Feeling Lucky?  Multi-armed bandits for Ordering Judgements in Pooling-based Evaluation

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Evaluation is crucial to compare retrieval algorithms, design new search solutions, ...
information retrieval evaluation:
3 main ingredients

docs
information retrieval evaluation:
3 main ingredients

queries
information retrieval evaluation: 3 main ingredients

relevance judgements
relevance assessments are incomplete
relevance assessments are incomplete

barack obama

search system 1  search system 2  search system 3  search system n
relevance assessments are incomplete
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rankings of docs by estimated relevance (runs)
relevance assessments are incomplete

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rankings of docs by estimated relevance (runs)
relevance assessments are incomplete
finding relevant docs is the key

Most productive use of assessors' time is spent on judging relevant docs

(Sanderson & Zobel, 2005)
Give priority to **pooled docs** that are potentially relevant.

Can **significantly reduce** the num. of **judgements** required to identify a given num. of relevant docs.

But most existing methods are **adhoc**...
Our main idea...

Cast **doc adjudication** as a **reinforcement learning** problem

Doc judging is an **iterative** process where we learn as judgements come in
Initially we know nothing about the quality of the runs. As judgements come in... And we can adapt and allocate more docs for judgement from the most promising runs.
Multi-armed bandits

unknown probabilities of giving a prize
Multi-armed bandits

play and observe the reward

unknown probabilities of giving a prize
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unknown probabilities of giving a prize
exploration vs exploitation

explores uncertain actions
gets more info about expected payoffs
may produce greater total reward in the long run

exploits current knowledge
spends no time sampling inferior actions
maximizes expected reward on the next action

allocation methods: choose next action (play) based on past plays and obtained rewards
implement different ways to trade between exploration and exploitation
Multi-armed bandits for ordering judgements

machines = runs

play a machine = select a run and get the next (unjudged) doc

\[ 1. \text{WSJ13} \]
\[ 2. \text{CR93E} \]
\[ \ldots \]

(binary) reward = relevance/non-relevance of the selected doc
Allocation methods tested

- **random**
- **ε<sub>n</sub>** -greedy
  - with prob 1-ε plays the machine with the highest avg reward
  - with prob ε plays a random machine
  - prob of exploration (ε) decreases with the num. of plays

**Upper Confidence Bound (UCB)**
- computes upper confidence bounds for avg rewards
- conf. intervals get **narrower** with the number of plays
- selects the machine with the highest optimistic estimate
Allocation methods tested: **Bayesian bandits**

**prior** probabilities of giving a relevant doc: **Uniform(0,1)** (or, equivalently, Beta(\(\alpha,\beta\)), \(\alpha,\beta=1\))

Evidence \((O \in \{0,1\})\) is Bernoulli (or, equivalently, Binomial(1,p))

**posterior** probabilities of giving a relevant doc: Beta(\(\alpha+O, \beta+1-O\)) (Beta: conjugate prior for Binomial)
Allocation methods tested: **Bayesian bandits**

We **iteratively update** our estimations using Bayes:
Allocation methods tested: **Bayesian bandits**

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Allocation methods tested: **Bayesian bandits**

we *iteratively update* our estimations using Bayes:

![Graphs showing posterior distribution evolution]

two strategies to select the **next machine**:

**Bayesian Learning Automaton (BLA):** draws a sample from each the *posterior* distribution and selects the machine yielding the *highest* sample

**MaxMean (MM):** selects the machine with the *highest* expectation of the posterior distribution
test different document adjudication strategies in terms of **how quickly** they find the **relevant docs** in the pool

# rel docs found at diff. number of judgements performed
experiments: data

<table>
<thead>
<tr>
<th></th>
<th>TREC5</th>
<th>TREC6</th>
<th>TREC7</th>
<th>TREC8</th>
</tr>
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<tbody>
<tr>
<td># queries</td>
<td>50</td>
<td>50</td>
<td>50</td>
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<tr>
<td># automatic runs</td>
<td>77</td>
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<td>77</td>
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<td># manual runs</td>
<td>24</td>
<td>15</td>
<td>7</td>
<td>0</td>
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<td># assessed docs</td>
<td>133681</td>
<td>72270</td>
<td>80345</td>
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<td>avg. # docs judged per query</td>
<td>2673.6</td>
<td>1445.4</td>
<td>1606.9</td>
<td>1736.6</td>
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<tr>
<td>% of rel docs in the pool</td>
<td>4.1%</td>
<td>6.4%</td>
<td>5.8%</td>
<td>5.4%</td>
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<tr>
<td>avg. # rels per query</td>
<td>110.48</td>
<td>92.22</td>
<td>93.48</td>
<td>94.56</td>
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</tbody>
</table>
experiments: baselines

