LEARNING USER INTERACTION MODELS FOR PREDICTING WEB SEARCH PREFERENCES

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Predicting User Preferences

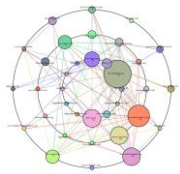
- Many successful supervised ranking methods…
- …but they require labeled data
  - *(e.g., pairwise preferences)*

Problem: *getting* labeled data

- Explicit human ratings:
  - Expensive
  - Difficult to obtain
  - No effective way of getting explicit user feedback
- User interaction history:
  - "free" implicit feedback—millions each day
  - Click patterns, dwell time, mouse movement
- …but how to model as pairwise preferences?

Implicitly Labeled Data

- Experiments with implicit ratings:
  - controlled text collections
  - selected queries/tasks
  - laboratory settings
- Real web:
  - Uncontrolled
    - Ill-defined queries/tasks
    - Automated bots
  - Noisy, non-expert users
    - Malicious
    - Irrational



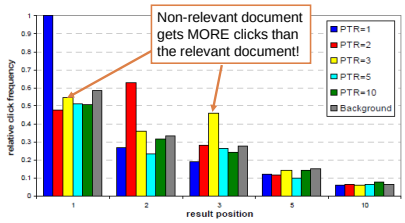
Main Questions

- Can explicitly accounting for "noisy" users provide more information?
- Can we automatically learn accurate user feedback interpretation models by representing user actions as a rich set of features?

Noisy Users

- Users click on non-relevant documents due to:
  - *Visual appearance/ layout*
  - *User history/context*
  - *Presentation order (position)*

(PTR: Position of Top Relevant Document)



Modeling Noisy Users

- 2 components to user behavior
- Relevance component
  - *Query-specific user reaction*
  - *based on perceived true relevance of documents*
- Background component:
  - *Users clicking indiscriminately*

$$q : query$$
$$r : result$$
$$p : position\ of\ r$$

$$clickthrough(q,r,p) = Expected(p) + relevance(q,r)$$

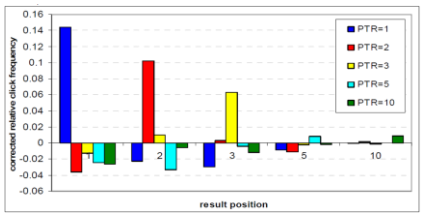
Calculating Background

- Calculate aggregated click frequency at position p:
  - Compute frequency of a click at p for each query q
    - (how often would a random click for query q land on p?)
- Average frequencies across all queries

$$C(p) = \frac{1}{\#queries} \sum_{\forall queries\, q} \frac{\#clicks\ at\ p}{\#clicks\ in\ q}$$

Finding Relevance

- Find the expected behavior for each position over full dataset… and subtract it to get true relevance



Click Deviation

- Relevance: deviation from "expected behavior" at position p

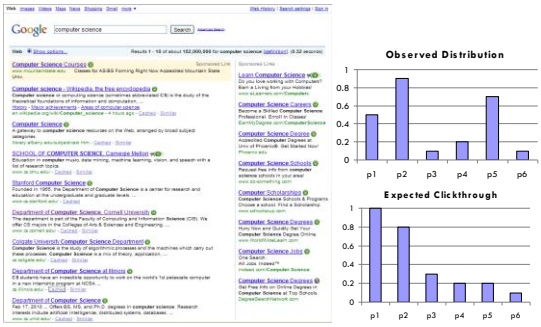
$$r : result$$
$$p : position$$

$$\underbrace{dev(r,p)}_{\text{Click deviation of result r at position p}} = \underbrace{obs(r,p)}_{\text{Observed click frequency at (r,p)}} - \underbrace{C(p)}_{\text{Expected clickthrough at position p}}$$

Model 1: CD (Click Deviation)

- *Filter out noisy clicks, then apply SA or SA+N strategies*
  - For each result r_i at position p_i
  - Given a parameter d:
  - If $dev(r_i, p_i) > d$:
  - retain click as input for SA or SA+N strategies

Example: CD (Click Deviation)



Example: CD (Click Deviation)

- *For a clicked result at position p:*
- **SA (Skip Above):**

  for all unclicked results i<p, relevance(p)>relevance(i).

