# Implicit User Feedback

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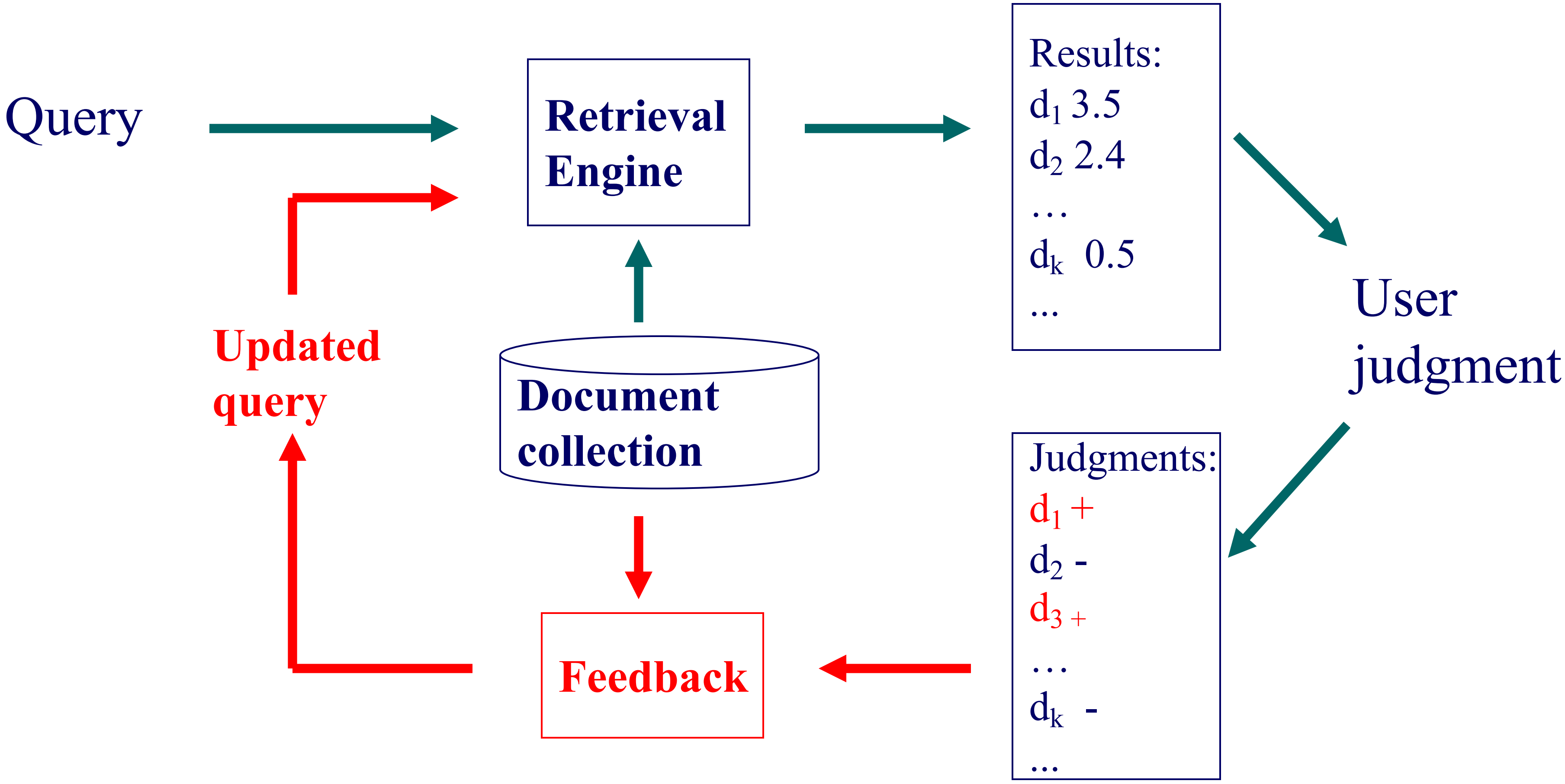
# Explicit relevance feedback



