Auditing Algorithms: Towards Transparency in the Age of Big Data

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Personalization is Ubiquitous

Search Results
- Google
- bing

Social Media
- Facebook

Goods and Services
- Amazon
- STAPLES
- Target

Music, Movies, Media
- Netflix
- Pandora
- iTunes
Dangers of Personalization?

Facebook faces UK probe over emotion study

The revelation of the study has sparked criticism from some Facebook users.

A UK regulator is investigating whether Facebook broke data protection laws when it conducted a psychological study on users without their consent.
Racial discrimination in Google’s AdSense system uncovered by Latanya Sweeney in 2013

Example of *unintended consequences* of big data

People exhibit racial bias in their search and clicks patterns

The ad-placement algorithm observed and learned these behaviors
Price Discrimination

Showing users different prices
  In econ: differential pricing

Example: Amazon in 2001
  DVDs were sold for $3-4 more to some users

Surprisingly, not illegal in the US
  Anti-Discrimination Act does not protect consumers

Article 20(2) of the Services Directive protects EU residents
  But companies seem to be flaunting the regulation :(
Price Steering

Altering the order or composition of products
E.g. high priced items rank higher for some people

Example: Orbitz in 2012
Users received hotels in a different order when searching
Normal users: cheap hotels first; Mac users: expensive hotels first

THE WALL STREET JOURNAL
On Orbitz, Mac Users Steered to Pricier Hotels
Auditing Algorithms

Governments and regulators are concerned about big data and algorithms

White House reports:

*Big Data: Seizing Opportunities, Preserving Values*

*Big Data and Differential Pricing*

FTC’s new Office of Technology Research and Investigation

*Tasked with monitoring the applications of big data and algorithms*

How do we measure and understand algorithms?

Algorithms may be trade secrets, constantly changing

Access to source code is not enough, data is equally important

Emerging scientific area: **Auditing Algorithms**
Goals of Our Work

1. Understanding how companies collect and share data about users
   Online and offline retailers
   Advertisers and marketers
   Data brokers like Acxiom, Datalogix, Equifax, Experian, etc...

2. Reverse-engineering online algorithms to assess their impact
   Search engines
   Online advertisements
   E-commerce
   Social networks
   etc...
Measuring Personalization
Case Study: Google Search
Case Study: E-commerce
Measuring Personalization
Case Study: E-commerce
Are All Differences Personalization?

Not necessarily! It could be:

- Updates to inventory/prices
- Tax/Shipping differences
- Distributed infrastructure
- Load-balancing

How can we reliably identify and quantify personalization?
Controlling for Noise

queries run at

Difference – Noise = Personalization

IP addresses in the same /24

129.10.115.14

Product 1
Lorem ipsum dolor sit amet, consectetur adipiscing elit. In mollis

Product 2
Lorem ipsum dolor sit amet, consectetur adipiscing elit. In mollis

129.10.115.15

129.10.115.16

Product 2
Lorem ipsum dolor sit amet, consectetur adipiscing elit. In mollis

Queries run at

Same Amazon IP address

74.125.225.67
Dual Methodology

Questions we want to answer:

1. To what extent is content personalized?
2. What user features drive personalization?

REAL USER ACCOUNTS

- Leverage real user accounts with lots of history
- Measure personalization in real life

SYNTHETIC USER ACCOUNTS

- Create accounts that each vary by one feature
- Measure the impact of specific features
Real User Experiment

Task on Amazon Mechanical Turk (AMT)
Over 1000s of participants
Each executed hundreds of search queries
Every query paired with two control queries

Run from empty accounts, i.e. no history
Baseline results for comparison
Measuring Personalization

Case Study: Google Search

Case Study: E-commerce
Results from Real Users

- On average, real users have a 12% higher chance of differing than the controls.
- Most changes are due to location.

Top ranks are less personalized.
What Causes of Personalization?

AMT results reveal extensive personalization

Next question: what user features drive this?

**Static Features**
- Gender
- Age
- Browser
- Operating System
- Location (IP Address)
- Logged In/Out

**Historical Features**
- Logged In/Out
- History of Searches
- History of Search Result Clicks
- Browsing History

Methodology: use synthetic (fake) accounts
Logged In/Out to Google

Average Jaccard Index

- No Cookies / No Cookies
- Logged In / No Cookies
- Logged Out / No Cookies

Average Edit Distance

Same results

...But in a different order
IP Address Geolocation

On average, 1 different result

...Plus 1 pair of reordered results
What About Search History?

Search for ‘healthcare’

Search for ‘obama,’ then ‘healthcare’

Subsequent queries may “carry-over”
Impact of Search History

Overlap in Results, Searching for ‘healthcare’ and ‘obama’ + ‘healthcare’

Average Jaccard Index

Time Between Queries (Minutes)

10 minute cutoff
Measuring Personalization
Case Study: Google Search
Case Study: E-commerce
Measuring Personalization
Case Study: E-commerce
Targeted Retailers

10 General retailers
BestBuy CDW HomeDepot JCPenney Macy’s NewEgg OfficeDepot Sears Staples Walmart

6 travel sites (hotels & car rental)
CheapTickets Expedia Hotels.com Priceline Orbitz Travelocity

Focus on products returned by searches, 20 search terms/site
Do Users See the **Same Prices for the Same Products?**

Many sites show inconsistencies for real users

Up to 3.6\% of all products
Inconsistencies can be $100s! (per day/night for hotels/cars)
What Features Trigger Personalization?