  rel(d2)>rel(d1) *rel(d5)>rel(d4)*
  rel(d5)>rel(d3) *rel(d5)>rel(d1)*
- **N (Skip Next):**

  if the result p+1 is unclicked, relevance(p)>relevance(p+1)

  rel(d2)>rel(d3) *rel(d5)>rel(d6)*
- **SA+N:**

  combine both strategies

Model 2: Cdiff (Click Difference)

- Idea: when two results are compared, a result is "skipped" if it is clicked less than expected, "clicked" if more than expected.
- For each query q, calculate the deviation for each result-position pair
  - Compare every (r,p)-pair against every other:

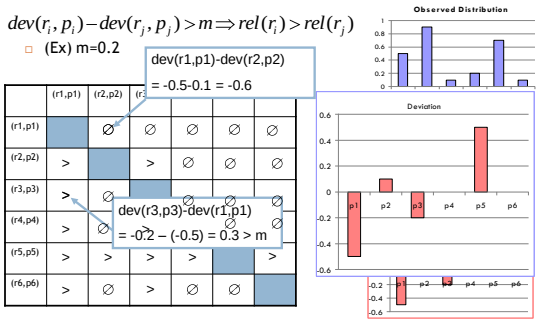
$$dev(r_i, p_i) - dev(r_j, p_j) > m \Rightarrow rel(r_i) > rel(r_j)$$

- Ignores positional information
- Can compare events when both results clicked
  - Informational versus navigational queries

Example: Cdiff (Click Difference)

$$dev(r_i, p_i) - dev(r_j, p_j) > m \Rightarrow rel(r_i) > rel(r_j)$$

- (Ex) m=0.2



Precision/Recall Parameters

- d and m: tradeoff between precision and recall:
  - d, m large: higher precision, lower recall
  - d, m small: lower precision, higher recall

$$dev(r_i, p_i) > d$$

$$dev(r_i, p_i) - dev(r_i, p_j) > m$$

Beyond Clickthrough: General User Behavior Model

- Large set of features to represent user behavior *before* and *after* the click
- Automatically derive implicit feedback interpretation

Background: Richer Feature Set

- Time users spent reading Usenet news articles predicts user interest *[Morita and Shinoda 1994]*
- Page activity correlates with reader interest *[Goecks and Shavlik 1999]*
  - (small sample size, no testing against explicit measurements)
- Curious Browser—combined implicit measurements with explicit queries *[Claypool et al. 2001]*
  - Time spent on page + scrolling correlated with interest
  - Individual scrolling/mouse-clicks not correlated
- Rich (but query-independent) feature set: clickthrough most important, but adding dwell time improved accuracy *[Fox et al. 2005]*

General User Behavior Model

- Represent user actions as features—rich feature set
- Query-specific model (behavior deviates with query)
- Capture actions before and after query
  - Observed : relate directly to query/result pair
  - Distributional: deviations from "expected" behavior
    - Derived—measure deviation of feature for given search result from expected value for any result.

User Behavior Model

$$f : feature$$
$$r : result$$
$$q : query$$
$$obs(q,r,f) = C(f) + rel(q,r,f)$$

- $obs(q,r,f)$: Observed value of a feature with respect to result r and query q
- $C(f)$: background
- $rel(q,r,f)$: Relevance-dependent component of behavior

(Observed feature values averaged across all search sessions and users for each query-result pair)

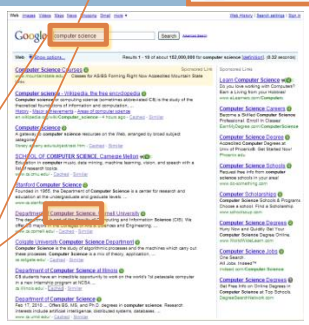
Features

- Query-text: text-based relations between query and document

Next query overlap

Query length

Title overlap, Summary overlap, Domain overlap



Features

- Query-text: text-based relations between query and document
- Clickthrough: frequency, timing, order of clicks

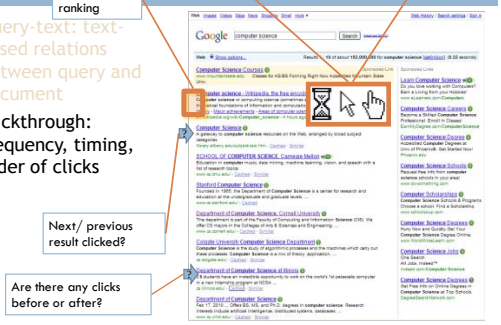
Position in ranking

Click frequency (query, URL), Relative frequency

Deviation from expected click frequency?