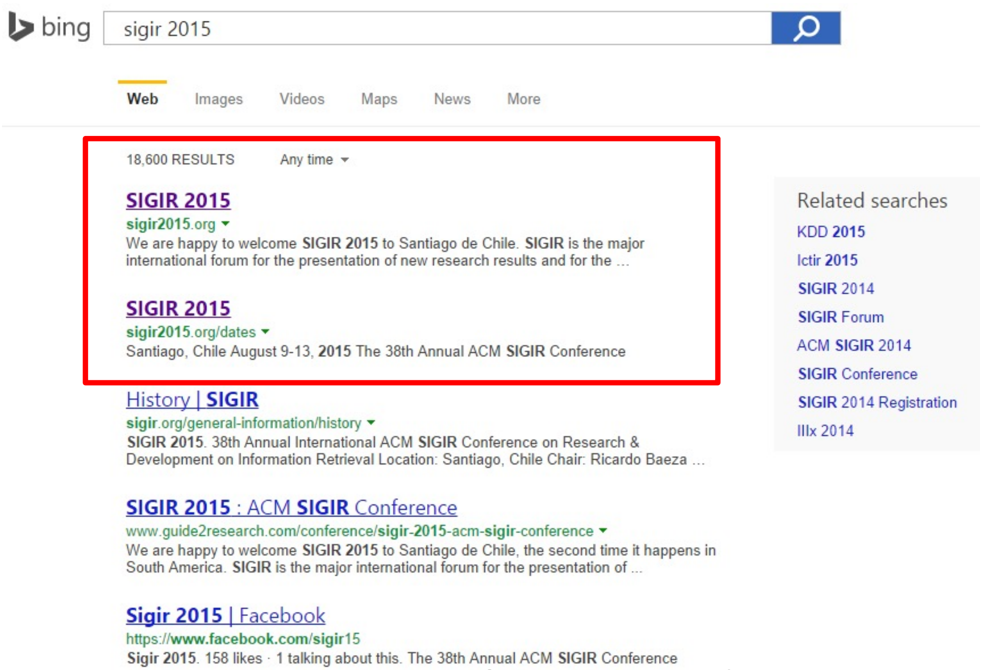
# Relevance feedback in real systems

- 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?*

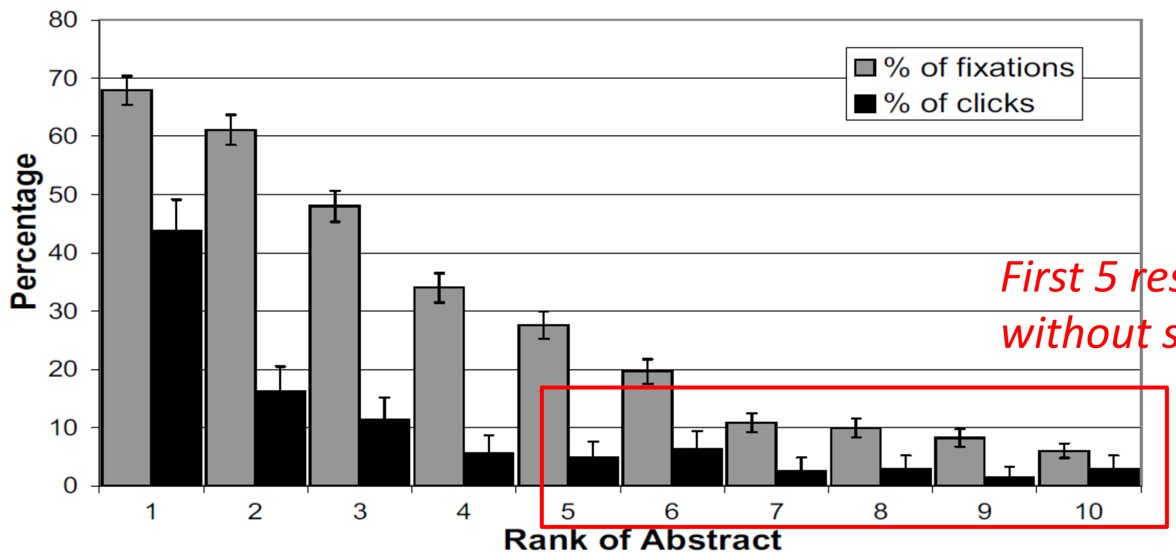
# Accurately Interpreting Clickthrough Data as Implicit Feedback [Joachims SIGIR'05]

- 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 200-300ms, 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*

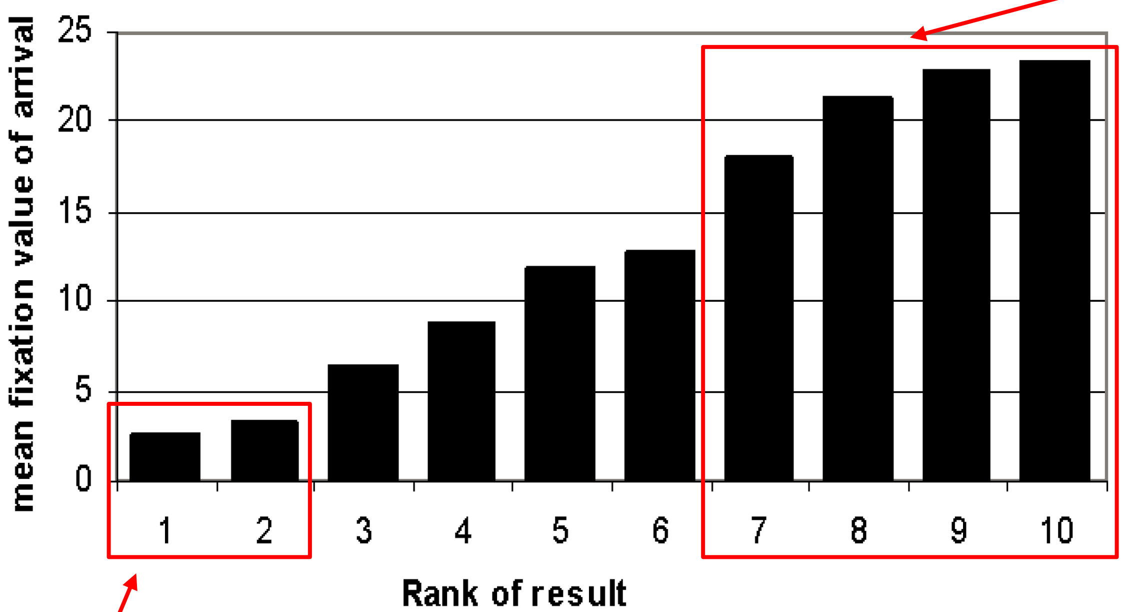



**Figure 2: Mean time of arrival (in number of previous fixations) depending on the rank of the result.**

*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 Rank | Clicked 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 | $\boxed{5}$ | $\boxed{2}$ | 2 | 20 |
| $rel(l_1) = rel(l_2)$ | 19 | $\boxed{9}$ | $\boxed{1}$ | 0 | 29 |
| total | 45 | 33 | 4 | 3 | 85 |

# Are clicks relative relevance judgments?

- Clicks as pairwise 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 | $80.8 \pm 3.6$ | $88.0 \pm 9.5$ | $79.6 \pm 8.9$ | $83.0 \pm 6.7$ | $83.1 \pm 4.4$ |
| Last Click > Skip Above | $83.1 \pm 3.8$ | $89.7 \pm 9.8$ | $77.9 \pm 9.9$ | $84.6 \pm 6.9$ | $83.8 \pm 4.6$ |
| ~~Click > Earlier Click~~ | $\cancel{67.2 \pm 12.3}$ | $\cancel{75.0 \pm 25.8}$ | $\cancel{36.8 \pm 22.9}$ | $\cancel{28.6 \pm 27.5}$ | $\cancel{46.9 \pm 13.9}$ |
| Click > Skip Previous | $82.3 \pm 7.3$ | $88.9 \pm 24.1$ | $80.0 \pm 18.0$ | $79.5 \pm 15.4$ | $81.6 \pm 9.5$ |
| ~~Click > No Click Next~~ | $\cancel{84.1 \pm 4.9}$ | $\cancel{75.6 \pm 14.5}$ | $\cancel{66.7 \pm 13.1}$ | $\cancel{70.0 \pm 15.7}$ | $\cancel{70.4 \pm 8.0}$ |

