Integration of News Content Into Web Search Results

Fernando Diaz

Yahoo! Labs Montreal

February 11, 2009
Inauguration Day - Wikipedia
The swearing-in of the President of the United States occurs upon the commencement of a new term of a President of the United States. The United States Constitution mandates that the President make the following oath or...
http://en.wikipedia.org/wiki/United_States_presidential_inauguration

Joint Congressional Committee on Inaugural Ceremonies
Charged with planning and conducting the inaugural activities at the Capitol: the swearing-in ceremony and the luncheon honoring the President and Vice President.
http://inaugural.senate.gov

Inauguration Day 2009
Official site for the 2009 Inauguration of Barack Obama. Provides information about events, tickets, and inaugural balls and parades.
http://inaugural.senate.gov/2009

Inaugural Addresses of the Presidents of the United States
From George Washington's first address in 1789 to the present. Includes a note on the presidents who took the oath of office without a formal inauguration.
http://www.bartleby.com/124
News Results for Inauguration

• **Online inauguration videos set records** CNN - 3 hours ago
• **Castro watched inauguration, Argentine leader says** CNN - 3 hours ago
• **Photographer: Inauguration like no moment I've ever witnessed** CNN - 4 hours ago

**Inauguration Day - Wikipedia**

The swearing-in of the President of the United States occurs upon the commencement of a new term of a President of the United States. The United States Constitution mandates that the President make the following oath or...

http://en.wikipedia.org/wiki/United_States_presidential_inauguration

**Joint Congressional Committee on Inaugural Ceremonies**

Charged with planning and conducting the inaugural activities at the Capitol: the swearing-in ceremony and the luncheon honoring the President and Vice President.

http://inaugural.senate.gov

**Inauguration Day 2009**

Official site for the 2009 Inauguration of Barack Obama. Provides information about events, tickets, and inaugural balls and parades.

http://inaugural.senate.gov/2009

**Inaugural Addresses of the Presidents of the United States**

From George Washington's first address in 1789 to the present. Includes a note on the presidents who took the oath of office without a formal inauguration.

http://www.bartleby.com/124
Newsworthy Query

- a query for which a user is likely to be satisfied by news results.
- a query which is likely to refer to a ephemeral news topic.
- e.g. *australia fire, inauguration, stimulus package vote*
Outline

Related Work

Clicks and News

Estimating CTR

Classifying Queries

Experiments
Related Work
Related Work

• **distributed information retrieval**: determine if any relevant content exists inside of a collection
  [Callan 2000]

• **topic detection and tracking**: detect the occurrence of news events
  [Allan 2002]

• **performance prediction**: determine if a retrieval is effective
  [Cronen-Townsend *et al.* 2002, Diaz 2007]

• **query classification**: map a query into taxonomy for advertising or retrieval
Clicks and News
Intuition

• a click on a news display suggests an appropriate presentation

• a skip over a news display suggests an inappropriate presentation

• click-through rate (CTR) summarizes clicks and skips,

\[
CTR = \frac{\text{clicks}}{\text{clicks} + \text{skips}}
\]
Analyzing Full Recall Data

• for a small percentage of search traffic, present a news display if there are any hits in the news index

• collect user click and skip information

• for each query, compute the click-through rate if we always present a display for that query
queries binned logarithmically
newsworthy $\rightarrow$ high CTR

- ask annotators to generate a set of newsworthy queries during our data collection
- annotators provided access to,
  - realtime news corpus
  - realtime query logs
  - other media sources (e.g. television, radio)
- average CTR of queries: 0.249
high CTR $\rightarrow$ newsworthy

- select 20 queries from each bin
- ask annotators to label each query on a five point scale between newsworthy and non-newsworthy
Approach

• when a query is submitted, predict its CTR
• if the predicted CTR is above some threshold, present the display
• if the predicted CTR is below some threshold, do not present the display
Estimating CTR
Estimating CTR