Next/ previous result clicked?

Are there any clicks before or after?



Features

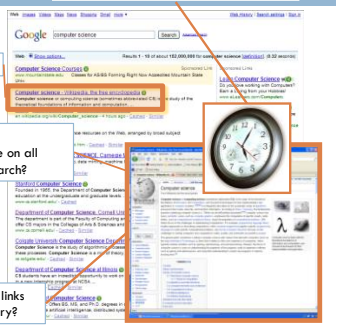
- Query-text: text-based relations between query and document
- Clickthrough: frequency, order of clicks
- Browsing: user behavior after click (intra-query diversity of page browsing)

Time on domain?
Time on url?
Average dwell time for query/result?
Dwell time deviation?

Redirected?

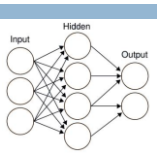
Time on page?
Cumulative time on all pages after search?

Followed links after query?



Learning User Behavior

- RankNet
  - Efficient
  - Scalable
  - Robust



- Train on pairs (r1, r2)
  - output: 1 if r1>r2, 0 otherwise
- Explicit boolean relevance judgments
- Gradient descent (multiple restarts) to set weights

Evaluation Metrics

- Evaluate based on pairwise agreement
- Query precision:

$$\frac{\#(predicted = human\ judgement)}{\#(predicted)}$$

- Query recall:

$$\frac{\#(predicted = human\ judgement)}{\#(human\ judgement)}$$

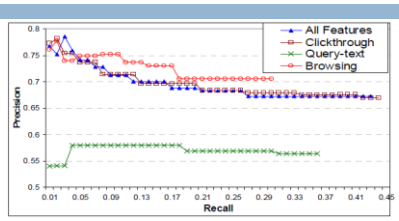
Datasets

- "Orders of magnitude larger than any study yet reported in the literature"
- Explicit pairwise relevance judgements for top-10 results
  - Q1: at least 1 click for each query
    - *(3500 queries, 28,093 query-URL pairs)*
  - Q10: at least 10 clicks
    - *(1300 queries, 18,728 query-URL pairs)*
  - Q20: at least 20 clicks
    - *(1000 queries, 12,922 query-URL pairs)*
- Training/test for UB: train/validate on 75%, test on 25% (no query overlap)

Strategies Compared

- Current:
  - *a "state-of-the art" ranking system from "a major websearch engine"*
- SA
- SA+N
- CD
- CDiff
- CDiff+CD
- UserBehavior

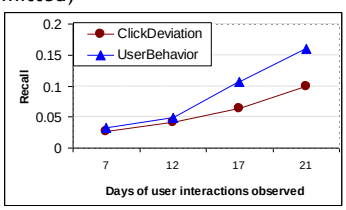
Results: User Behavior Model Features



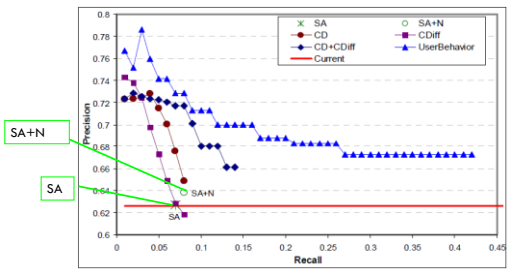
- Browsing features outperform combinations
- Query-text features by themselves perform badly

Results: adding more data

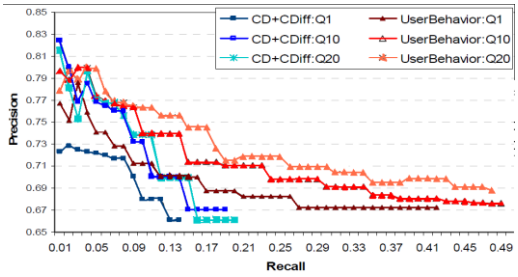
- Intelligent aggregation of large amounts of data improves precision (higher recall permitted)



Results: Q1 (at least 1 click)



Results



Extensions?

- Targeting divergent access patterns (clustering)
- Modeling time-dependency of query distributions
- Automatically finding “reliable users”

Conclusions

- Explicitly accounting for “noisy” user behavior greatly improves accuracy
- New model presented which represents user actions as a rich set of features based on actions before and after search
- More extensive feature-based characterization of user behavior: dramatic improvement in accuracy over human-defined heuristics

Questions?