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

- Accuracy against manual relevance judgment

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

# What do we get from this user study?

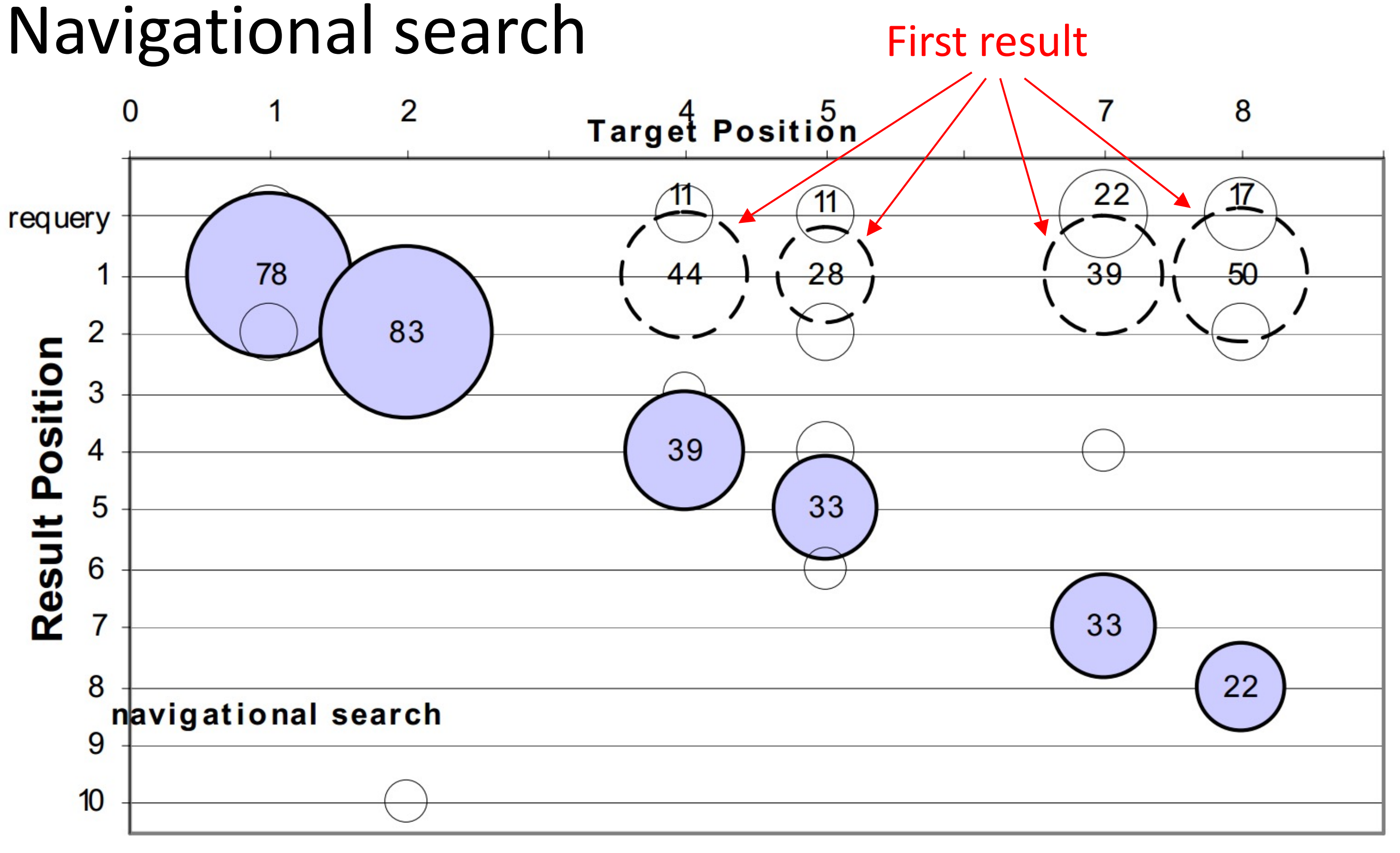
- Clicks are influenced by the relevance of results
  - Biased by the trust over rank positions
- Clicks as relative preference statement is more accurate
  - Several heuristics to generate the preference pairs

# How to utilize such preference pairs?

- Pairwise learning to rank algorithms
  - We have covered it in learning to rank discussions

# 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]

- Break down of users' click accuracy
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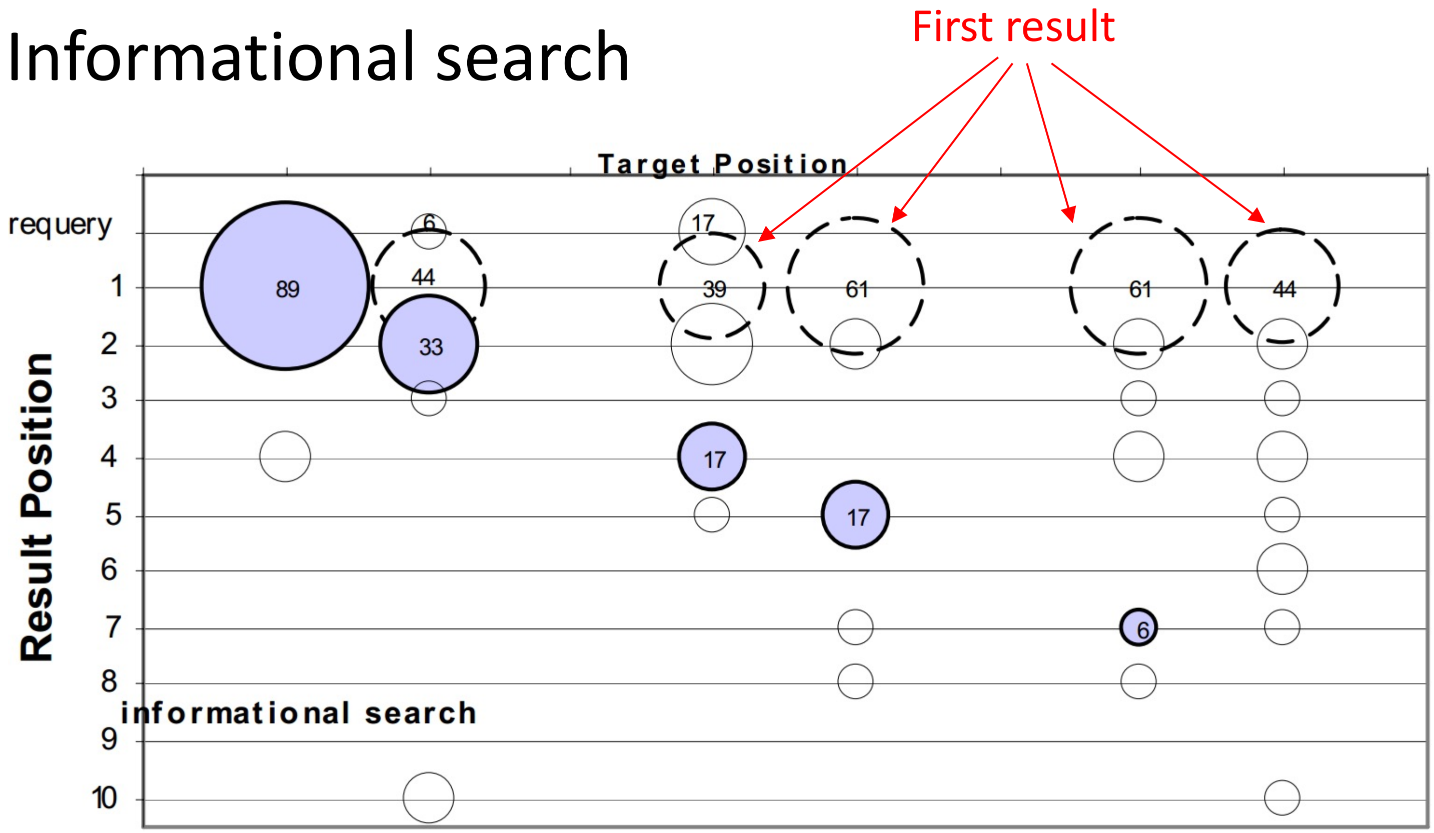
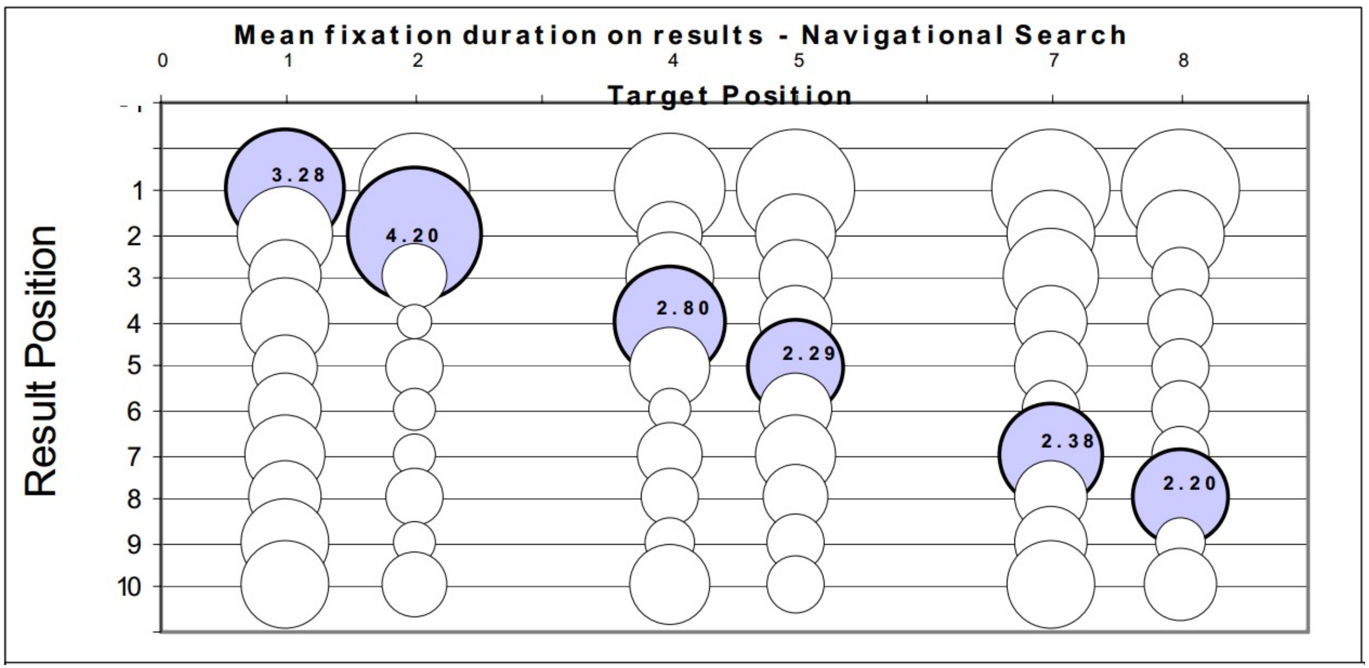


