Reusing Historical Interaction Data for Faster Online Learning to Rank for IR

Anne Schuth, University of Amsterdam
Reusing Historical Interaction Data for Faster Online Learning to Rank for IR

Anne Schuth, University

based on work with Katja Hofmann, Shimon Whiteson, Maarten de Rijke

dinsdag 12 maart 13
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based on work with Katja Hofmann, Shimon Whiteson, Maarten de Rijke

short version presented at WSDM’13 by Katja Hofmann

dinsdag 12 maart 13
Outline

- Introduction into Online Learning to Rank for IR
- Three ingredients
  - Learning from listwise relative feedback
  - Historical Interaction Data
  - Comparing rankers
- Two Ideas
  - Reliable Historical Comparison
  - Candidate Pre-Selection
- Experiments
- Results
- Conclusions
Online Learning to Rank for Information Retrieval
Online Learning to **Rank for Information Retrieval**
Online Learning to Rank for Information Retrieval
Online Learning to Rank for Information Retrieval

Reusing Historical Interaction Data
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Online Learning to Rank for Information Retrieval
Online Learning to Rank for Information Retrieval

query

Web

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Online Learning to Rank for Information Retrieval
Online Learning to **Rank for Information Retrieval**
Online Learning to Rank for Information Retrieval
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Online Learning to Rank for Information Retrieval

query

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Online Learning to Rank for Information Retrieval

\[ d_{l,q} = f_{l1} f_{l2} \ldots f_{ln} \]
Online Learning to Rank for Information Retrieval

query

\[
\begin{align*}
  d_1, q &= f_{11} \quad f_{12} \quad \ldots \quad f_{1n} \\
  d_2, q &= f_{21} \quad f_{22} \quad \ldots \quad f_{2n} \\
  d_3, q &= f_{31} \quad f_{32} \quad \ldots \quad f_{3n} \\
  d_4, q &= f_{41} \quad f_{42} \quad \ldots \quad f_{4n} \\
  d_5, q &= f_{51} \quad f_{52} \quad \ldots \quad f_{5n} \\
  d_6, q &= f_{61} \quad f_{62} \quad \ldots \quad f_{6n}
\end{align*}
\]
Reusing Historical Interaction Data

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Online Learning to Rank for Information Retrieval

d1,q = f11 + f12 + ... + f1n
s(d1,q) = w1* f11 + w2* f12 + ... + wn* f1n

d2,q = f21 + f22 + ... + f2n
d3,q = f31 + f32 + ... + f3n
d4,q = f41 + f42 + ... + f4n
d5,q = f51 + f52 + ... + f5n
d6,q = f61 + f62 + ... + f6n

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Online Learning to Rank for Information Retrieval

\[
\begin{align*}
\text{s}(d_1,q) &= w_1 f_{11} + w_2 f_{12} + \ldots + w_n f_{1n} \\
\text{s}(d_2,q) &= w_1 f_{21} + w_2 f_{22} + \ldots + w_n f_{2n} \\
\text{s}(d_3,q) &= w_1 f_{31} + w_2 f_{32} + \ldots + w_n f_{3n} \\
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\text{s}(d_6,q) &= w_1 f_{61} + w_2 f_{62} + \ldots + w_n f_{6n}
\end{align*}
\]
Online Learning to Rank for Information Retrieval

\[
\begin{align*}
\text{s}(d_1, q) &= w_1^* f_{11} + w_2^* f_{12} + \ldots + w_n^* f_{1n} \\
\text{s}(d_2, q) &= w_1^* f_{21} + w_2^* f_{22} + \ldots + w_n^* f_{2n} \\
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\end{align*}
\]
Online Learning to Rank for Information Retrieval

query

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Online Learning to Rank for Information Retrieval

- Find the $w$ that puts most relevant documents on top (or has a high MAP, NDCG, ...)

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Online Learning to Rank for Information Retrieval

- Find the $\mathbf{w}$ that puts most relevant documents on top (or has a high MAP, NDCG, ...)
- For all queries
Find the $w$ that puts most relevant documents on top (or has a high MAP, NDCG, ...)

