Implicit User Feedback

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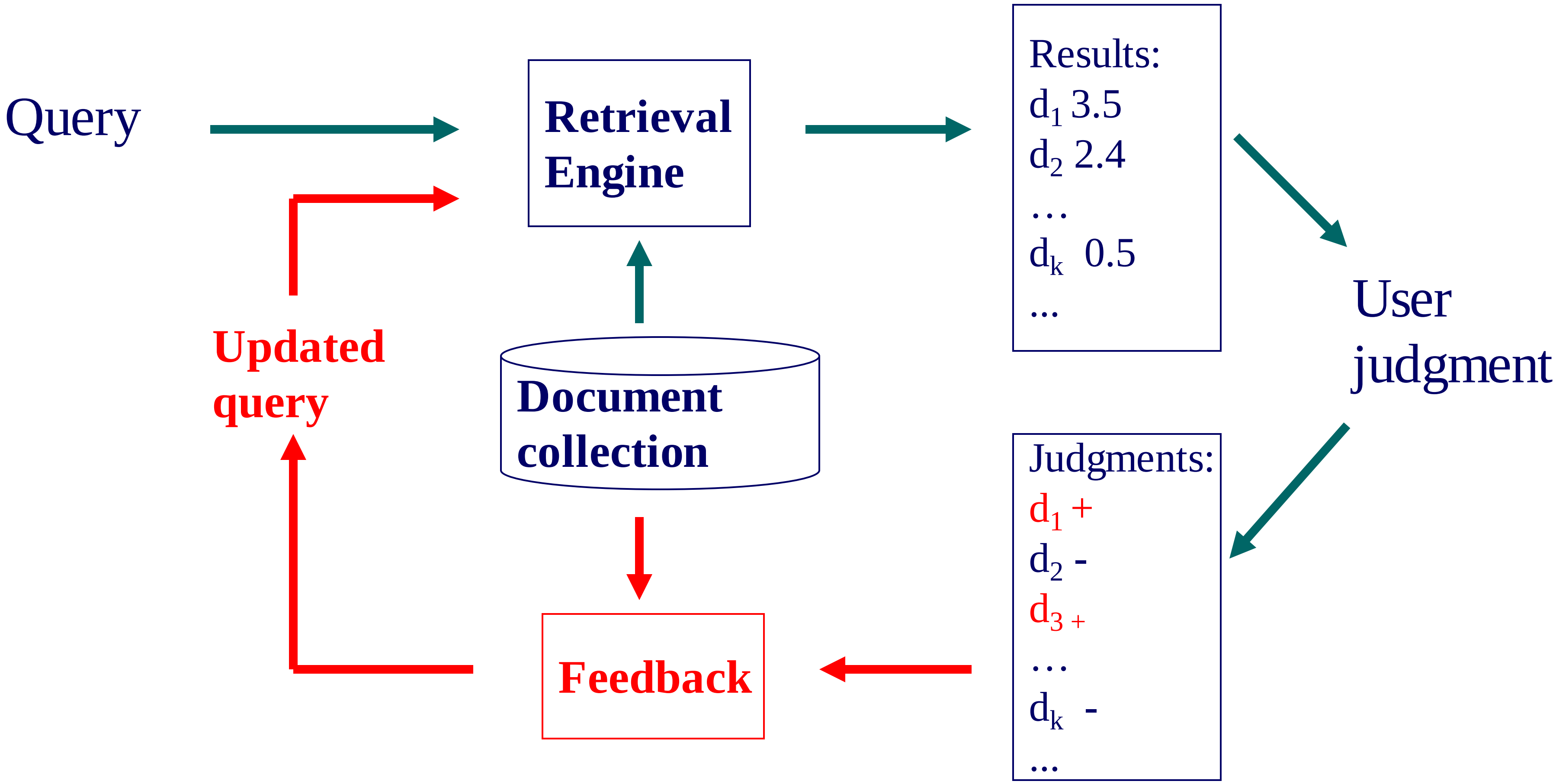
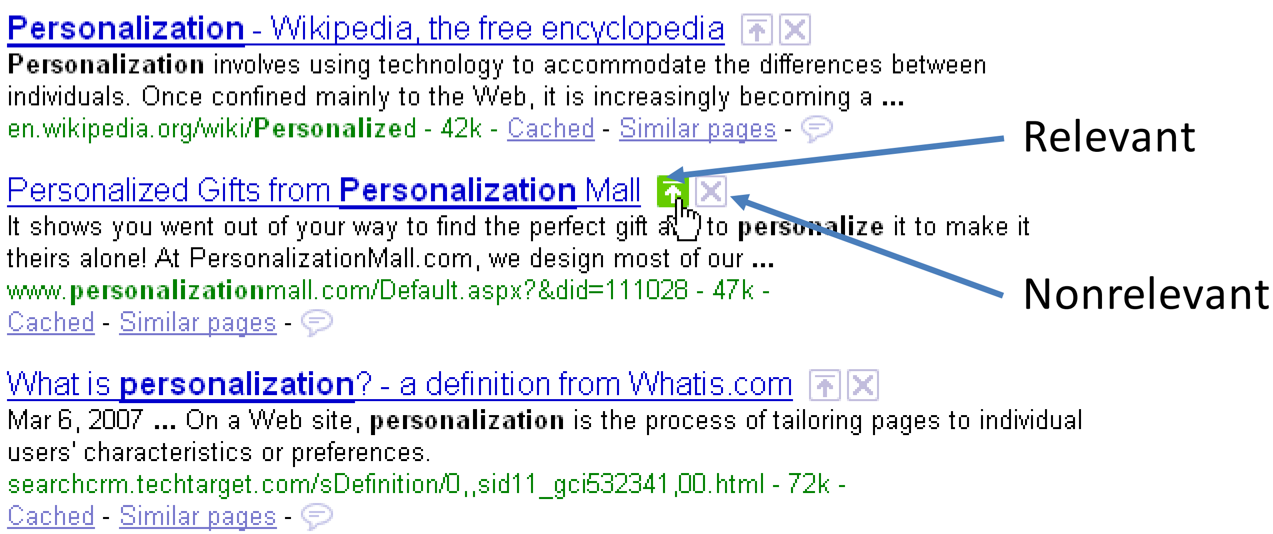
Explicit relevance feedback



Relevance feedback in real systems

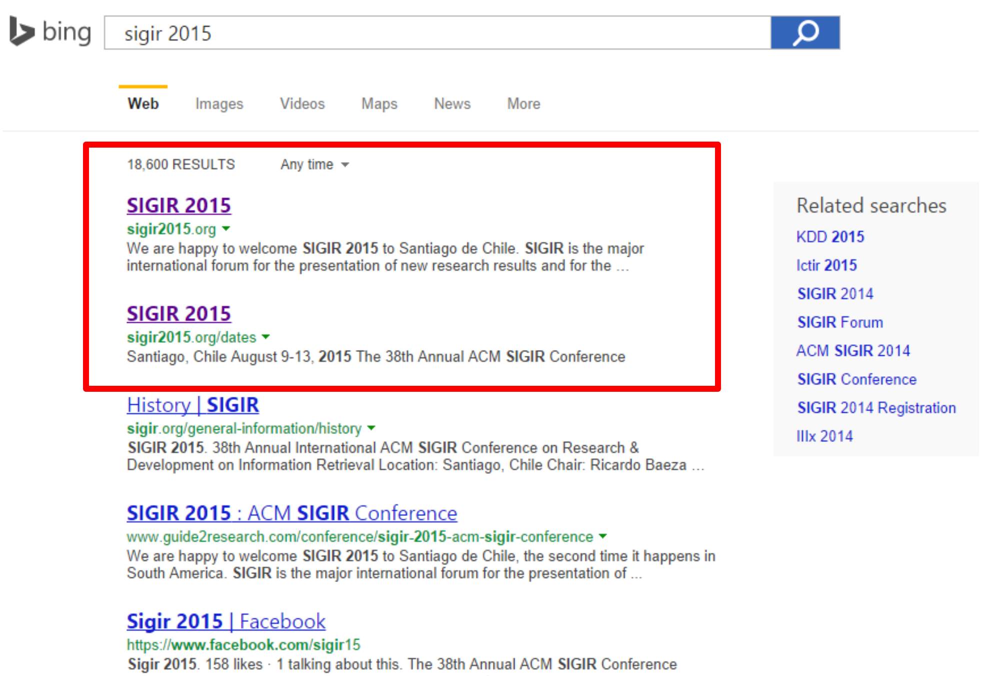
- Google used to provide such functions



  - Vulnerable to spammers

How about using clicks

- Clicked document as relevant, non-clicked as non-relevant
  - Cheap, largely available



Is click reliable?