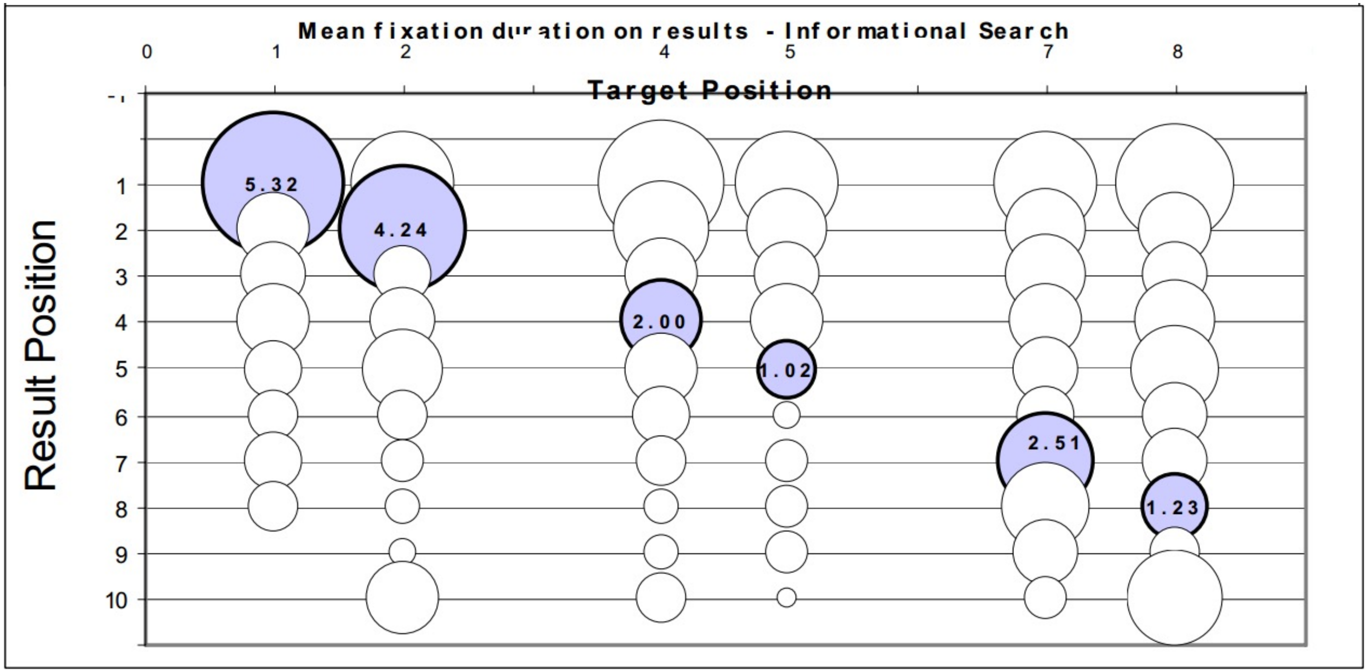
# Users failed to recognize the target because they did not read it!

- Navigational search



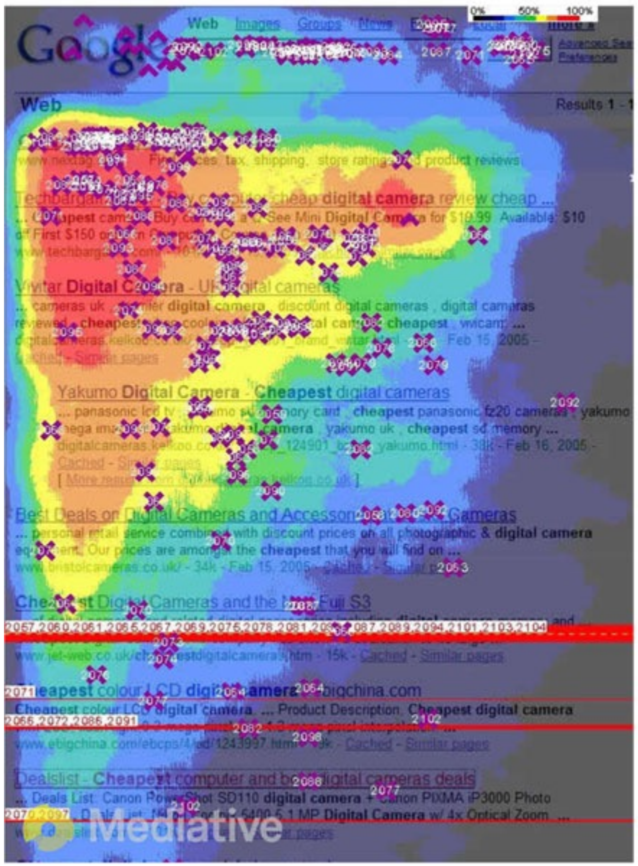
# Users did not click because they did not read the results!

