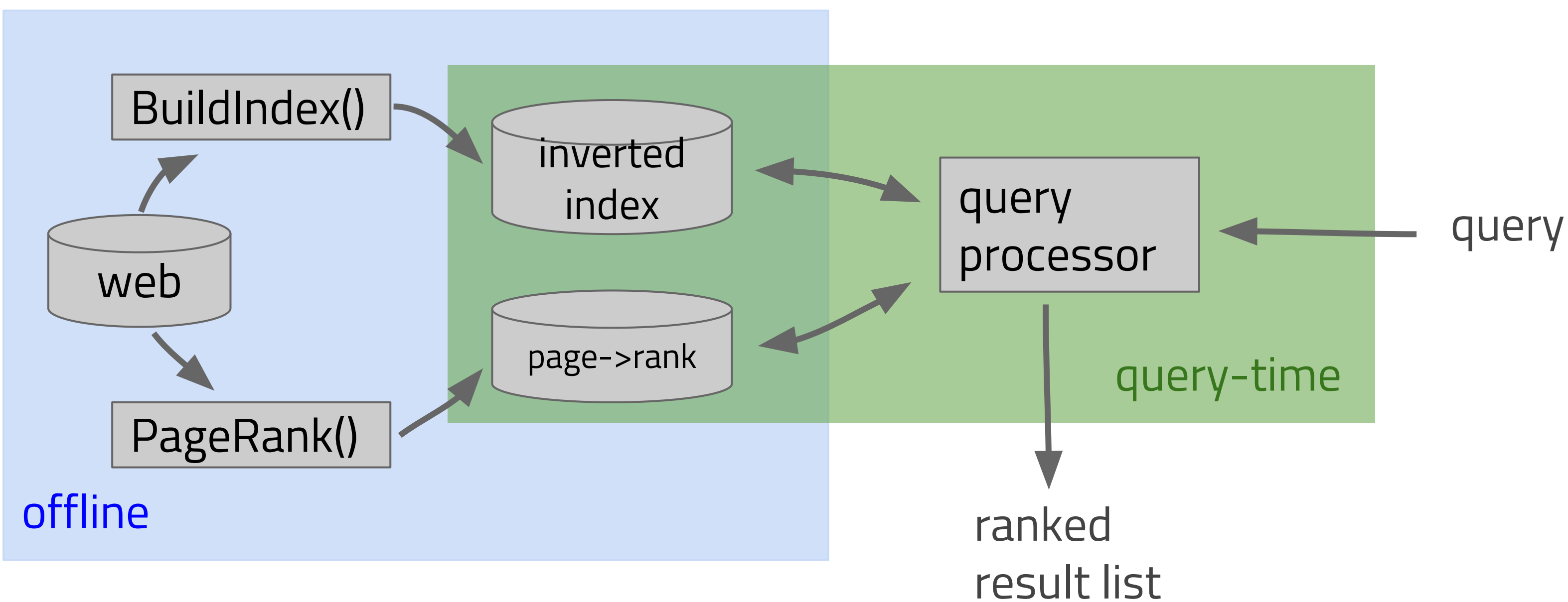

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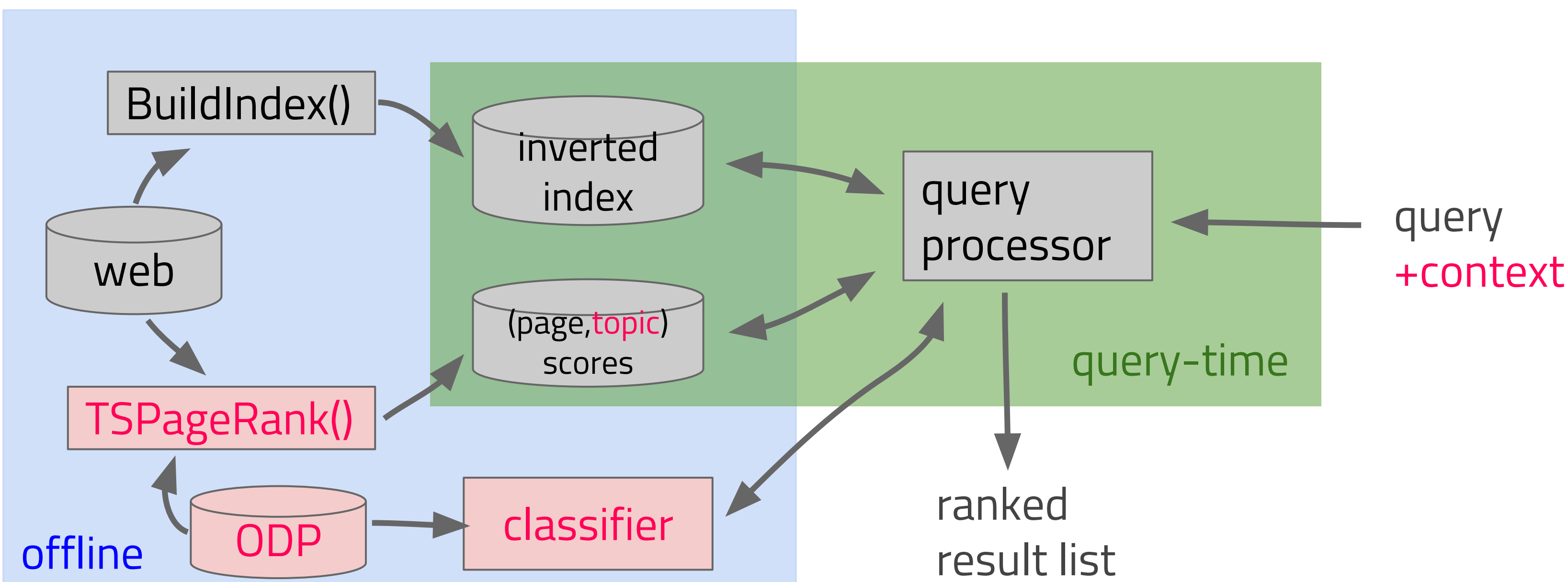