- Why do we click on the returned document?
  - Title/snippet looks attractive
    - We haven’t read the full text content of the document
  - It was ranked higher
    - Belief bias towards ranking
  - We know it is the answer!

Is click reliable?

- Why do not we click on the returned document?
  - Title/snippet has already provided the answer
    - Instant answers, knowledge graph
  - Extra effort of scrolling down the result page
    - The expected loss is larger than skipping the document
  - We did not see it....

Can we trust click as relevance feedback?

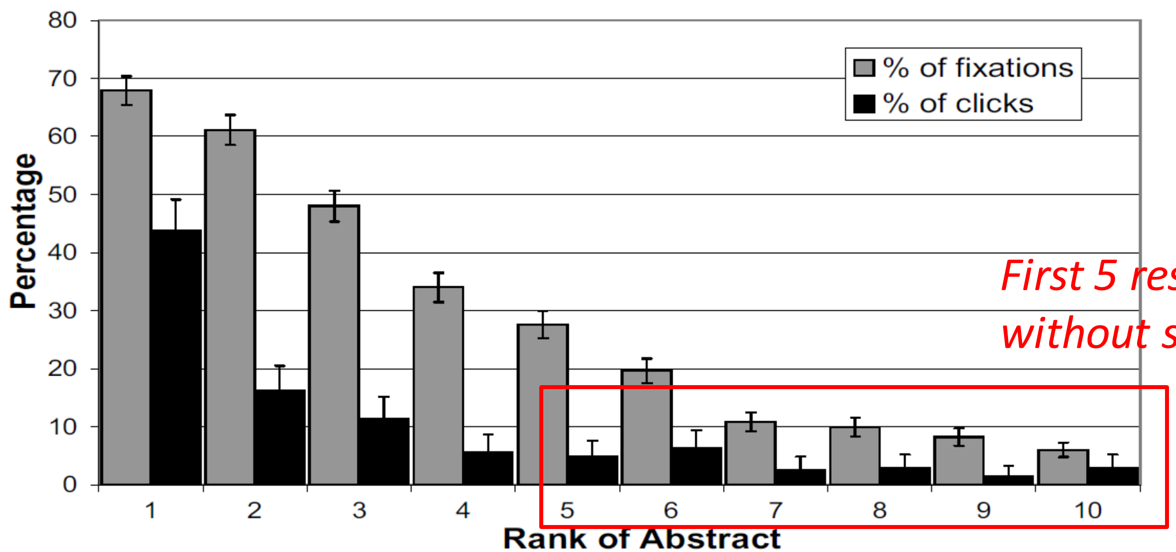
Accurately Interpreting Clickthrough Data as Implicit Feedback [Joachims SIGIR'05]

- Eye tracking, click and manual relevance judgment to answer
  - Do users scan the results from top to bottom?
  - How many abstracts do they read before clicking?
  - How does their behavior change, if search results are artificially manipulated?

Which links do users view and click?

- Positional bias

Fixations: a spatially stable gaze lasting for approximately 200-300 ms, indicating visual attention



First 5 results are visible without scrolling

Figure 1: Percentage of times an abstract was viewed/clicked depending on the rank of the result.

Do users scan links from top to bottom?

Need scroll down to view these results

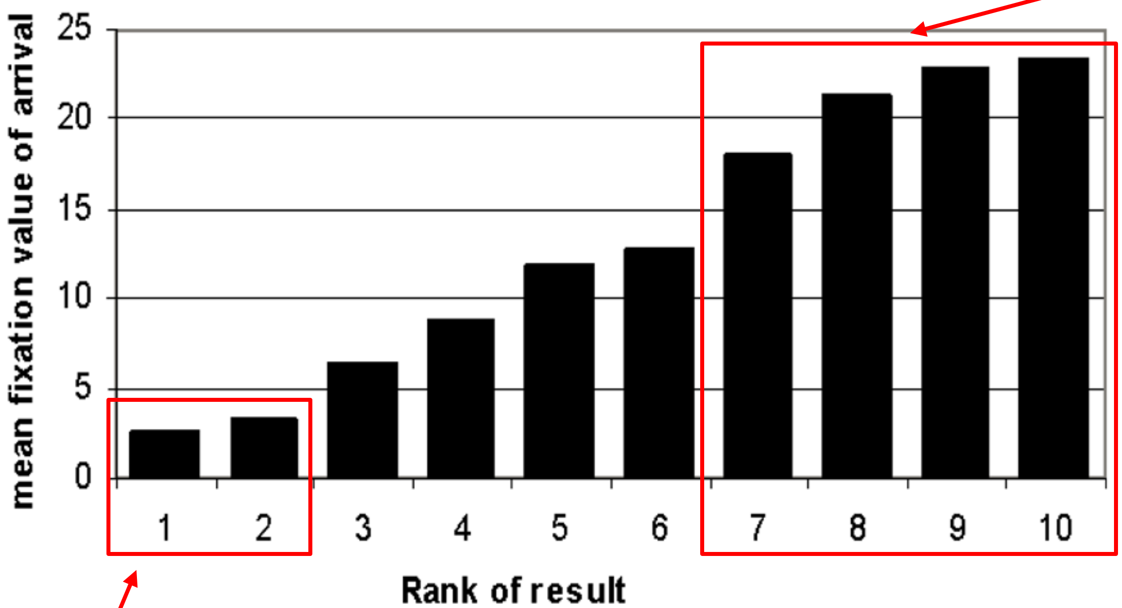


Figure 2: Mean time of arrival (in number of previous fixations) depending on the rank of the result.

View the top two results within the second or third fixation

Which links do users evaluate before clicking?

- The lower the click in the ranking, the more abstracts are viewed before the click

Table 2: Percentage of times the user viewed an abstract at a particular rank before he clicked on a link at a particular rank.

Viewed	Clicked Rank					
Rank	1	2	3	4	5	6
1	90.6%	76.2%	73.9%	60.0%	54.5%	45.5%
2	56.8%	90.5%	82.6%	53.3%	63.6%	54.5%
3	30.2%	47.6%	95.7%	80.0%	81.8%	45.5%
4	17.3%	19.0%	47.8%	93.3%	63.6%	45.5%
5	8.6%	14.3%	21.7%	53.3%	100.0%	72.7%
6	4.3%	4.8%	8.7%	33.3%	18.2%	81.8%

Does relevance influence user decisions?

- Controlled relevance quality
  – Reverse the ranking from search engine
- Users’ reactions
  – Scan significantly more abstracts than before
  – Less likely to click on the first result
  – Average clicked rank position drops from 2.66 to 4.03
  – Average clicks per query drops from 0.8 to 0.64

Are clicks absolute relevance judgments?