- Informational search

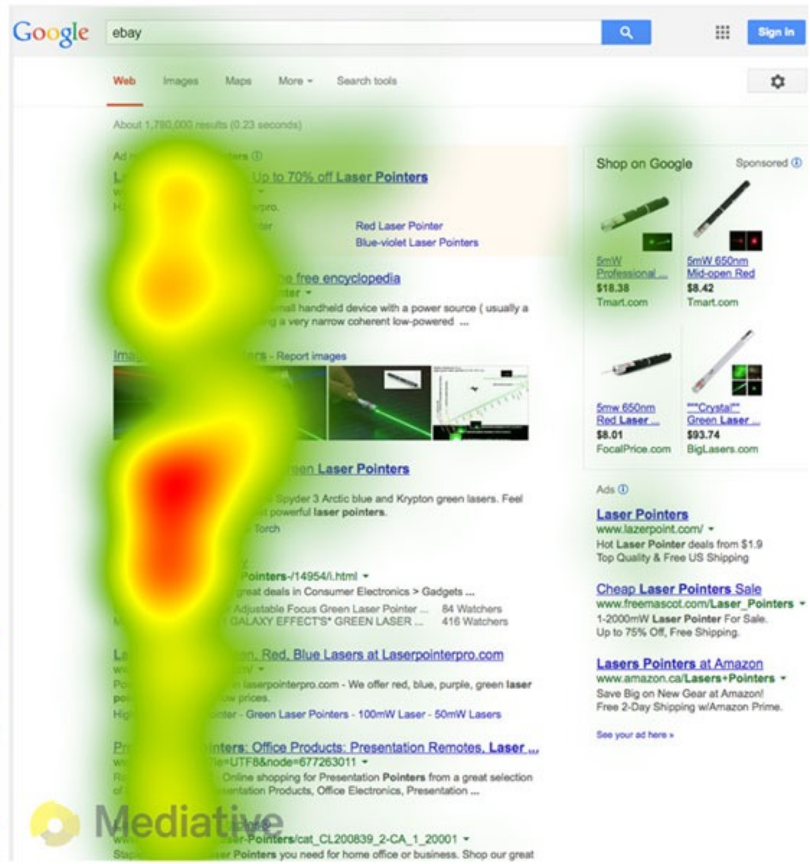


# Where do we pay attention to?

2005




2014



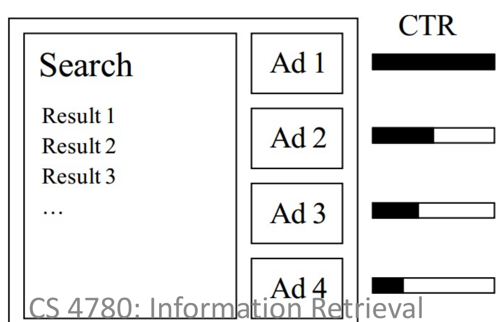
# Predicting clicks: estimating the click-through rate for new ads [Richardson WWW’07]

- 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 displayed positions!



# Combat position-bias by explicitly modeling it

- Being clicked is related to its quality and position
  - $p(click|ad,pos) = p(click|ad,pos,seen)p(seen|pos)$

    $= \underbrace{p(click|ad,seen)}_{\text{Calibrated CTR for ads ranking}}\underbrace{p(seen|pos)}_{\text{Discounting factor}}$
  - $p(click = 1|ad, seen = 0) = 0$
  - $p(click = 1|ad, seen = 1) = \frac{1}{1+\exp(-w^T f_{ad})}$

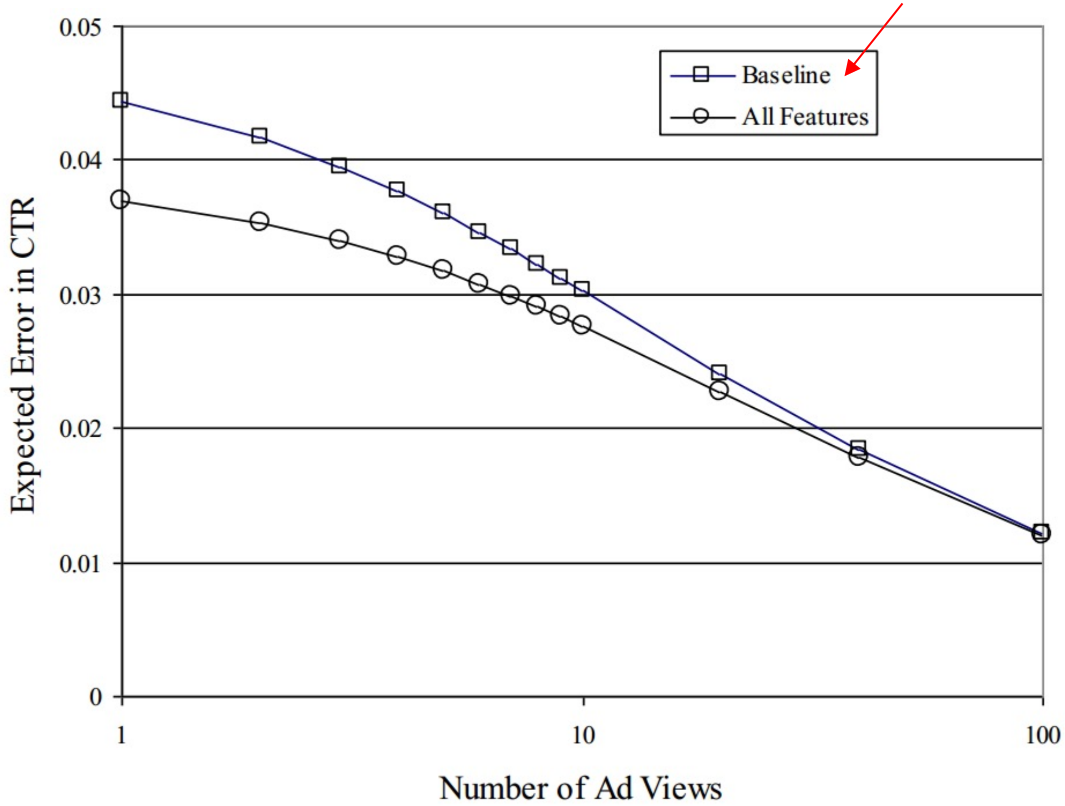
Logistic regression by features of the ad

# 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
    - $\hat{w} = argmax_w \sum_{ad} \log p(click|ad, pos)$

# 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

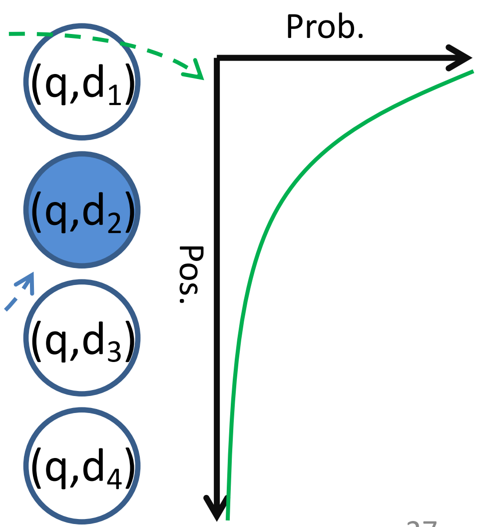
# Click models

- Decompose relevance-driven skips from position-driven skips
  - 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"?*