• for each query event, we would like to estimate the probability that the display will be clicked
• naïve estimation
  1. always present display, gather click and skip evidence
  2. $\hat{p}_q^t = \frac{c_q^t}{\nu_q^t}$
• problems with naïve estimation
  • requires presenting a display for many inappropriate queries
when a new query enters the system, we have information which may help predict the CTR,

- volume in web query log
- volume in news vertical query log
- growth in query logs
- document hits in the last $k$ hours, days
- mean age of retrieved documents
- precision predictors (e.g. clarity)
- distributed IR metrics (e.g. ReDDE)
Predicting CTR Without Click Information

- without click information, we can use contextual features to predict CTR
  - query-independent features allow extension to unseen queries
- model using logistic regression trained on full-recall data
- $\pi^t_q$: predicted CTR for query $q$ at time $t$ using only contextual features
Assume that the CTR is Beta distributed,

\[ p^t_q \sim \text{Beta}(a, b) \]

We can set the parameters of the prior using our contextual prediction,

\[ a = \mu \pi^t_q \quad b = \mu (1 - \pi^t_q) \]
Prior Distribution over CTR

\[ \mu = 10 \quad \pi_q^t = 0.30 \]
Prior Distribution over CTR

\[ \mu = 100 \quad \pi_q^t = 0.30 \]
Posterior Distribution over CTR

Given $C^t_q$ clicks and $S^t_q$ skips,

$$p_q^t|C^t_q, S^t_q \sim \text{Beta}(a + C^t_q, b + S^t_q)$$

And the posterior mean,

$$\tilde{p}_q^t = \frac{C^t_q + \mu \pi^t_q}{\nu^t_q + \mu}$$
Posterior Distribution over CTR

\[ C_q = 0 \quad \pi_q^t = 0.30 \]
\[ S_q = 10 \quad \mu = 10 \]
Posterior Distribution over CTR

\[ C_q = 10 \quad \pi_q^t = 0.30 \]
\[ S_q = 0 \quad \mu = 10 \]
Modification: Exploiting Similar Queries

- evidence can also be provided by topically related queries
- query similarity
  - build relevance model for each query
  - compute Bhattacharyya correlation between relevance models
- incorporate evidence from similar queries as partial pseudo-counts
Classifying Queries
From Probabilities to Decisions

• Present a display if $\tilde{p}_q^t > \tau$
• If clicks indicate relevance, then $\tau = \frac{1}{2}$
• We know from motivating experiments that clicks $\neq$ relevance
• Therefore, we derive our threshold from an accuracy measure.
Accuracy

\[ A = \frac{C_q^+ + S_q^+}{C_q^* + S_q^*} \]

- \( C_q^+ \): correctly predicted clicks
- \( S_q^+ \): correctly predicted skips
- \( C_q^* \): total clicks, seen and unseen
- \( S_q^* \): total skips, seen and unseen

Given this formula, we can derive \( \tau = \frac{1}{2} \)
$\alpha$-Accuracy

$$A_\alpha = \frac{\alpha C_q^+ + S_q^+}{\alpha C_q^* + S_q^*}$$

- $C_q^+$ correctly predicted clicks
- $S_q^+$ correctly predicted skips
- $C_q^*$ total clicks, seen and unseen
- $S_q^*$ total skips, seen and unseen

where $\alpha \geq 1$ and controls the importance we place on detecting clicks. Given $\alpha$, we can derive $\tau = \frac{1}{\alpha + 1}$
Modification: Opportunistic Sampling

- Sometimes the value of feedback information outweighs a small degradation in performance
- Addresses false negatives predicted by the contextual model
- Naïve method: if $\tilde{p}_q^t < \tau$, then present a display for the first $k$ issuances of a query
Sampling from the Posterior