- Position bias
  - Focus on position one and two, equally likely to be viewed

"normal"	l_1^-, l_2^-	l_1^+, l_2^-	l_1^-, l_2^+	l_1^+, l_2^+	total
$rel(l_1) > rel(l_2)$	15	19	1	1	36
$rel(l_1) < rel(l_2)$	11	5	2	2	20
$rel(l_1) = rel(l_2)$	19	9	1	0	29
total	45	33	4	3	85

"swapped"	l_1^-, l_2^-	l_1^+, l_2^-	l_1^-, l_2^+	l_1^+, l_2^+	total
$rel(l_1) > rel(l_2)$	11	15	1	1	28
$rel(l_1) < rel(l_2)$	17	10	7	2	36
$rel(l_1) = rel(l_2)$	36	11	3	0	50
total	64	36	11	3	114

Are clicks relative relevance judgments?

- Clicks as <u>pairwise</u> preference statements
  - Given a ranked list and user clicks

$$l_1^{*(2)} \quad l_2 \quad l_3^{*(1)} \quad l_4 \quad l_5^{*(3)} \quad l_6 \quad l_7$$

- Click > Skip Above
- Last Click > Skip Above
- Click > Earlier Click
- Last Click > Skip Previous
- Click > Skip Next

Clicks as pairwise preference statements

- Accuracy against manual relevance judgment

Explicit Feedback	Abstracts				
Data	Phase I	Phase II			
Strategy	"normal"	"normal"	"swapped"	"reversed"	all
Inter-Judge Agreement	89.5	N/A	N/A	N/A	82.5
Click > Skip Above	80.8 ± 3.6	88.0 ± 9.5	79.6 ± 8.9	83.0 ± 6.7	83.1 ± 4.4
Last Click > Skip Above	83.1 ± 3.8	89.7 ± 9.8	77.9 ± 9.9	84.6 ± 6.9	83.8 ± 4.6
~~Click > Earlier Click~~	~~67.2 ± 12.3~~	~~75.0 ± 25.8~~	~~36.8 ± 22.9~~	~~28.6 ± 27.5~~	~~46.9 ±13.9~~
Click > Skip Previous	82.3 ± 7.3	88.9 ± 24.1	80.0 ± 18.0	79.5 ± 15.4	81.6 ± 9.5
~~Click > No Click Next~~	~~84.1 ± 4.9~~	~~75.6 ± 14.5~~	~~66.7 ± 13.1~~	~~70.0 ± 15.7~~	~~70.4 ± 8.0~~

How accurately do clicks correspond to explicit judgment of a document?

- Accuracy against manual relevance judgment

Explicit Feedback Data Strategy	Pages Phase II all
Inter-Judge Agreement	86.4
Click > Skip Above	78.2 ± 5.6
Last Click > Skip Above	80.9 ± 5.1
~~Click > Earlier Click~~	~~64.3 ±15.4~~
Click > Skip Previous	80.7 ± 9.6
~~Click > No Click Next~~	~~67.4 ± 8.2~~

What do we get from this user study?

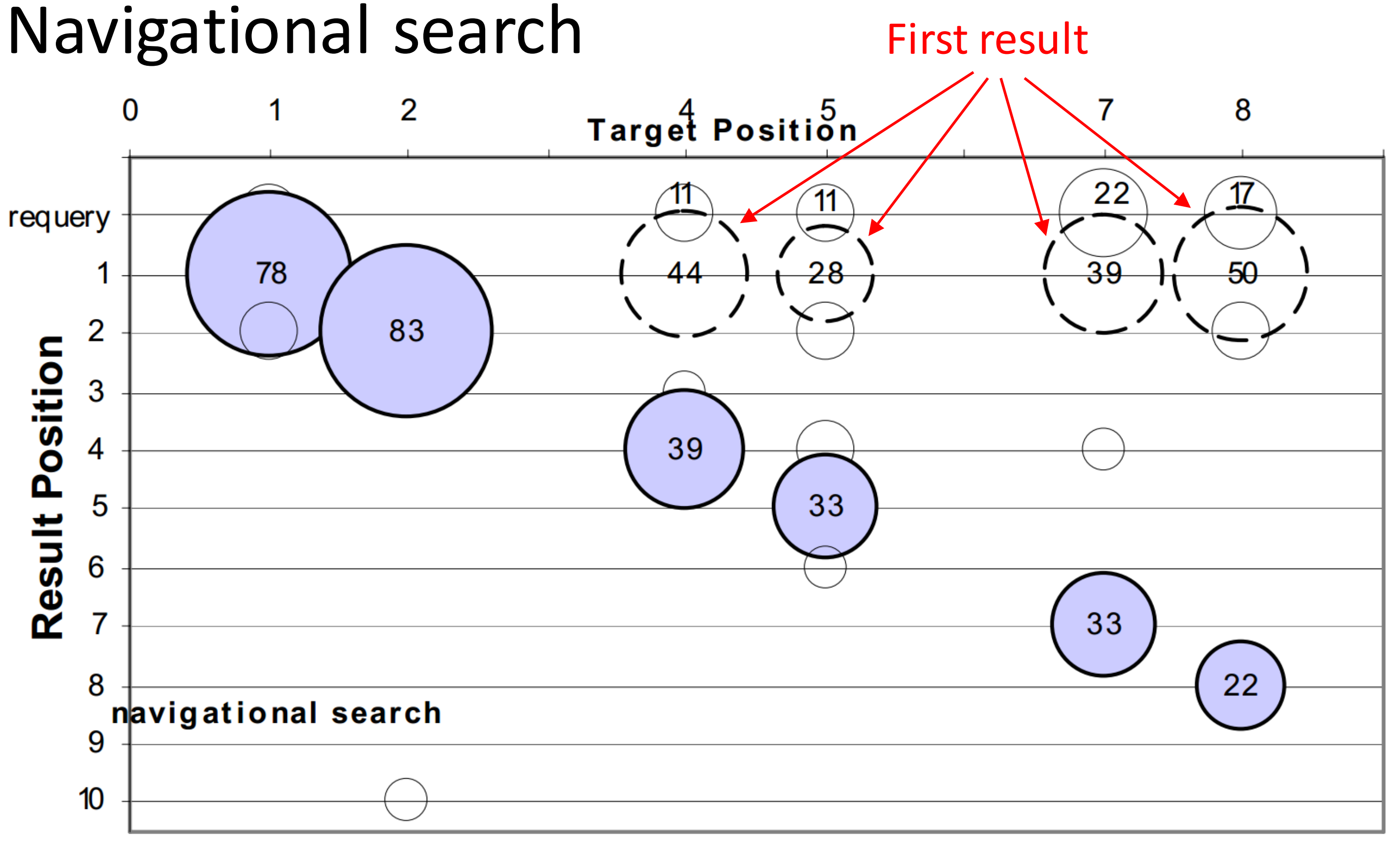
- Clicks are influenced by the relevance of results
  - Biased by the trust over rank positions
- Clicks as relative preference statement is more accurate
  - Several heuristics to generate the preference pairs

How to utilize such preference pairs?