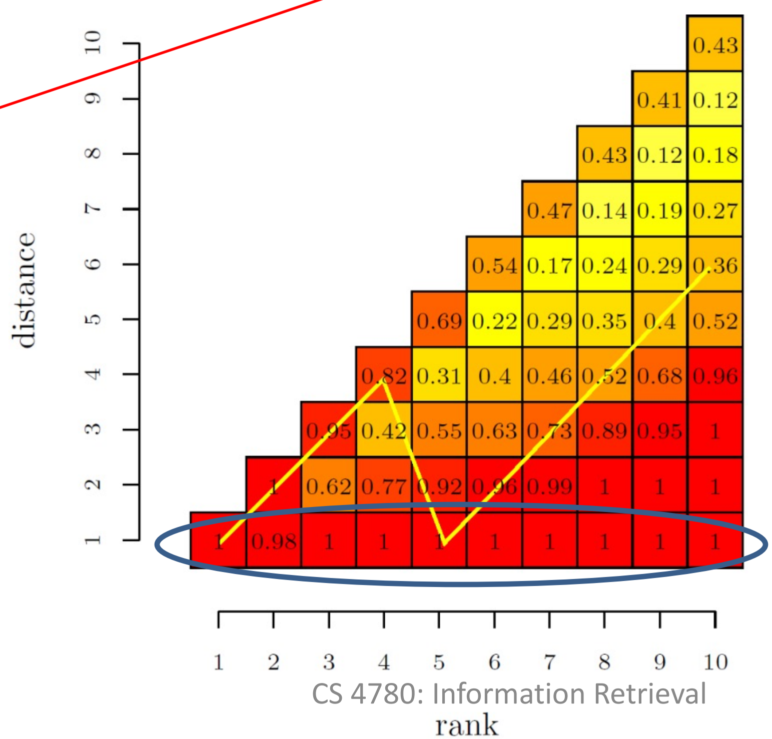
# User Browsing Model [Dupret et al. SIGIR'08]