For all queries

There is absolute feedback for $w$'s
Online Learning to Rank for Information Retrieval
Online Learning to Rank for Information Retrieval
Online Learning to Rank for Information Retrieval
Online Learning to Rank for Information Retrieval
Online Learning to Rank for Information Retrieval

- Find the $w$ that puts clicked documents on top
Online Learning to Rank for Information Retrieval

- Find the $w$ that puts clicked documents on top
- Clicks are noisy
Online Learning to Rank for Information Retrieval

- Find the $\mathbf{w}$ that puts clicked documents on top
- Clicks are noisy
- Presentation bias becomes an issue
Online Learning to Rank for Information Retrieval

- Find the $w$ that puts clicked documents on top
- Clicks are noisy
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- Regret (abandonment) becomes an issue
Online Learning to Rank for Information Retrieval

- Find the \( w \) that puts clicked documents on top
- Clicks are noisy
- Presentation bias becomes an issue
- Regret (abandonment) becomes an issue
- We can no longer test a \( w \) for all queries
Online Learning to Rank for Information Retrieval

- Find the \( w \) that puts clicked documents on top
- Clicks are noisy
- Presentation bias becomes an issue
- Regret (abandonment) becomes an issue
- We can no longer test a \( w \) for all queries
- We can only obtain relative feedback: \( w' > w \) (using interleaving) for one query
Online Learning to Rank for Information Retrieval

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Online Learning to Rank for Information Retrieval

- **Goal:** search engines that learn directly from user interactions
  - adaptation
  - personalization
Online Learning to Rank for Information Retrieval

- **Goal:** search engines that learn directly from user interactions
  - adaptation
  - personalization

- **Challenge:** learn quickly and reliably from noisy, relative feedback
Online Learning to Rank for Information Retrieval

- **Goal:** search engines that learn directly from user interactions
  - adaptation
  - personalization
- **Challenge:** learn quickly and reliably from noisy, relative feedback
- **Idea:** Reuse historical interaction data to speed up learning
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First Ingredient

**Learning from listwise relative feedback**

Dueling bandit gradient descent (DBGD) [1] optimizes a weight vector for weighted-linear combinations of ranking features

---

First Ingredient

Learning from listwise relative feedback

First Ingredient

Learning from listwise relative feedback

First Ingredient

Learning from listwise relative feedback

sample unit sphere to generate candidate ranker

current best weight vector


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First Ingredient

Learning from listwise relative feedback

First Ingredient

Learning from listwise relative feedback


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First Ingredient

Learning from listwise relative feedback

First Ingredient

Learning from listwise relative feedback

---

First Ingredient

Learning from listwise relative feedback

Second Ingredient

Historical Interaction Data
Second Ingredient

**Historical Interaction Data**

query
Second Ingredient

**Historical Interaction Data**

query ranking
Second Ingredient

Historical Interaction Data

query ranking click
Second Ingredient

**Historical Interaction Data**

< query  ranking  click  >
Second Ingredient

Historical Interaction Data
Second Ingredient

Historical Interaction Data

< query ranking click >
< query ranking click >
< query ranking click >
< query ranking click >
Second Ingredient

Historical Interaction Data

- Keep the last few interactions

<query ranking click>
<query ranking click>
<query ranking click>
<query ranking click>
Second Ingredient

**Historical Interaction Data**

- Keep the last few interactions
- Consisting of query, ranking and clicks

```xml
<query ranking click>
<query ranking click>
<query ranking click>
<query ranking click>
```
Second Ingredient

**Historical Interaction Data**

- Keep the last few interactions
- Consisting of query, ranking and clicks
- More recent data is more like current data ...

```xml
<query ranking click/>
<query ranking click/>
<query ranking click/>
<query ranking click/>
```
Second Ingredient

Historical Interaction Data

- Keep the last few interactions
- Consisting of query, ranking and clicks
- More recent data is more like current data ...
- ... and thus has a higher weight when applying importance sampling ...
Second Ingredient

**Historical Interaction Data**

- Keep the last few interactions
- Consisting of query, ranking and clicks
- More recent data is more like current data ...
- ... and thus has a higher weight when applying importance sampling ...
- ... and is as such more useful
Third Ingredient

Comparing rankers

Interleaved comparison methods:

- Team Draft
- Balanced Interleave
- Optimized Interleave
- Probabilistic Interleave [2]

Infer listwise relative feedback from user clicks

Third Ingredient

Comparing rankers
Exploitative Ranking

Third Ingredient

Comparing rankers

Reusing Historical Interaction Data
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**Third Ingredient**