- Pairwise learning to rank algorithms
  – Will be covered later

An eye tracking study of the effect of target rank on web search [Guan CHI'07]

- Break down of users' click accuracy
  - Navigational search



An eye tracking study of the effect of target rank on web search [Guan CHI'07]

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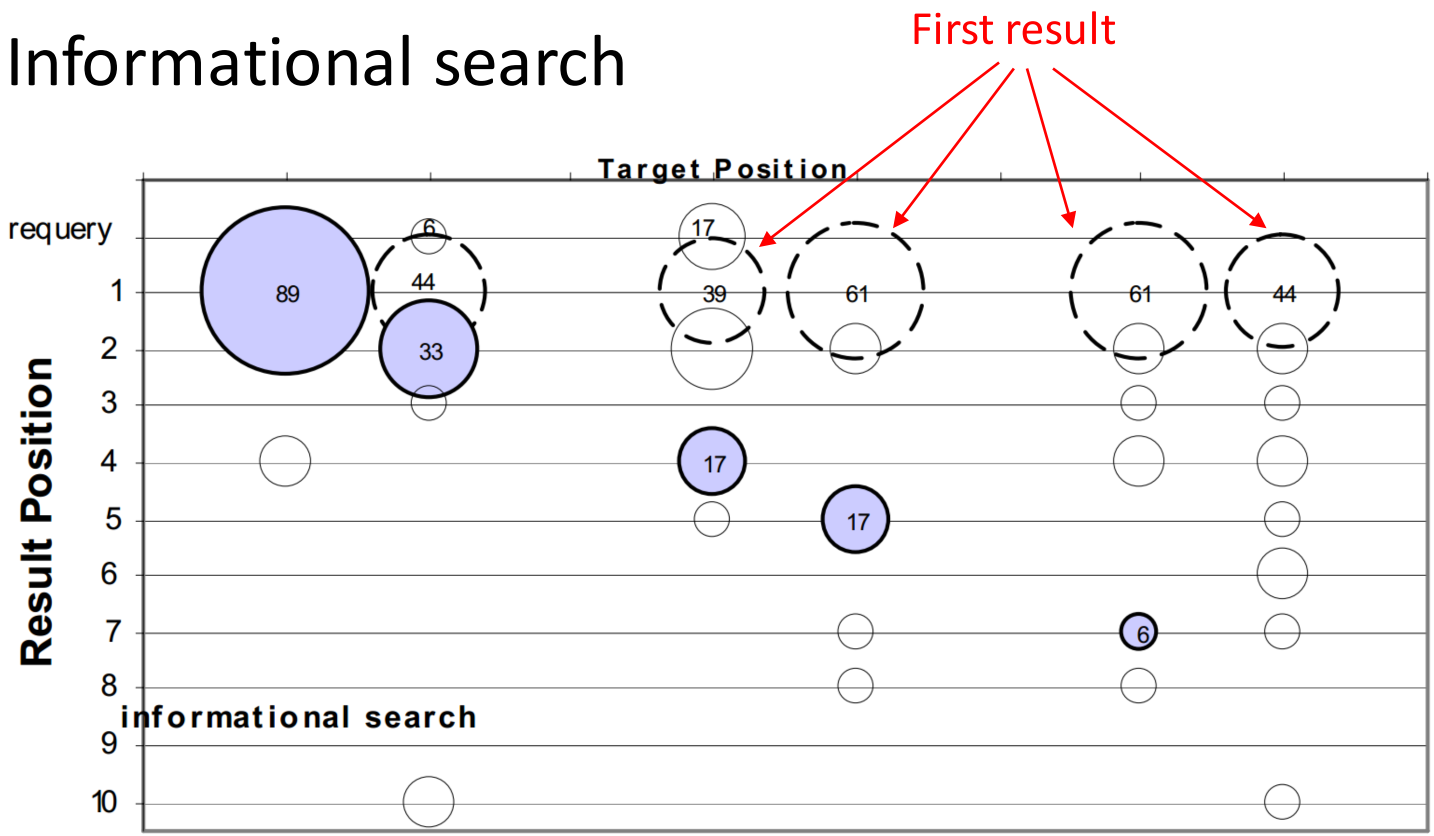
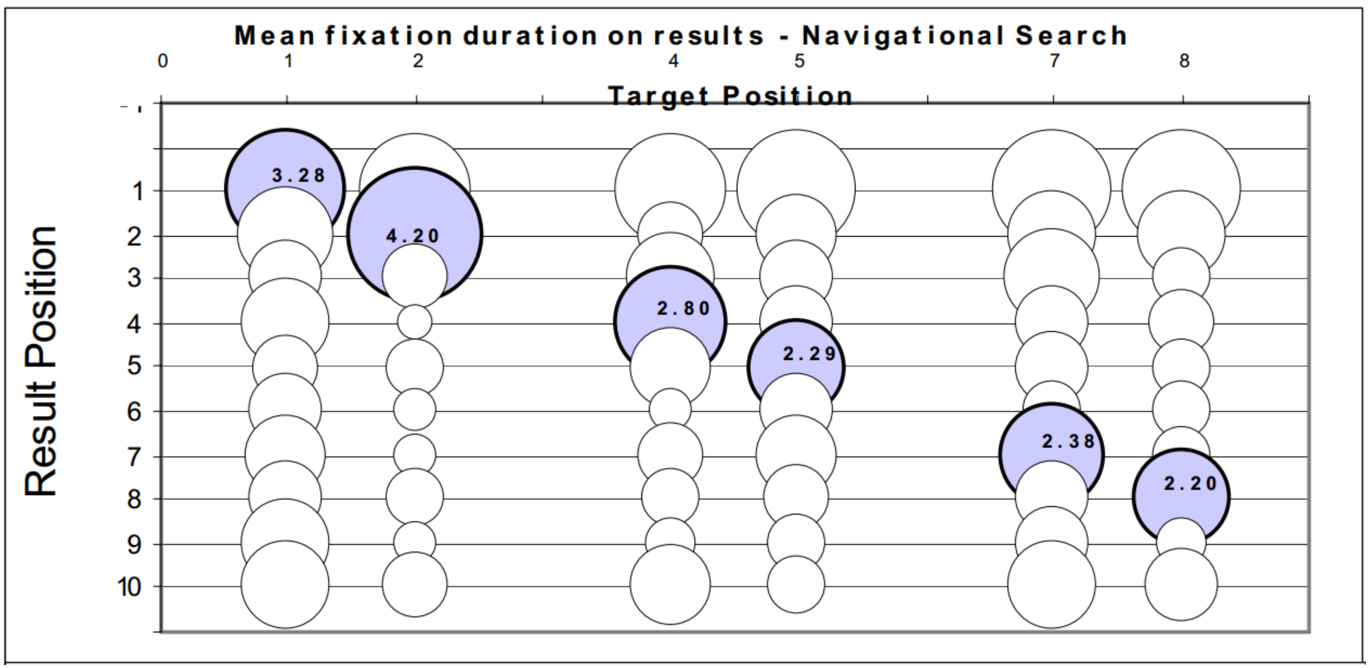