DocId: sorts by Doc Id

AP111, AP881, AP567, CR93E, FT967, WSJ13, ...

barack obama

WSJ13, WSJ17, AP111, WSJ19, AP567, CR93E, FT967, ZF207, AP881, ...

pool
experiments: baselines

rank #1 docs go 1st, then rank #2 docs, ...

WSJ13, FT941, ZF207, WSJ17, CR93E, AP881 ...

Rank: rank #1 docs go 1st, then rank #2 docs, ...
experiments: baselines

MoveToFront (MTF) (Cormack et al 98)

starts with uniform priorities for all runs (e.g. max priority=100)
selects a random run (from those with max priority)
experiments: baselines

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stays in the run until a non-rel doc is found
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WSJ13, CR93E, AP111
experiments: baselines

MoveToFront (MTF) (Cormack et al 98)

extracts & judges docs from the selected run
stays in the run until a non-rel doc is found
when a non-rel doc is found, priority is decreased

WSJ13, CR93E, AP111
experiments: baselines

MoveToFront (MTF) (Cormack et al 98)

and we jump again to another max priority run
experiments: baselines

Moffat et al.'s method (A) (Moffat et al 2007)

based on rank-biased precision (RBP)
sums a rank-dependent score for each doc

<table>
<thead>
<tr>
<th>score</th>
<th>1. WSJ13</th>
<th>1. FT941</th>
<th>1. WSJ13</th>
<th>1. ZF207</th>
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<td>2. AP881</td>
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<td>0.16</td>
<td>3. AP567</td>
<td>3. WSJ19</td>
<td>3. AP111</td>
<td>3. FT967</td>
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<tr>
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<th>Doc 3</th>
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**WSJ13**: 0.20 + 0.16 + 0.20 + ... all docs are ranked by decreasing accumulated score and the ranked list defines the order in which docs are judged
experiments: baselines

Moffat et al.'s method (B) (Moffat et al 2007)

- evolution over A's method
- considers not only the rank-dependent doc's contributions but also the runs' residuals
- promotes the selection of docs from runs with many unjudged docs

Moffat et al.'s method (C) (Moffat et al 2007)

- evolution over B's method
- considers not only the rank-dependent doc's and the residuals
- promotes the selection of docs from effective runs
experiments: baselines

MTF: best performing baseline
## Experiments: MTF vs Bandit-Based Models

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experiments: MTF vs bandit-based models

Random: weakest approach

BLA/UCB/$\epsilon_n$-greedy are suboptimal
(sophisticated exploration/exploitation trading not needed)

MTF and MM: best performing methods
improved bandit-based models

MTF: forgets quickly about past rewards
(a single non-relevance doc triggers a jump)

non-stationary bandit-based solutions:
not all historical rewards count the same

MM-NS and BLA-NS non-stationary variants of MM and BLA
stationary bandits

\[ \text{Beta}(\alpha, \beta), \, \alpha, \beta = 1 \]

rel docs add 1 to \( \alpha \)
non-rel docs add 1 to \( \beta \)

(after n iterations)

\[ \text{Beta}(\alpha_n, \beta_n) \]

\[ \alpha_n = 1 + j_{rel_s} \]
\[ \beta_n = 1 + j_{ret_s} - j_{rel_s} \]

\( j_{rel_s} \): # judged relevant docs (retrieved by s)
\( j_{ret_s} \): # judged docs (retrieved by s)

all judged docs count the same

non-stationary bandits

\[ \text{Beta}(\alpha, \beta), \, \alpha, \beta = 1 \]

\[ j_{rel_s} = \text{rate} \cdot j_{rel_s} + \text{rel}_d \]
\[ j_{ret_s} = \text{rate} \cdot j_{ret_s} + 1 \]