**Comparing rankers**

<table>
<thead>
<tr>
<th>Exploitative Ranking</th>
<th>Explorative Ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>C</td>
</tr>
<tr>
<td>B</td>
<td>G</td>
</tr>
<tr>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>D</td>
<td>A</td>
</tr>
<tr>
<td>E</td>
<td>B</td>
</tr>
<tr>
<td>F</td>
<td>E</td>
</tr>
</tbody>
</table>

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Third Ingredient

Comparing rankers

Exploitative Ranking

Interleaved Ranking

Explorative Ranking

A

B

C

D

E

F

query

query

query

C

G

D

A

B

E

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Comparing rankers

Exploitative Ranking

Interleaved Ranking

Explorative Ranking

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Comparing rankers

Exploitative Ranking

Interleaved Ranking

Explorative Ranking

Third Ingredient

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Third Ingredient

Comparing rankers

Exploitative Ranking

Interleaved Ranking

Explorative Ranking

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Comparing rankers

Exploitative Ranking

Interleaved Ranking

Explorative Ranking

query

query

query

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Third Ingredient

Comparing rankers

Exploitative Ranking

Interleaved Ranking

Explorative Ranking

Query

A
B
D
E
F

Query

C

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G
D
A
B
E

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Comparing rankers

Exploitative Ranking

Interleaved Ranking

Explorative Ranking

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Comparing rankers

Exploitative Ranking

Interleaved Ranking

Explorative Ranking

G was more likely

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Comparing rankers

Exploitative Ranking

Interleaved Ranking

Explorative Ranking

Third Ingredient

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Third Ingredient

Comparing rankers

Exploitative Ranking

Interleaved Ranking

Explorative Ranking

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Comparing rankers

Exploitative Ranking

Interleaved Ranking

Explorative Ranking

Third Ingredient

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Third Ingredient

Comparing rankers

Interleaved Ranking

query

C
A
D
G
B
E
Comparing rankers

- In principle, all permutations are possible

Interleaved Ranking

<p>| | |</p>
<table>
<thead>
<tr>
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</table>
Third Ingredient

Comparing rankers

- In principle, all permutations are possible.
- Rankings that look more like the original ones, are more likely.
Third Ingredient

Comparing rankers

- In principle, all permutations are possible
- Rankings that look more like the original ones, are more likely
- Given a historical interleaved ranking, we can compute how likely it is (given the current two rankings)

Interleaved Ranking

- C
- A
- D
- G
- B
- E

query
In principle, all permutations are possible.

Rankings that look more like the original ones, are more likely.

Given a historical interleaved ranking, we can compute how likely it is (given the current two rankings).
Third Ingredient

Comparing rankers

- In principle, all permutations are possible
- Rankings that look more like the original ones, are more likely
- Given a historical interleaved ranking, we can compute how likely it is (given the current two rankings)

![Interleaved Ranking]

- explorative wins
**Comparing rankers**

- In principle, all permutations are possible.
- Rankings that look more like the original ones, are more likely.
- Given a historical interleaved ranking, we can compute how likely it is (given the current two rankings).

**Interleaved Ranking**

- query
- C
- A
- D
- G
- B
- E

- explorative wins
- exploring paid off
Third Ingredient

Comparing rankers

- In principle, all permutations are possible
- Rankings that look more like the original ones, are more likely
- Given a historical interleaved ranking, we can compute how likely it is (given the current two rankings)

- explorative wins
- exploring paid off
- move exploitative ranking towards explorative ranking
Outline

- Introduction into Online Learning to Rank for IR
- Three ingredients
  - Learning from listwise relative feedback
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- Two Ideas
  - Reliable Historical Comparison
  - Candidate Pre-Selection
- Experiments
- Results
- Conclusions
First Idea

**Reliable Historical Comparison (RHC)**

**Idea:** supplement the interleaved comparisons on live data with *comparisons on historical data*
First Idea
Reliable Historical Comparison (RHC)
First Idea

Reliable Historical Comparison (RHC)
First Idea

Reliable Historical Comparison (RHC)
First Idea

Reliable Historical Comparison (RHC)

compare weight vectors on each datapoint

< query ranking click >
< query ranking click >
< query ranking click >
< query ranking click >
First Idea

**Reliable Historical Comparison (RHC)**

- for each datapoint
First Idea

Reliable Historical Comparison (RHC)

