Auditing Search Engines for Differential Satisfaction across Demographics

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*Work conducted while at Microsoft Research
About Me

• PhD Candidate at University College London
  • Advisor: Emine Yilmaz
  • Feb 2014 – ? early 2017 (expected)

• Research Interests
  • Search Tasks & User Effort
    • Task Behavior, Multitasking & Applications [SIGIR 2016, CHIIR 2016, ICTIR 2015]
    • Deep sequential models for task satisfaction [SIGIR 2017]
  • User Modeling & Personalization
    • Crowd-contributed platforms [ICTIR 2017, WWW 2015]
    • LinkedIn/Slideshare data [under review]
    • Cross-domain News Personalization [HIA‘16 Workshop, under review]
  • Counterfactuals & Causal Analysis
    • Information seeking [CHIIR 2016], Related Searches
    • Bayesian Structural Models for Taxi/Bike rides [under review]
  • Undergrad
    • Topic Models [SIGIR 2013], Domain Adaptation [CIKM 2012], Structured Sparsity [NIPS 2012 xLiTe]
Fairness across demographics

• Online services - advertised as being available to any user

• Ethical
  • Equal access to everyone

• Practical
  • Equal access helps attract a large and diverse population of users
  • Service providers are scrutinized for seemingly unfair behavior [1,2,3]

• Onus on us
  • develop fair systems

Auditing services for fairness

We offer methods for **auditing a system’s performance** for detection of **differences in user satisfaction** across demographics.
From public libraries to search engines

- Modern analogue of public libraries
- Dominant role in information access
- Fairness in performance!
Are Search Engines Fair*?

* Fairness in performance; differential satisfaction across demographics!
From public libraries to search engines

Search Engines:
• Rely on ML models to optimize for user satisfaction
• Make use of implicit signals
• Metric driven development

... not easy to audit
Tricky: straightforward optimization can lead to differential performance

**Goal:** estimate difference in user satisfaction between two demographic groups.

- **Age:** <30 years
  - 80% users

- **Age:** >50 years
  - 10% users

- Search engine uses a standard metric: **time spent** on clicked result page as an indicator of satisfaction.

- Suppose older users issue more of “*retirement planning*” queries
1. Aggregate Metrics can be misleading

• Overall metrics can hide differential satisfaction

• **Average user satisfaction for “retirement planning” may be high.**

But,

• Average satisfaction for younger users=0.7
• Average satisfaction for older users=0.2
2. Query-level metrics can hide differential satisfaction

Assuming same user satisfaction for “retirement planning” for both older and younger users = 0.7

What if average satisfaction for <query-X> = 0.9? (e.g. <query-X> = “facebook”)

Older users still receive more of lower-quality results than younger users.
3. More critically, even individual-level metrics can also hide differential satisfaction

**Metric itself could be confounded with demographics**

**Consider:** Reading time for the same webpage result for the same user satisfaction

Younger Users -> Time spent on a webpage

Older Users
We must **control** for natural demographic variation to meaningfully audit for differential satisfaction.
Outline

1 Background
2 Data & metrics
3 Proposed approaches:
   1 Context Matching
   2 Hierarchical Multi-level model
4 From metrics to satisfaction
5 Discussion
Data: Demographic characteristics of search engine users

- Internal logs from Bing.com for two weeks
- 4 M users | 32 M impressions | 17 M sessions
- Demographics: Age & Gender

Age:
- post-Millenial: <18
- Millenial: 18-34
- Generation X: 35-54
- Baby Boomer: 55-74

... also perform external auditing using comScore data
Demographic distribution of user activity

**fraction of users**

- **Female**
  - Age Group 1: 0.0
  - Age Group 2: 0.1
  - Age Group 3: 0.2
  - Age Group 4: 0.3

- **Male**
  - Age Group 1: 0.0
  - Age Group 2: 0.1
  - Age Group 3: 0.2
  - Age Group 4: 0.3

**query frequency**

- **Female**
  - Age Group 1: 0.0
  - Age Group 2: 0.1
  - Age Group 3: 0.2
  - Age Group 4: 0.3

- **Male**
  - Age Group 1: 0.0
  - Age Group 2: 0.1
  - Age Group 3: 0.2
  - Age Group 4: 0.3

**Loadings**

- **Head**
  - Age Group 1: 0.0
  - Age Group 2: 0.1
  - Age Group 3: 0.2
  - Age Group 4: 0.3

- **Torso**
  - Age Group 1: 0.0
  - Age Group 2: 0.1
  - Age Group 3: 0.2
  - Age Group 4: 0.3

- **Tail**
  - Age Group 1: 0.0
  - Age Group 2: 0.1
  - Age Group 3: 0.2
  - Age Group 4: 0.3
Metrics Considered

1. Graded Utility (GU)
   • based on search outcome and user effort

2. Reformulation Rate (RR)
   • fraction of queries that were reformulated

3. Successful Click Count (SCC)
   • clicks with significant dwell times

4. Page Click Counts (PCC)
   • total no of clicks on SERP

Goal: estimate difference in user satisfaction between demographic groups

Obvious solution: demographic binning!
### Overall metrics across Demographics

<table>
<thead>
<tr>
<th></th>
<th>GU</th>
<th>PCC</th>
</tr>
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<tbody>
<tr>
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<td>0.00</td>
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<tr>
<td>SCC</td>
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<th>GU</th>
<th>PCC</th>
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<td></td>
<td>1.00</td>
<td>1.00</td>
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- Substantial differences in performance across age
- Gender – not so much

... how true are these?
Pitfalls with Overall Metrics

Conflates two separate effects:

• natural **demographic variation** caused by the differing traits among the different demographic groups e.g.
  • Different queries issued
  • Different information need for the same query
  • Even for the same satisfaction, demographic A tends to click more than demographic B