(after n iterations)

\[ \text{Beta}(\alpha_n, \beta_n) \]

\[ \alpha_n = 1 + j_{rel_s} \]
\[ \beta_n = 1 + j_{ret_s} - j_{rel_s} \]

rate > 1: weights more early relevant docs
rate < 1: weights more late relevant docs
rate = 0: only the last judged doc counts (BLA-NS, MM-NS)
rate = 1: stationary version
experiments: improved bandit-based models

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multi-arm bandits: **formal & effective** framework for doc adjudication in a pooling-based evaluation

It's good to react quickly to non-relevant docs (non-stationary variants)

It's not good to increasingly reduce exploration (UCB, $\epsilon_n$-greedy)
future work

query-related variabilities

metasearch

hierarchical bandits

stopping criteria
reproduce our experiments & test new ideas!

http://tec.citius.usc.es/ir/code/pooling_bandits.html
(our R code, instructions, etc)

Pooling - Bandits


Any scientific publication derived from the use of this software should explicitly refer to this ACM SAC paper.

Next, we explain the data used for experimentation and provide our R code, which implement all pooling strategies.

Data

We used four TREC collections (http://trec.nist.gov): TREC5, TREC6, TREC7 and TREC8.

NIST kindly provided the runs that contributed to the pools of the adhoc tasks of TREC5, TREC6, TREC7 and TREC8 (http://trec.nist.gov/data/Intro_eng.html).

The pooled runs are archived by NIST within a password protected area. If you want to reproduce our experiments you need to request access to the protected area (follow the instructions given at http://trec.nist.gov/results.html).

- TREC5
  - 101 runs in the pool (77 adhoc + 24 other).

  The 77 adhoc runs are: input.anu5aut1 input.anu5aut2 input.anu5man4 input.anu5man6 input.brkly15 input.brkly16 input.brkly18 input.city96a1 input.city96a2 input.CLCLUS input.CLTHES input.colm1 input.colm4 input.Cor5A1se input.Cor5A2cr input.Cor5M1le
  input.Cor5M2rf input.Ctfr1 input.Ctfr2 input.DCU961 input.DCU962 input.DCU963 input.DCU964 input.DCU965 input.DCU96C input.DCU96D input.erliA1 input.ETHa1 input.ETHas1 input.ETHme1 input.fsclt3 input.fsclt4 input.genri1 input.genri2 input.genri3 input.gnri4 input.glair4 input.gmu96au1 input.gmu96au2 input.gmu96ma1 input.gmu96ma2 input.ibmgd1 input.ibmgd2 input.ibmgd4 input.ibmge1 input.ibmgd2 input.ibmge2 input.ibms96a input.ibms96b input.INQ301 input.INQ302 input.KUSSG2 input.KUSSG3 input.LNaDesc1 input.LNaDesc2 input.LNmFull1 input.LNmFull2 input.mds001 input.mds002 input.mds003 input.Mercur-eal input.Mercur-eas input.MONASH input.pircsAAL input.pircsAAS input.pircsAM1 input.pircsAM2 input.sdmi1 input.sdmi2 input.umcpc1 input.uncis1 input.uncis2 input.UniNE7 input.UniNE8 input.uwgcx0 input.uwgcx1 input.utwnA1 input.utwnB1

  The other 24 runs are: input.anu5mrg0 input.anu5mrg1 input.anu5mrg7 input.CLATMC input.CLATMN input.CLPHR0 input.CLPHR1 input.CLPHR2 input.fsclt3m input.genlp1 input.genlp2 input.genlp3 input.genlp4 input.MTRA961 input.sbse1 input.sbse2 input.UniNE0 input.UniNE9 input.xerox_nlp1 input.xerox_nlp2 input.xerox_nlp3 input.xerox_nlp4 input.xerox_nlp5 input.xerox_nlp6
Feeling Lucky? Multi-armed bandits for Ordering Judgements in Pooling-based Evaluation

David E. Losada

Javier Parapar, Álvaro Barreiro

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