- 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***

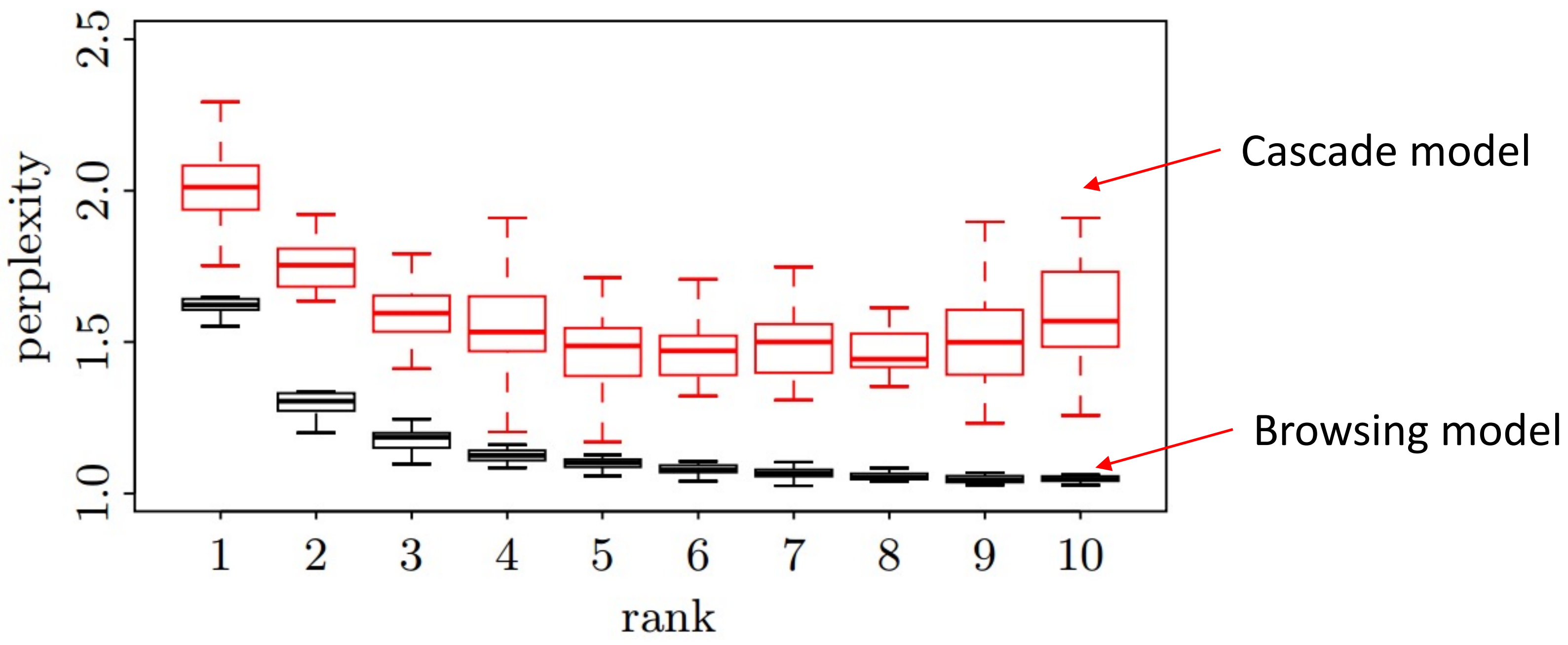



From absolute discount to relative discount

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

# More accurate prediction of clicks

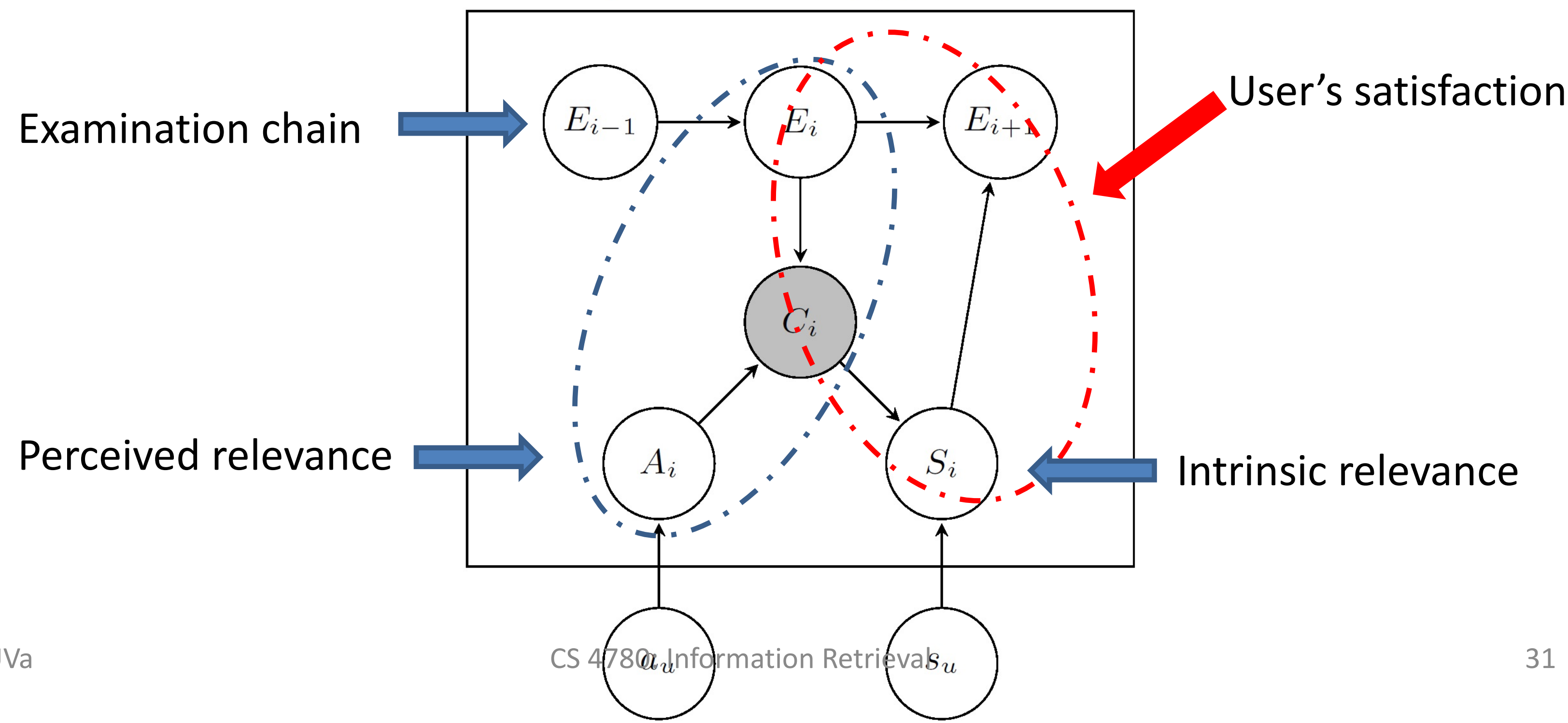
- Perplexity – randomness of prediction



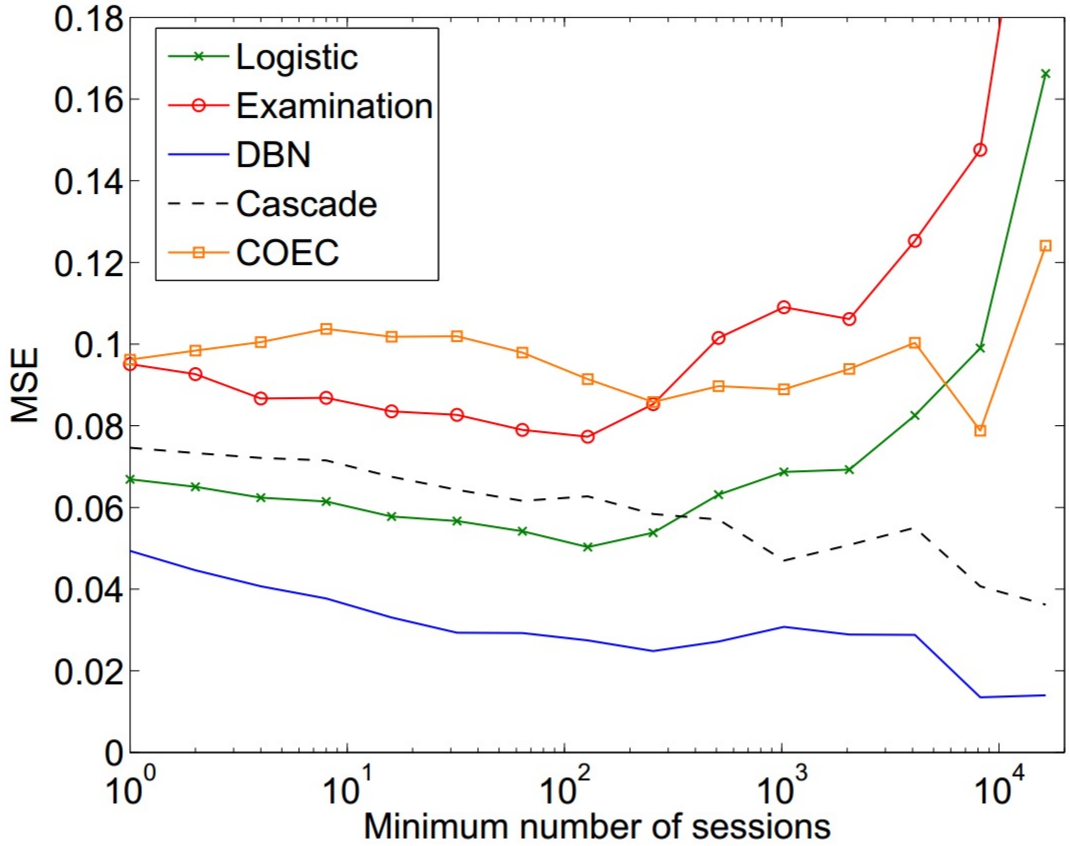
# Dynamic Bayesian Model [Chapelle et al. WWW'09]

- A cascade model
  - Relevance quality:

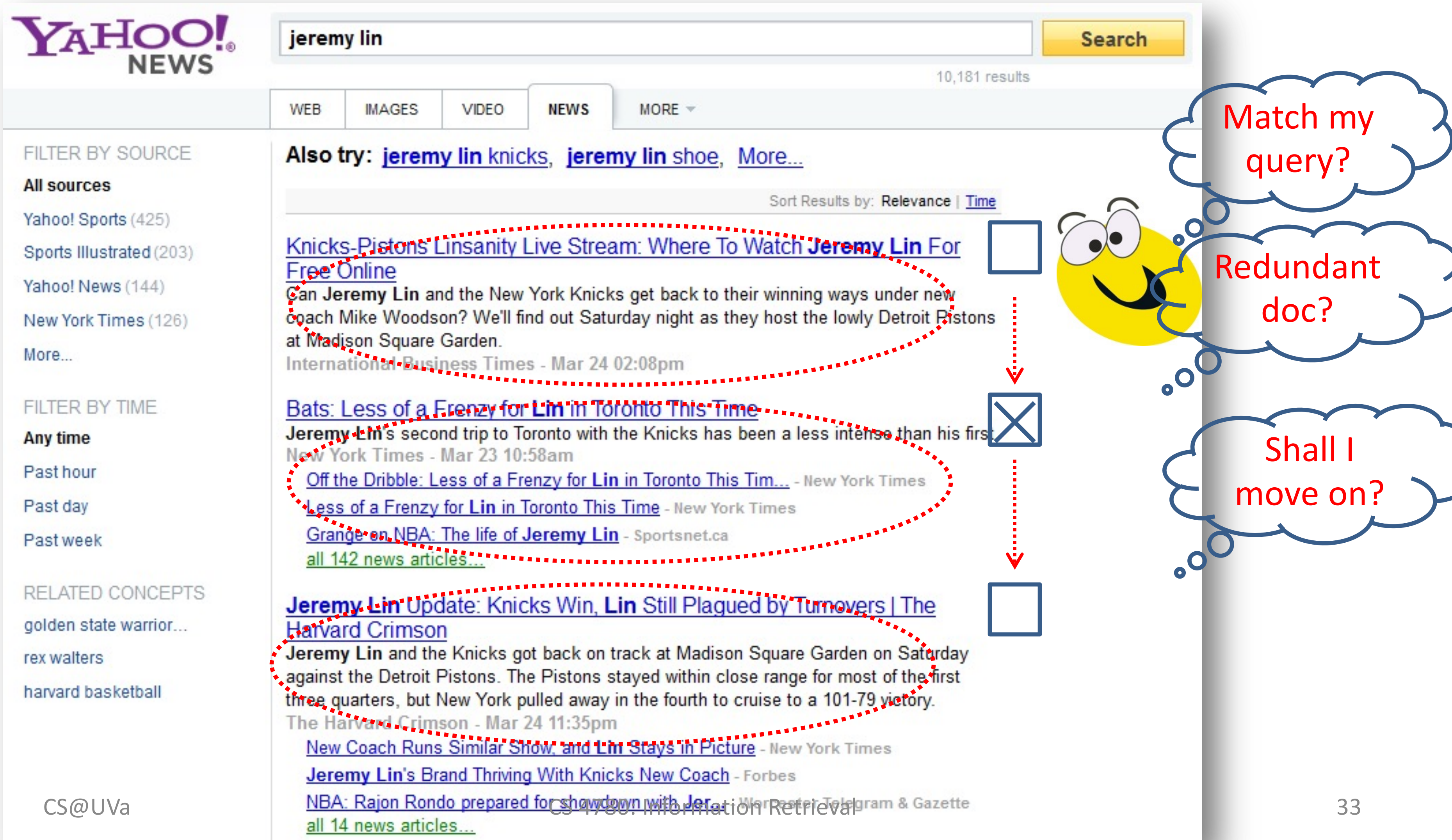
$$P(E_{i+1} = 1 | E_i = 1, S_i = 0) = \gamma$$
$$S_i = 1 \Rightarrow E_{i+1} = 0$$



# Accuracy in predicting CTR



# Revisit User Click Behaviors

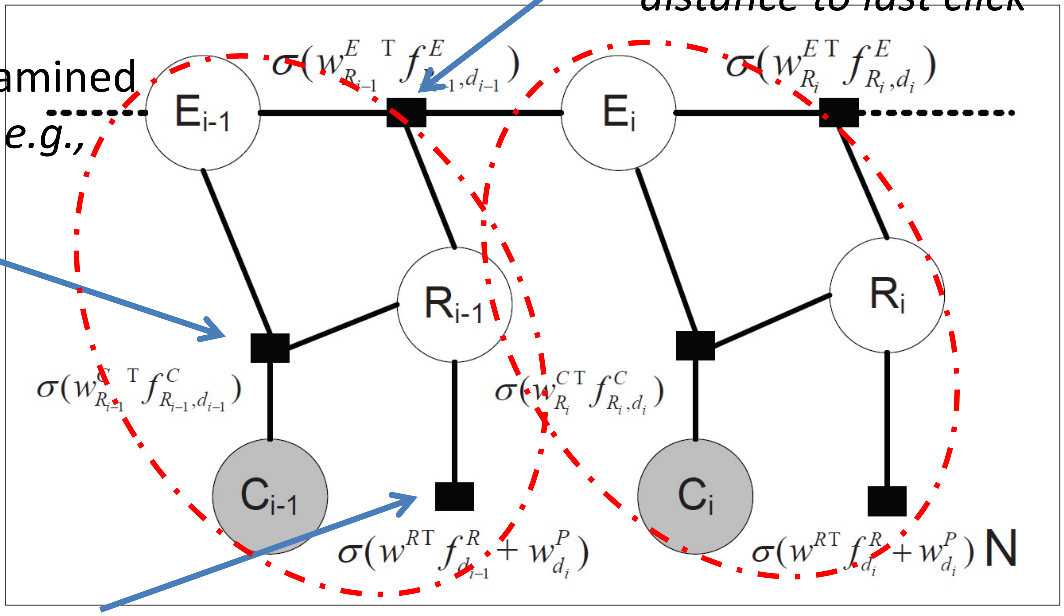


# Content-Aware Click Modeling [Wang et al. WWW'12]

- Encode dependency within user browsing behaviors via descriptive features

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

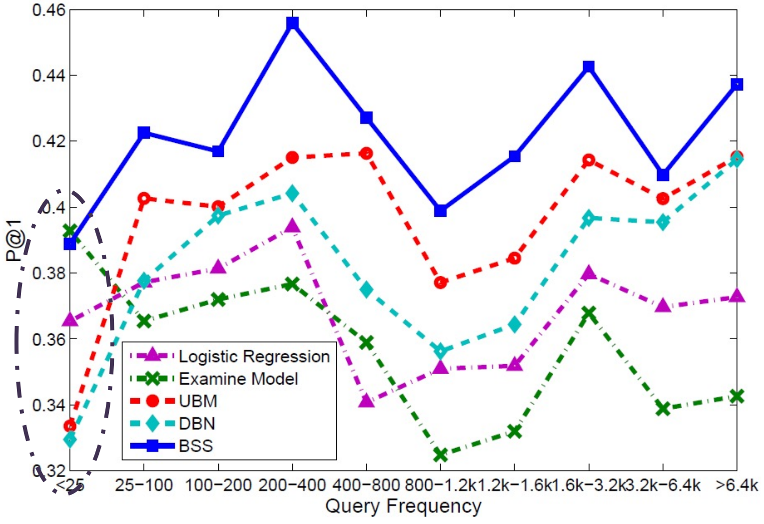
Chance to click on an examined and relevant document: *e.g., clicked/skipped content similarity*



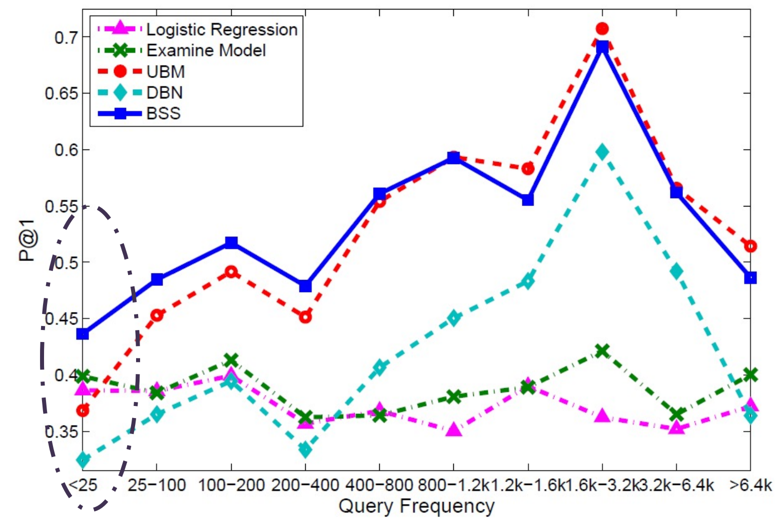

Relevance quality of a document: *e.g., ranking features*

# 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