- for each datapoint
- take current two rankers

\[
\text{compare weight vectors on each datapoint}
\]
First Idea

Reliable Historical Comparison (RHC)

- for each datapoint
  - take current two rankers
  - rank for historical query

```plaintext
< query ranking click >
< query ranking click >
< query ranking click >
< query ranking click >
```
First Idea

**Reliable Historical Comparison (RHC)**

- for each datapoint
  - take current two rankers
  - rank for historical query
  - compute probability of historical ranking

![Diagram](image)

**compare weight vectors on each datapoint**

<query ranking click>
<query ranking click>
<query ranking click>
<query ranking click>

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First Idea

Reliable Historical Comparison (RHC)

- for each datapoint
  - take current two rankers
  - rank for historical query
  - compute probability of historical ranking
  - compute outcome using historical clicks

compare weight vectors on each datapoint

< query ranking click >
< query ranking click >
< query ranking click >
< query ranking click >

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First Idea

**Reliable Historical Comparison (RHC)**

- for each datapoint
  - take current two rankers
  - rank for historical query
- compute probability of historical ranking
- compute outcome using historical clicks

For each datapoint:

1. Take current two rankers.
2. Rank for historical query.
3. Compute probability of historical ranking.
First Idea

Reliable Historical Comparison (RHC)
First Idea

Reliable Historical Comparison (RHC)

- Biased outcomes
First Idea

**Reliable Historical Comparison (RHC)**

- Biased outcomes
  - Historical data was gathered with different rankers
First Idea

**Reliable Historical Comparison (RHC)**

- Biased outcomes
  - Historical data was gathered with different rankers
  - It is *not* guaranteed that each target ranker has an equal chance of contributing its highly ranked documents to the interleaved list
First Idea

Reliable Historical Comparison (RHC)

- Biased outcomes
  - Historical data was gathered with different rankers
  - It is *not* guaranteed that each target ranker has an equal chance of contributing its highly ranked documents to the interleaved list
  - Weigh using Importance Sampling
First Idea

Reliable Historical Comparison (RHC)

- Biased outcomes
  - Historical data was gathered with different rankers
  - It is *not* guaranteed that each target ranker has an equal chance of contributing its highly ranked documents to the interleaved list
  - Weigh using Importance Sampling

- Graybill-Deal estimator combines
First Idea

**Reliable Historical Comparison (RHC)**

- Biased outcomes
  - Historical data was gathered with different rankers
  - It is *not* guaranteed that each target ranker has an equal chance of contributing its highly ranked documents to the interleaved list
  - Weigh using Importance Sampling

- Graybill-Deal estimator combines
  - No variance for live outcome
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Second Idea

**Candidate Pre-Selection (CPS)**

**Idea:** generate several candidate rankers, and select the best one by running a *tournament on historical data*
Second Idea

Candidate Pre-Selection (CPS)

![Graph showing feature 1 and feature 2](image-url)
Second Idea

Candidate Pre-Selection (CPS)
Second Idea

Candidate Pre-Selection (CPS)
Second Idea

Candidate Pre-Selection (CPS)

generate several candidate rankers
Second Idea

**Candidate Pre-Selection (CPS)**
Second Idea

Candidate Pre-Selection (CPS)

select the best one by running a tournament on historical data

query ranking click >
query ranking click >
query ranking click >
query ranking click >
Second Idea

Candidate Pre-Selection (CPS)

- for each pair of candidates

select the best one by running a tournament on historical data

<query ranking click>
<query ranking click>
<query ranking click>
<query ranking click>
Second Idea

Candidate Pre-Selection (CPS)

- for each pair of candidates
- rank both for historical query

Select the best one by running a tournament on historical data.
Second Idea

**Candidate Pre-Selection (CPS)**

- for each pair of candidates
- rank both for historical query
- compute outcome using historical clicks

select the best one by running a tournament on historical data

< query ranking click >
< query ranking click >
< query ranking click >
Second Idea

**Candidate Pre-Selection (CPS)**

- for each pair of candidates
  - rank both for historical query
  - compute outcome using historical clicks
  - discard losing ranker

Select the best one by running a tournament on historical data.
Second Idea

**Candidate Pre-Selection (CPS)**

- for each pair of candidates
- rank both for historical query
- compute outcome using historical clicks
- discard losing ranker
- return winner

select the best one by running a tournament on historical data
Second Idea

**Candidate Pre-Selection (CPS)**

- for each pair of candidates
  - rank both for historical query
  - compute outcome using historical clicks
  - discard losing ranker
- return winner