Methodology: use synthetic (fake) accounts
Give them different features, look for personalization
Each day for 1 month, run standard set of searches

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<tr>
<th>Category</th>
<th>Feature</th>
<th>Tested Features</th>
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<tr>
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<td>Cookie</td>
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<td>User-Agent</td>
<td>OS</td>
<td>Win XP, Win 7, OS X, Linux</td>
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<tr>
<td></td>
<td>Purchase</td>
<td>Big Spender, Low Spender</td>
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</table>
Smartphone users see totally different products than desktop users.

7% of products have different prices on Android.

... but the prices only go up by $0.50 on average.
Travel Sites

Cheaptickets and Orbitz offer lower prices on hotels for users who log-in to the sites
1 hotel per page, $12 off per night on average

Travelocity offers discounts on hotels for users on mobile devices
1 hotel per page, $15 off per night on average

Priceline changes the order of search results based on click and purchase history

Example of price steering
• 2 accounts click/reserve high price hotels
• 2 accounts click/reserve low price hotels
• 2 accounts do nothing
Cheaptickets/Orbitz

Save 30% Off - 4 Nights Or More

Eden Roc Miami Beach
4.1 | 182 reviews

Price is 47% less than usual

Miami Beach
Landmark Miami Beach hotel brings on the beachside glamour
Famed architect Morris Lapidus changed the face of Miami Beach with this 631-room hotel; an... More

There are 6 people viewing this hotel.
Last booked 13 hours ago.

$25 Elle Spa Credit

MEMBERS ONLY
Stay 3 nights, Save 35%

Eden Roc Miami Beach
4.1 | 182 reviews

Miami Beach
Landmark Miami Beach hotel brings on the beachside glamour
Famed architect Morris Lapidus changed the face of Miami Beach with this 631-room hotel; an... More

There is 1 person viewing this hotel.
Last booked -12 hours ago.

$25 Elle Spa Credit
Cheaptickets and Orbitz offer lower prices on hotels for users who log-in to the sites.

About 1 hotel per page has a lower price.

Prices drop by around $12 per night.
Travelocity offers discounts on hotels for users on mobile devices.

- iOS users see different hotels.
- About 1 hotel per page has a lower price.
- Price drops by around $15/night.
Priceline changes the order of search results based on click and purchase history:

- 2 accounts click/reserve high price hotels
- 2 accounts click/reserve low price hotels
- 2 accounts do nothing
Hotels.com/Expedia

Hotels and Expedia are conducting large-scale A/B tests on their users. When you visit the site, you are randomly placed in a “bucket”.

2 out of 3 buckets see high-price hotels at the top of search results. The remaining bucket sees low-price hotels at the top of the page.

Exemplifies price steering.

The only way to see the hidden hotel results is to clear your cookies and reload the site.
Conclusions and Future Work
The Era of Big Data

Algorithms driven by big data shape your world
Search results you are given
Prices and products you are shown
Movie, music, and book recommendations
The directions you use to drive

In many cases, these systems are wonderful

Eligibility for social services
Access to credit and banking
Allocation of police forces

In other cases, they may be detrimental
Unintended consequences
Intentional manipulation
Our Goal: Transparency

Personalization is problematic when it is not transparent
   How is data being collected and shared?
   How is data being used to alter content?

Use algorithm audits to investigate deployed systems, assess their impact

Our goal is to increase transparency
   Building tools to help users and regulators
   Reverse-engineering systems to understand how they work
   Raising public awareness of these issues
Peeking Beneath the Hood of Uber
Borders on Google Maps

Ukraine
Discrimination in the Gig-economy

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<th>How I can help</th>
<th>Reviews &amp; Profile</th>
<th>How many Completed Cleaning Tasks</th>
<th>How many Cleaning Reviews</th>
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<td>Joseph C.</td>
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<td>Joseph C.</td>
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<td>Enthusiastic and detail oriented cleaner here to help you with your needs. Engineer by trade, so you know I'll find the right solution for you. Happy to help and listen to your needs and get the job done.</td>
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<td>Paul C.</td>
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<td>Very clean individual. Works efficiently and quickly. Takes pride in the work and final product. Animal lover. Kid friendly. Very personable (human or animal) Punctuality is a must. Detail oriented. GPS in my car, so there is no getting lost.</td>
<td></td>
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<td>Meredith R.</td>
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* Paul was great, left everything crispy clean, excellent! * 
- March 19, 2017
All of our code, data, and papers are available at:

http://personalization.ccs.neu.edu