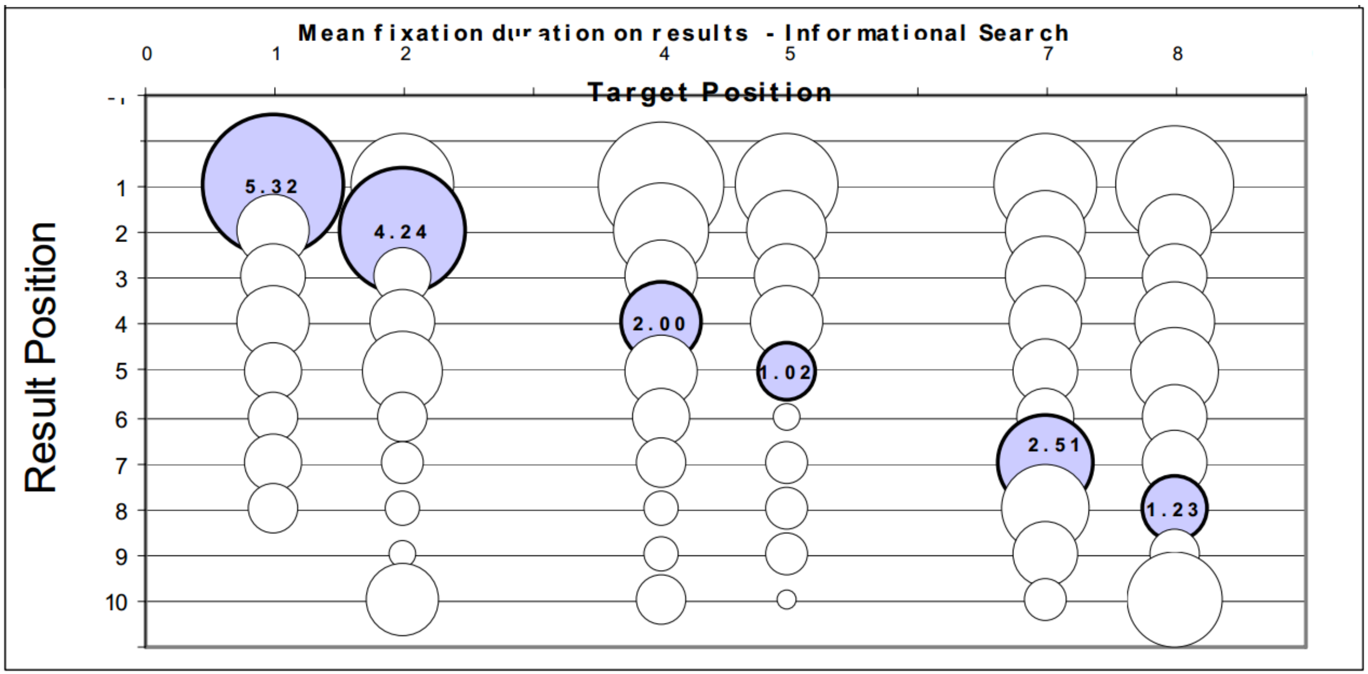
Users failed to recognize the target because they did not read it!

- Navigational search



Users did not click because they did not read the results!

- Informational search



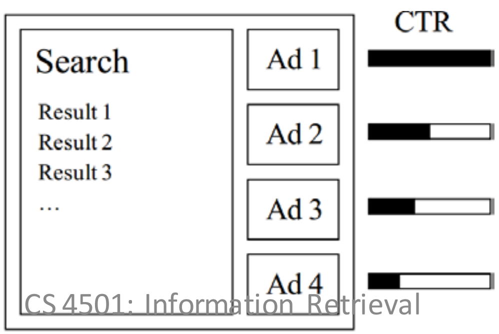
Predicting clicks: estimating the click-through rate for new ads [Richardson WWW'07]

- To maximize ad revenue
  - $E_{ad}[Revenue] = \sum_{ad} p(click|ad)CPC(ad)$

Estimated click-through rate

Cost per click: basic business model in search engines

- Position-bias is also true in online ads
  - Observed low CTR is not just because of ads' quality, but also their display positions!



Combat position-bias by explicitly modeling it

- Being clicked is related to its quality and position
  - $p(click|ad,pos) = p(click|ad,pos,seen)p(seen|pos)$
    $= \underbrace{p(click|ad,seen)}_{\text{Calibrated CTR for ads ranking}}\underbrace{p(seen|pos)}_{\text{Discounting factor}}$
  - $p(click=1|ad,seen=0) = 0$
  - $p(click=1|ad,seen=1) = \frac{1}{1+\exp(-w^t f_{ad})}$

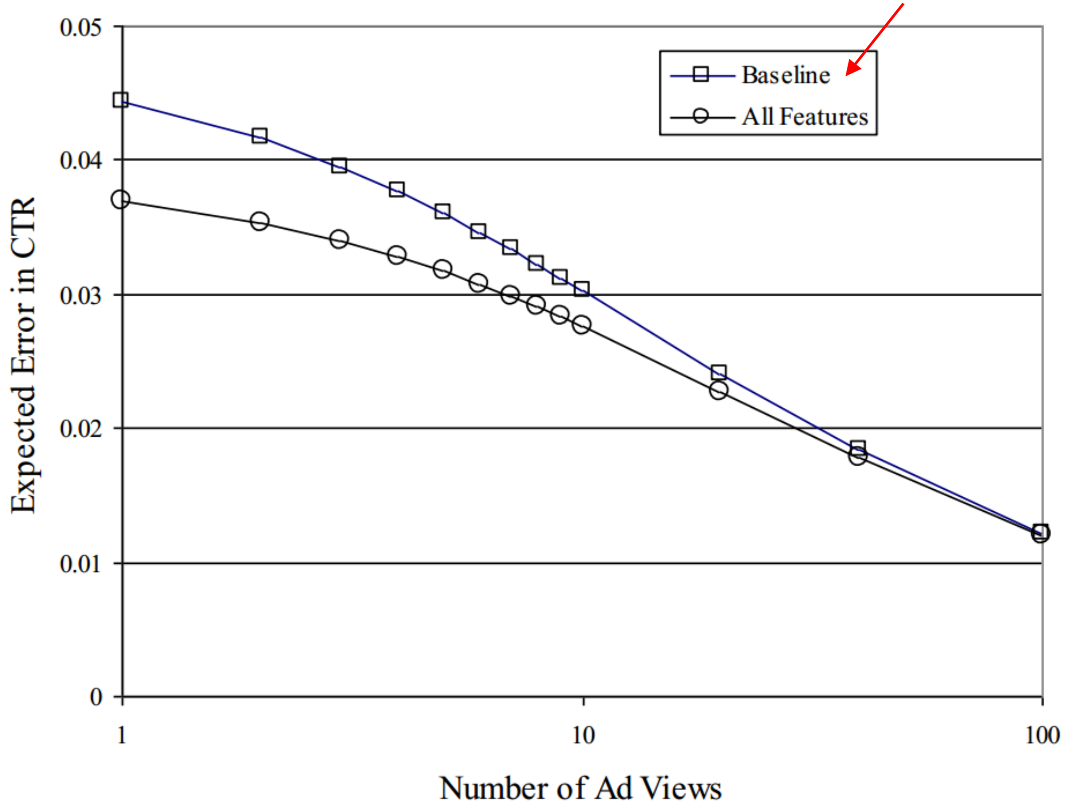
Logistic regression by features of the ad

Parameter estimation

- Discounting factor
  - Approximation: positions being clicked must be seen already
    - $p(seen|pos) \propto \#clicks\_at\_pos$
- Calibrated CTR
  - Maximum likelihood for w with historic clicks
    - $\hat{w} = argmax_w \sum_{ad} logp(click|ad,pos)$

Calibrated CTR is more accurate for new ads

Simple counting of CTR



- Unfortunately, their evaluation criterion is still based on biased clicks in testing set

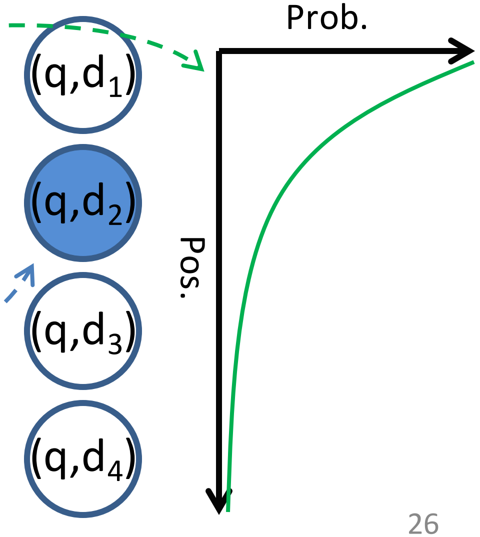
Click models

- Decompose relevance-driven clicks from position-driven clicks
  - Examine: user reads the displayed result
  - Click: user clicks on the displayed result
  - Atomic unit: (query, doc)

$$P(C=1|d,i) = \sum_{e\in\{0,1\}} P(C=1|d,i,E=e)P(E=e|d,i)$$

Relevance quality

$$= \underbrace{P(C=1|d,E=1)}_{\text{Click probability}}\underbrace{P(E=1|i)}_{\text{Examine probability}}$$



Cascade Model [Craswell et al. WSDM'08]

- Sequential browsing assumption
  - At each position decides whether to move on
    - $p(C_i = 1) = p(R_i = 1) \prod_{j=1}^{i-1} (1 - p(R_j = 1))$
    - Assuming $R_i = 1 \rightarrow C_i = 1$
  - Only one click is allowed on each search result page

Kind of "Click > Skip Above"?