![Diagram showing feature 1 and feature 2 with a reliable candidate weight vector](image)

select the best one by running a tournament on historical data

<query ranking click>
<query ranking click>
<query ranking click>
<query ranking click>
Second Idea

Candidate Pre-Selection (CPS)
Second Idea

**Candidate Pre-Selection (CPS)**

- Biased outcomes (just like RHC)
Second Idea

Candidate Pre-Selection (CPS)

- Biased outcomes (just like RHC)
  - But many more, in the tournament
Second Idea

Candidate Pre-Selection (CPS)

- Biased outcomes (just like RHC)
  - But many more, in the tournament
  - Solved with Importance Sampling
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Experiments

Online learning to rank system (DBGD)
- TeamDraft
- RHC
- CPS
Experiments

Online learning to rank system (DBGD)
- TeamDraft
- RHC
- CPS
Experiments

Online learning to rank system (DBGD)
- TeamDraft
- RHC
- CPS

Queries
Experiments

Online learning to rank system (DBGD)
- TeamDraft
- RHC
- CPS

Queries

Result lists
Experiments

Online learning to rank system (DBGD)
- TeamDraft
- RHC
- CPS

Queries, Clicks

Result lists

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Experiments

Probabilistic click model (variants for testing different settings – *perfect, navigational, informational*)

Learning to rank data set (LETOR 3.0, 4.0)

Online learning to rank system (DBGD)
- TeamDraft
- RHC
- CPS

Queries, Clicks

Interaction simulator

Result lists

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Experiments

Probabilistic click model (variants for testing different settings – *perfect, navigational, informational*)

Learning to rank data set (LETOR 3.0, 4.0)

Measure online performance (cumulative discounted NDCG)

Online learning to rank system *(DBGD)*
- TeamDraft
- RHC
- CPS

Queries, Clicks

Interaction simulator

Result lists

Anne Schuth *(anne.schuth@uva.nl)*

Reusing Historical Interaction Data

*dinsdag 12 maart 13*
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Results: Online Performance (cumulative NDCG)

**Research question:** Can historical interaction data be reused to improve online performance?

[Biased, NP2003, 1K queries]
Results: Online Performance (cumulative NDCG)

Research question: Can historical interaction data be reused to improve online performance?

[Biased, NP2003, 1K queries]
Results: Online Performance (cumulative NDCG)

Research question: Can historical interaction data be reused to improve online performance?

Reusing historical interaction data using CPS significantly improves online performance.

[Biased, NP2003, 1K queries]
Analysis: Speed of Learning

Why does online performance improve under CPS?

[NP2003, 1K queries, informational]
Analysis: Speed of Learning

**Analysis:** Why does online performance improve under CPS?

![Graph showing offline performance](image)

- **[NP2003, 1K queries, informational]**

Reusing Historical Interaction Data
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Analysis: Why does online performance improve under CPS?

Reusing historical interaction data with CPS leads to **significantly faster** online learning, especially **when** click feedback is **noisy**.

---

Analysis: Speed of Learning

[NP2003, 1K queries, informational]
Analysis: Speed of Learning

Analysis: Why does online performance improve under CPS?

Reusing historical interaction data with CPS leads to significantly faster online learning, especially when click feedback is noisy.

Hardly any impact of bias

[NP2003, 1K queries, informational]
Analysis: Number of Candidates

Analysis: How many candidates are optimal for CPS?

[Unbiased, NP2003, 1K queries, navigational]
Analysis: Number of Candidates

Analysis: How many candidates are optimal for CPS?

---

[Unbiased, NP2003, 1K queries, navigational]

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Analysis: Number of Candidates

**Analysis:** How many candidates are optimal for CPS?

More is better but increasingly less so
(6-10 is not significant)

---

[Unbiased, NP2003, 1K queries, navigational]
**Analysis: Number of Candidates**

**Analysis:** How many candidates are optimal for CPS?

More is better but increasingly less so

(6-10 is not significant)

More is computationally much (quadratic) more expensive

---

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Analysis: Number of Historical datapoints

Analysis: What is the optimal history length?