- Naïve method treats all below threshold queries equally
- The posterior distribution contains confidence information
- Alternative method: if $\hat{p}_q^t < \tau$, then sample a CTR, $\hat{p}_q^t$, from the posterior. If $\hat{p}_q^t > \tau$, then present.
Threshold

\[ \mu = 10 \quad \pi_q^t = 0.15 \]

\[ P(p_q^t > \tau) = 0.272 \quad \tau = 0.20 \]
Threshold

\[ \mu = 100 \quad \pi^t_q = 0.15 \]

\[ P(p^t_q > \tau) = 0.088 \quad \tau = 0.20 \]
Experiments
Experimental Setup

• Data
  • Two full recall datasets gathered in Spring 2007 and Winter 2008.
  • Simulate decision-making with recorded click and skip information

• Evaluation
  • binned macro-averaged (by query) accuracy
Binned, Macro-averaged Accuracy

- evaluation algorithm
  - bin queries by empirical CTR using full recall data
  - compute accuracy ($A_4$) for each query
  - compute the average accuracy for each bin
- these numbers are normalized by performance of an omniscient algorithm
## Runs

<table>
<thead>
<tr>
<th>run</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>baseline</td>
<td>only use the contextual prior</td>
</tr>
<tr>
<td>history</td>
<td>use the prior and click feedback</td>
</tr>
<tr>
<td>similarity</td>
<td>use the prior and click feedback using similar queries</td>
</tr>
<tr>
<td>posterior</td>
<td>use similarity baseline but present by sampling from the posterior</td>
</tr>
</tbody>
</table>
## Binned, Macro-averaged Accuracy

<table>
<thead>
<tr>
<th></th>
<th>baseline</th>
<th>history</th>
<th>similarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.358</td>
<td><strong>0.421</strong></td>
<td><strong>0.615</strong></td>
</tr>
<tr>
<td>2</td>
<td>0.576</td>
<td>0.636</td>
<td><strong>0.820</strong></td>
</tr>
<tr>
<td>3</td>
<td>0.598</td>
<td><strong>0.680</strong></td>
<td>0.776</td>
</tr>
<tr>
<td>4</td>
<td>0.620</td>
<td><strong>0.654</strong></td>
<td><strong>0.738</strong></td>
</tr>
<tr>
<td>5</td>
<td>0.722</td>
<td>0.731</td>
<td><strong>0.796</strong></td>
</tr>
<tr>
<td>6</td>
<td>0.901</td>
<td><strong>0.885</strong></td>
<td>0.896</td>
</tr>
<tr>
<td>7</td>
<td>0.978</td>
<td>0.982</td>
<td>0.979</td>
</tr>
<tr>
<td>8</td>
<td>0.964</td>
<td><strong>0.984</strong></td>
<td><strong>0.977</strong></td>
</tr>
<tr>
<td>9</td>
<td>0.973</td>
<td><strong>0.991</strong></td>
<td><strong>0.987</strong></td>
</tr>
<tr>
<td>10</td>
<td>0.985</td>
<td><strong>0.995</strong></td>
<td><strong>0.992</strong></td>
</tr>
<tr>
<td>all</td>
<td>0.964</td>
<td><strong>0.978</strong></td>
<td><strong>0.978</strong></td>
</tr>
</tbody>
</table>

significant increases over baseline in **bold**; decreases under baseline in *italic*. significant increases over history indicated by *; decreases under history indicated by o.
Binned, Macro-averaged Accuracy
Sampling from Posterior

![Box plots for similarity and mu=10](image)
Conclusions

• contextual model can be used as a lightweight detector
• feedback information valuable for handling false positives
• sampling valuable for handling false negatives
“happy valentine’s day”

baseline

CTR

Feb 15 Feb 17 Feb 19 Feb 21

presentation

no presentation

history

CTR

Feb 15 Feb 17 Feb 19 Feb 21

presentation

no presentation
“beef recall”
“b2 crash”

![Graph 1: Similarity](image)

![Graph 2: Posterior](image)