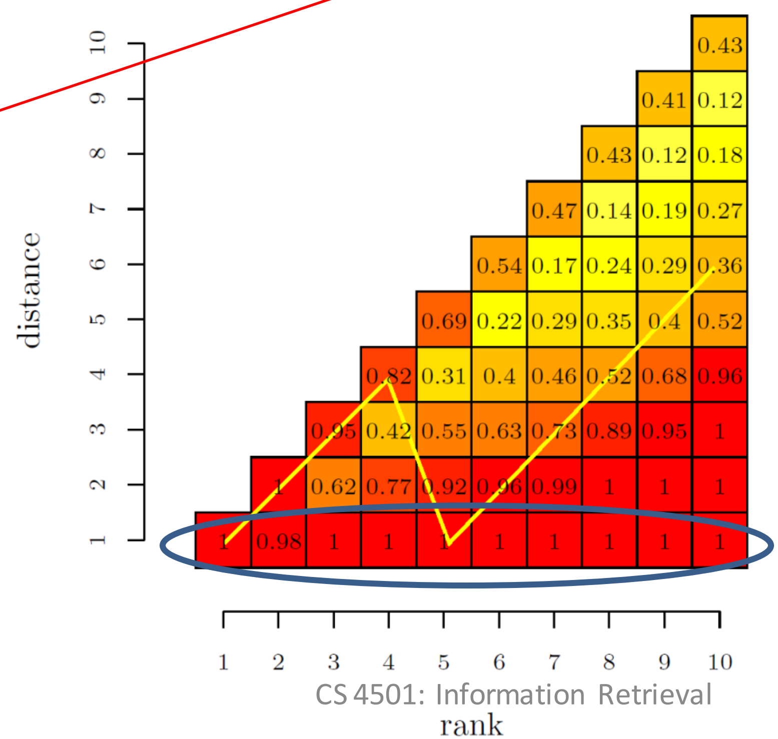
User Browsing Model [Dupret et al. SIGIR'08]

- Examination depends on distance to the last click
  - $P(c=1|u,q,r,d) = \alpha_{uq}\gamma_{rd}$

Attractiveness, determined by query and URL

Examination, determined by position and distance to last click

EM for parameter estimation

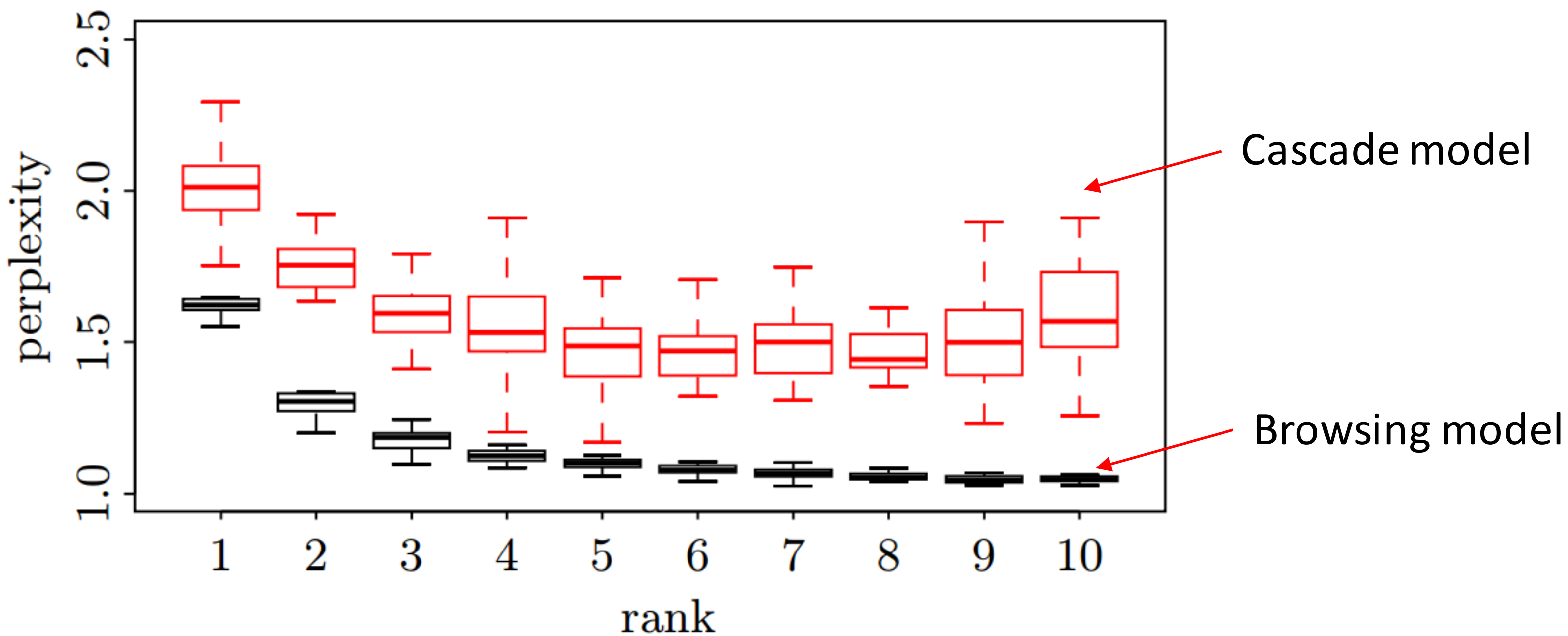


From absolute discount to relative discount

Kind of "Click > Skip Next" + "Click > Skip Above"?