[Unbiased, NP2003, 1K queries, navigational]
Analysis: Number of Historical datapoints

Analysis: What is the optimal history length?

[Unbiased, NP2003, 1K queries, navigational]
Analysis: Number of Historical datapoints

**Analysis:** What is the optimal history length?

More is not necessarily better

[Unbiased, NP2003, 1K queries, navigational]

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dinsdag 12 maart 13
Analysis: Number of Historical datapoints

**Analysis:** What is the optimal history length?

More is not necessarily better

Variance in outcomes increases

![Graph showing online performance vs. history length for CPS and RHC](image)

- **CPS - history length**
  - CPS has three parameters: the history length constitutes a performance change of only 6%. Further increases (under CPS-B, bias would increase), leading to diminished performance.
  - CPS is not recommended.

- **RHC - history length**
  - The sensitivity of RHC-U to changes in historic data points is kept in memory, and are used to compare the candidate rankers, thereby improving the quality of the rankers that are evaluated in live interactions with search engine users.

Overall, we find that performance under CPS can be further increased by using larger candidate pools. However, returns are expected to diminish as ever more candidates are used.

In this paper we investigated whether and how historical data can be reused to speed up online learning to rank for IR. We proposed additional resources to increase online performance. We can conclude that the performance of this part (d). Setting \( \eta = 5 \), \( \zeta = 10 \), the size of the candidate pool, a smaller pool (thus, investing in \( t_{op1mal} \)的历史数据池大小 \( \lambda \), default: 10). This parameter determines how many historic data points are kept in memory, and are used to compare the candidate ranker to the candidate ranker.

Table 3: Offline performance after 1000 iterations in terms of N@1, N@3, and N@10.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>N@1</th>
<th>N@3</th>
<th>N@10</th>
</tr>
</thead>
<tbody>
<tr>
<td>NP2004</td>
<td>0.261</td>
<td>0.296</td>
<td>0.331</td>
</tr>
<tr>
<td>HP2003</td>
<td>0.226</td>
<td>0.243</td>
<td>0.249</td>
</tr>
<tr>
<td>OHSUMED</td>
<td>0.188</td>
<td>0.200</td>
<td>0.188</td>
</tr>
</tbody>
</table>

Analysis:

- **Number of Historical datapoints**
  - Variance in outcomes increases

[Unbiased, NP2003, 1K queries, navigational]

Reusing Historical Interaction Data
Anne Schuth (anne.schuth@uva.nl)
Outline

- Introduction into Online Learning to Rank for IR
- Three ingredients
  - Learning from listwise relative feedback
  - Historical Interaction Data
  - Comparing rankers
- Two Ideas
  - Reliable Historical Comparison
  - Candidate Pre-Selection
- Experiments
- Results
- Conclusions
Summary
Summary

- Introduced
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  - ... Historical interaction data and how to deal with it
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  - Historical interaction data and how to deal with it
  - RHC
    a method for obtaining more reliable relative feedback using historical interaction data
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  - ... Historical interaction data and how to deal with it
  - ... RHC
    a method for obtaining more reliable relative feedback using historical interaction data
  - ... CPS
    a method for reusing historical interaction data in online learning to rank for IR
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- Introduced
  - Historical interaction data and how to deal with it
  - RHC
    a method for obtaining more reliable relative feedback using historical interaction data
  - CPS
    a method for reusing historical interaction data in online learning to rank for IR
- Reusing historical interaction data with CPS significantly improves online performance
Summary

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  - ... Historical interaction data and how to deal with it
  - ... RHC
    a method for obtaining more reliable relative feedback using historical interaction data
  - ... CPS
    a method for reusing historical interaction data in online learning to rank for IR

- Reusing historical interaction data with CPS significantly improves online performance
  - especially under noisy (realistic) feedback
What’s next?
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- Combining RHC + CPS?
  - can we hope to beat CPS?
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  - can we hope to beat CPS?

- We use historical interaction data to ..
  - ... be more sure about whether to update (RHC)
  - ... be more sure about the direction of an update (CPS)
  - ... be more sure about the size of an update?
What’s next?

- Combining RHC + CPS?
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- We use historical interaction data to ..
  - ... be more sure about whether to update (RHC)
  - ... be more sure about the direction of an update (CPS)
  - ... be more sure about the size of an update?

- Getting the direction of an update right (CPS) seems crucial, can we do better?
Thank you