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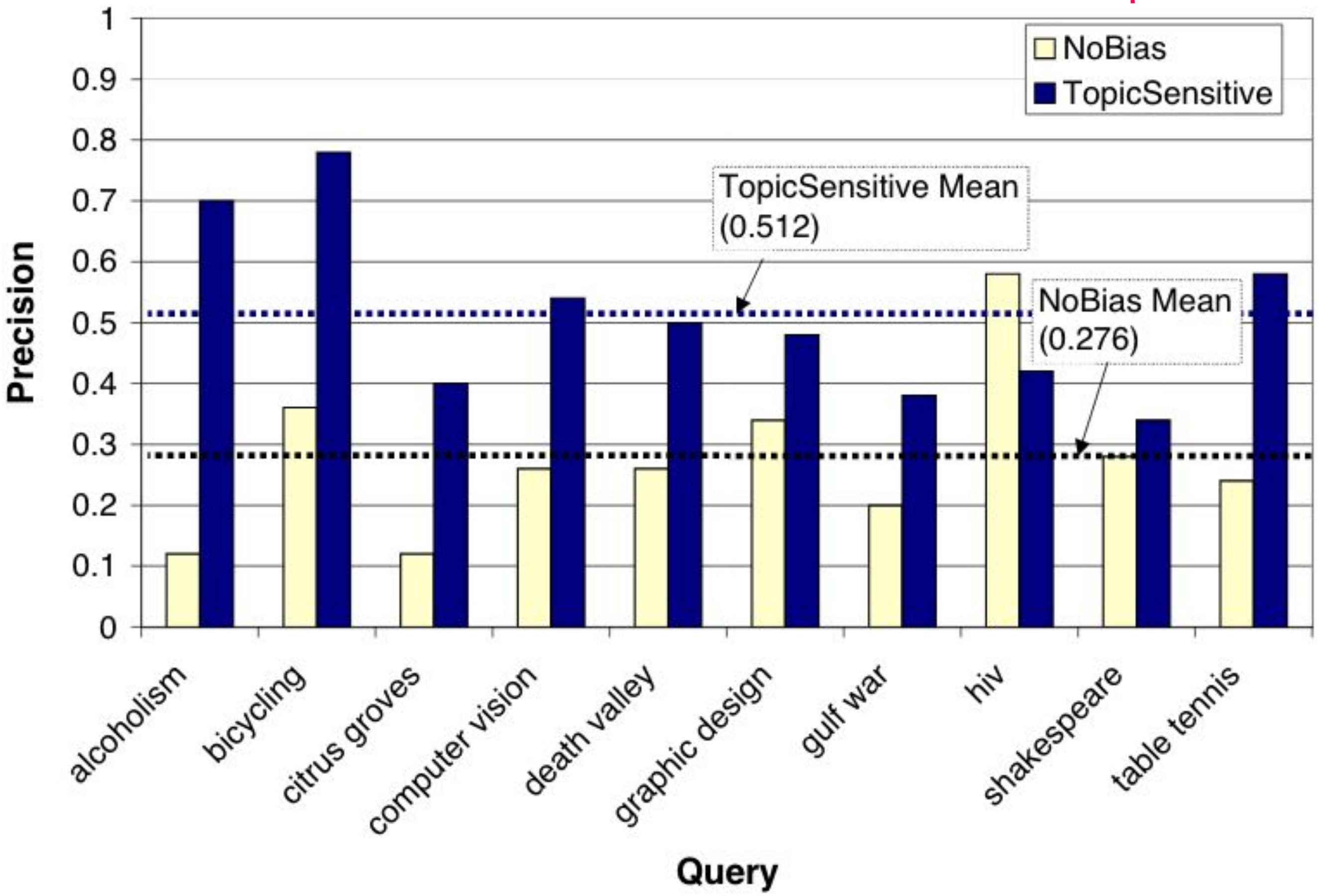
Personalized PageRank

10 test queries



That's it for today!

Next week Friday: submit your intermediate report!

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