More accurate prediction of clicks

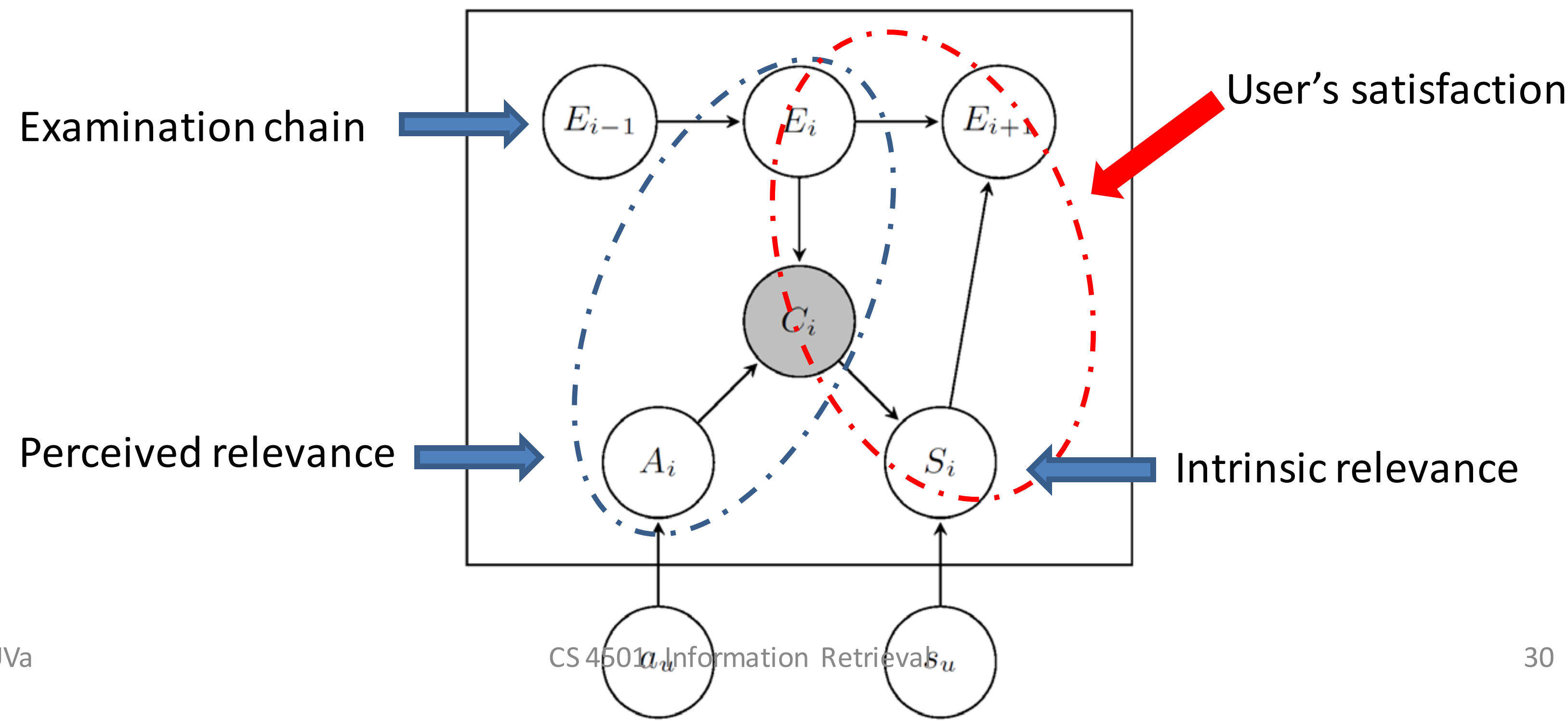
- Perplexity – randomness of prediction



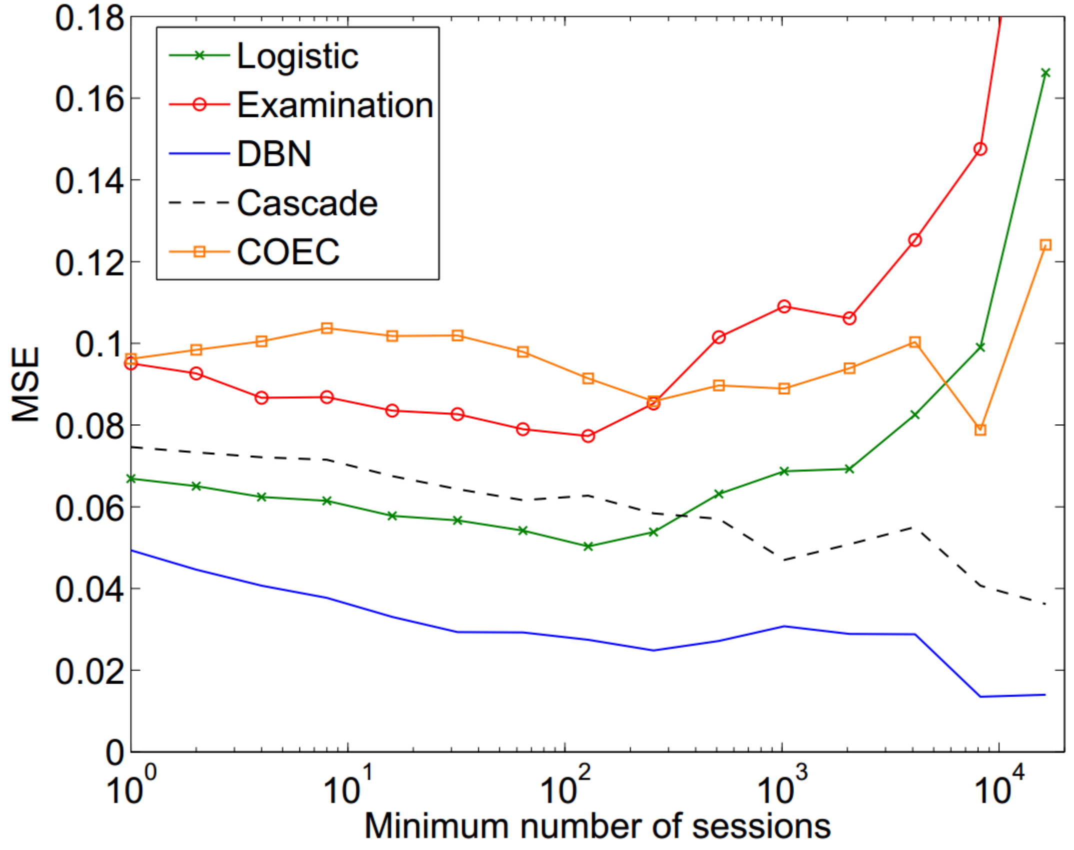
Dynamic Bayesian Model [Chapelle et al. WWW'09]

- A cascade model
  - Relevance quality:

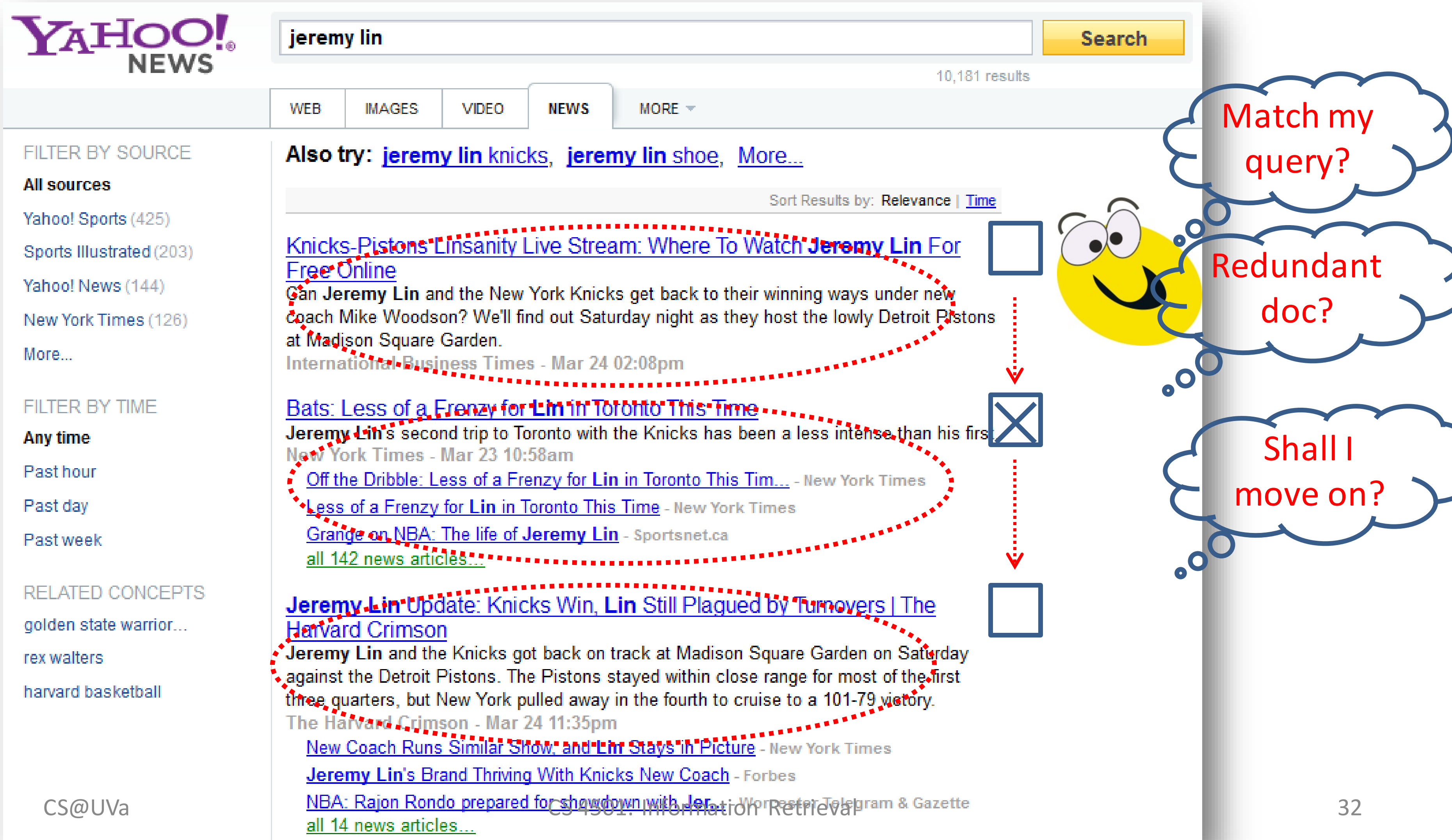
$$P(E_{i+1} = 1 | E_i = 1, S_i = 0) = \gamma$$
$$S_i = 1 \Rightarrow E_{i+1} = 0$$