• **Systemic difference** in user satisfaction due to the search engine

... we need to disentangle them!
Utilize work from causal inference
Utilize work from causal inference
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Utilize work from causal inference
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1  Motivation
2  Problems with naïve auditing
3  Data & Metrics
4  Proposed approaches:
   1  Context Matching
   2  Hierarchical Multi-level model
5  From metrics to satisfaction
6  Discussion
Proposed Approaches

1) Context Matching

Extremely restrictive
More robust

2) Multi-level model

Generalizable
Less Robust
I. Context Matching:
selecting for activity with near-identical context

For any two users from different demographics,

1. **Same Query**
2. **Same Information Need:**
   1. Control for user intent: same final SAT click
   2. Only consider navigational queries
3. **Identical top-8 Search Results**

1.2 M impressions
19K unique queries
617K users
Age-wise differences in metrics disappear

- General auditing tool: robust
- Very low coverage across queries
  - Did we control for too much? – lose over 60% of data!
Proposed Approaches

1) Context Matching
   - Extremely restrictive
     - More robust

2) Multi-level model
   - Generalizable
     - Less Robust
Query-level Multilevel Model

- A hierarchical approach that treats the data as a mixture of distributions based on demographics and queries

- Non-nested multi-level model
  - Users & Queries: nested within non-nested age and gender groups & topics
  - second level captures variation with individual query properties
  - Age effects
  - Gender effects
  - Topic effects
  - \(<\text{age, gender, topic}\>\)
    interaction effects

\[
E(Y) = f^{-1} (\alpha_{agt} + \beta_{agt} X)
\]

\[
\begin{pmatrix}
\alpha_{agt} \\
\beta_{agt}
\end{pmatrix} = 
\begin{pmatrix}
\mu_0 \\
\mu_1
\end{pmatrix} +
\begin{pmatrix}
\alpha_a \\
\beta_a
\end{pmatrix} +
\begin{pmatrix}
\alpha_g \\
\beta_g
\end{pmatrix} +
\begin{pmatrix}
\alpha_t \\
\beta_t
\end{pmatrix} +
\begin{pmatrix}
\alpha_{agxt} \\
\beta_{agxt}
\end{pmatrix}
\]

\[
\begin{pmatrix}
\alpha_k \\
\beta_k
\end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \Sigma_k\right) \quad k \in \{a, g, t\}
\]

Specific example: \(GU_i \sim \mathcal{N}(\alpha_{agt} + \beta_{agt} X_i, \sigma_y^2)\)
Age-wise differences appear again: bigger differences for harder queries

**EASY QUERIES**

**DIFFICULT QUERIES**
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From Metric to Satisfaction

• Estimating absolute satisfaction is non-trivial
From Metric to Satisfaction

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• We estimate relative satisfaction by considering pairs of impressions
  • which impression led to a higher satisfaction
From Metric to Satisfaction

- Estimating absolute satisfaction is non-trivial

- We estimate **relative satisfaction** by considering pairs of impressions
  - which impression led to a higher satisfaction

- Construct a **conservative “high-precision, low-recall”** proxy for pairwise satisfaction
  - by only considering “big” differences in observed metric for the same query

---

**Algorithm 1** Compute satisfaction label

1: if $RR_i < RR_j$ then return +1
2: if $RR_i > RR_j$ then return -1
3: if $GU_i - GU_j > \delta_{GU}^1$ then return +1
4: if $GU_j - GU_i > \delta_{GU}^1$ then return -1
5: if $SCC_i - SCC_j > \delta_{SCC}^1$ then return +1
6: if $SCC_j - SCC_i > \delta_{SCC}^1$ then return -1
7: if $GU_i - GU_j > \delta_{GU}^2 \land SCC_i - SCC_j > \delta_{SCC}^2$ then return +1
8: if $GU_j - GU_i > \delta_{GU}^2 \land SCC_j - SCC_i > \delta_{SCC}^2$ then return -1
9: else return 0
From Metric to Satisfaction

- Estimating absolute satisfaction is non-trivial
- We estimate relative satisfaction by considering pairs of impressions
  - which impression led to a higher satisfaction
- Construct a conservative “high-precision, low-recall” proxy for pairwise satisfaction
  - by only considering “big” differences in observed metric for the same query

Logistic regression model for estimating probability of impression \( i \) being more satisfied than impression \( j \):

\[
P(S_i > S_j) = \logit^{-1}(\beta_0 + \beta_{a_i}a_i + \beta_{a_j}a_j + \beta_{g_i}g_i + \beta_{g_j}g_j + \beta_{i,j}a_ia_jg_ig_j)
\]
Again, see a small age-wise difference in satisfaction

- Older users are slightly more satisfied than younger users
External Auditing

- Experiment on a publicly available dataset
- 2 weeks logs of comScore data
- Use PCC metric to gauge satisfaction
- Probability of impression $i$ being more satisfied than impression $j$: $P(S_i > S_j)$
Discussion

- Auditing is more nuanced than merely measuring metrics on demographically-binned traffic
  - developed techniques to auditing search engines
- We find light trend towards older users being more satisfied.
- General framework for internally auditing systems
  - Plug-in different metrics
  - Plug-in different demographics/user groups
Discussion

- Auditing is more nuanced than merely measuring metrics on demographically-binned traffic
  - developed techniques to auditing search engines
- We find light trend towards older users being more satisfied.
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Future Work

- develop metrics which are not confounded with demographics
- Investigate causes of metric differences
  - Query level analysis
  - SERP level analysis
- Dwell time thresholds for SAT prediction based on demographic information
Auditing is more nuanced than merely measuring metrics on demographically-binned traffic.

General framework for auditing systems
  Plug-in different metrics
  Plug-in different demographics/user groups

Thank You!

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