Accuracy in predicting CTR



Revisit User Click Behaviors

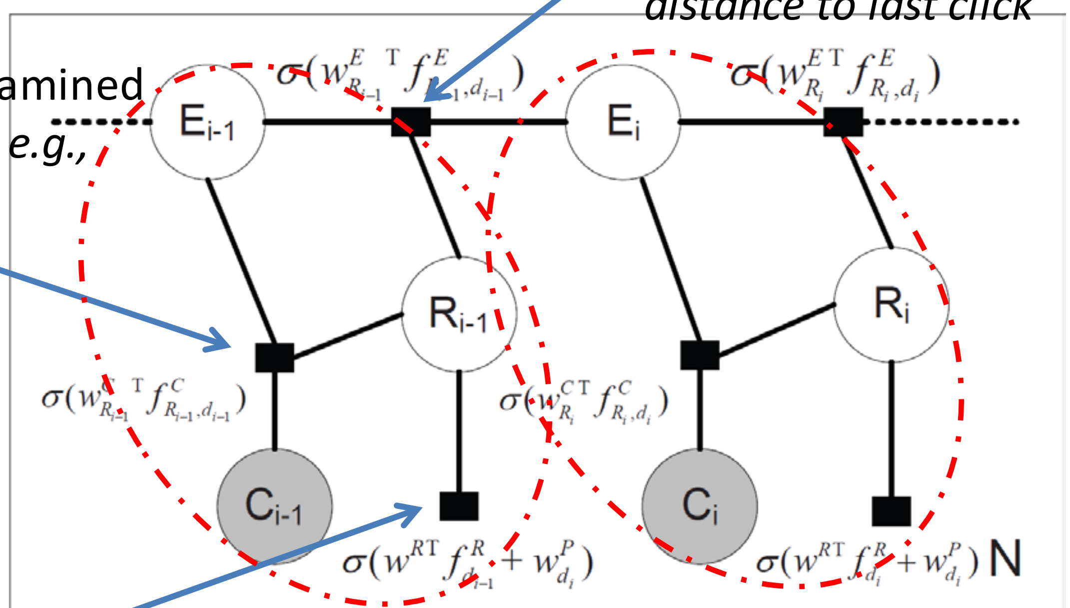


Content-Aware Click Modeling [Wang et al. WWW'12]

- Encode dependency within user browsing behaviors via descriptive features

Chance to further examine the result documents: *e.g., position, # clicks, distance to last click*

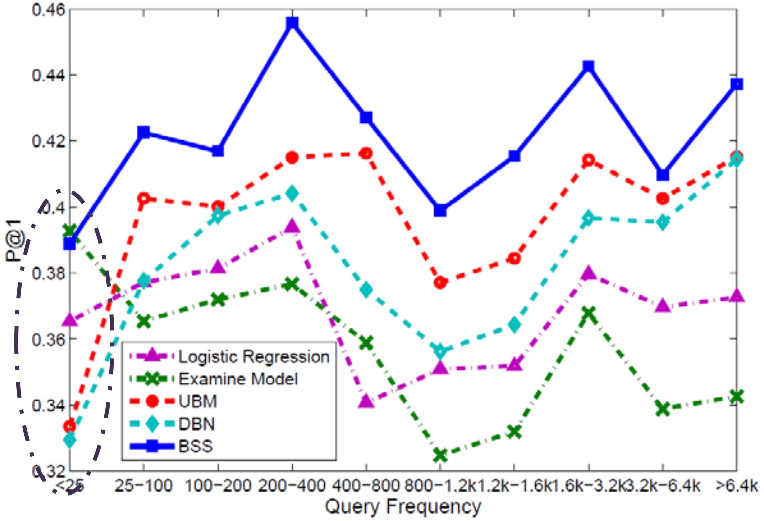
Chance to click on an examined and relevant document: *e.g., clicked/skipped content similarity*



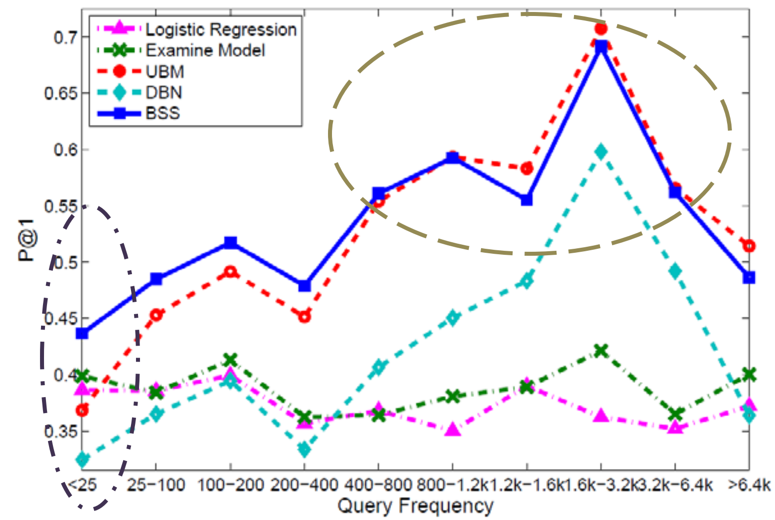
Relevance quality of a document: *e.g., ranking features*

Quality of relevance modeling

- Estimated relevance for ranking



(a) P@1 ranking performance under different query frequency categories on the random bucket click set



(b) P@1 ranking performance under different query frequency categories on the normal click set

Understanding user behaviors

- Analyzing factors affecting user clicks

f^R	age	authority	title match	abs. match	body match
w^R	-0.839	0.007	0.098	0.167	0.020
f^C	pos	# click	dis. to last click	query length	bias
$w^C_{R=0}$	-1.133	-0.351	-0.445	-3.659	-4.654
$w^C_{R=1}$	0.149	0.335	0.415	3.707	4.405
f^E	pos	# click	dis. to last click	avg cont. sim.	bias
$w^E_{R=0}$	1.807	-0.418	0.684	2.947	5.325
$w^E_{R=1}$	-1.381	0.665	-3.395	-2.237	3.266

What you should know

- Clicks as implicit relevance feedback
- Positional bias
- Heuristics for generating pairwise preferences
- Assumptions and modeling approaches for click models