New Faces of Bias in Online Labor Markets

Aniko Hannak
Central European University
Brave New Online World

Interaction with site

User generated data

Filter Bubble?

Big Data Algorithms

Echo Chamber?

Algorithms Discriminating?
Algorithms & Discrimination

Study Finds Racial Discrimination by Uber and Lyft Drivers

Study: Uber and Lyft have ‘pattern of discrimination’ against black passengers
Waiting times for black Seattle passengers were 35% longer, and Boston drivers cancelled rides for black passengers more than twice as frequently, study found.

Can the algorithm police use to predict crimes be racist?

Even algorithms are biased against black men

A study on offenders in Florida refutes the notion that computers are more objective than people

Study Finds Racial Discrimination by Airbnb Hosts

The New York Times

Does Airbnb Enable Racism?

Google’s algorithm shows prestigious job ads to men, but not to women. Here’s why that should worry you.

Facebook charged with racism in job and housing ads
Online Labor Markets

The Internet is fundamentally changing the labor economy

Job Search: Millions of people use online hiring sites to find employment
Freelancing: In 2014, 53m people, 34% of total workforce in US
Policymaking has to catch up and protect employees online

So much simpler than Yellow Pages

Easy access to job opportunities, information
Equality: access to the same information independent from class, location
Goals of my Work

Observe biases known to occur in the real world in online platforms
identify mechanisms that bring the inequality into the system
(e.g.: selection of workers, reviewing them)
examine algorithms that retain, reinforce them
(e.g.: recommendation, search)
quantify the extent to which minority groups are affected

Come up with mitigation strategies, design recommendations
1. Freelance Marketplaces

2. Online Professional Communities

3. Job Search Sites / Resume Search services

Conclusion
1. Freelance Marketplaces

2. Online Professional Communities

3. Job Search Sites / Resume Search services

Conclusion
Search

Event Planning

Matthew P.

John G.

Why I'm your Tasker:

I'm the right person for the job...

I have been one of TaskRabbit's Runners for over 5 years. I have excellent reviews. I give a 100% to every job I am assigned. There are a couple of negative reviews you might see. The 1st task he is not complaining about the work I did. The 2nd task I have no idea why she gave me a thumbs down.

When I'm not tasking...

I work for the new England Patriots and several other Arenas in the area. I enjoy spending time with my Family. I also volunteer for The Moose Fraternity raising money for Children and Seniors.

Cleaning:

Done is great at communicating and getting the job done! Will hire again for sure!

Rochell G., November 17, 2015

Cleaning:

Rochell G., November 10, 2016

Organization:

Done is fantastic! We've hired her multiple times, all great experiences.

Jessica S., November 04, 2015

Profile Information
Data

User features
Age, Education, Bio, Verified, Elite, etc

Search results
position of each user in the result list of a given query

How do demographic features relate to social feedback or position on the search result page?

small online tasks
75k profiles (~50%)
Bias in Search Results

TaskRabbit
Rank 0 denotes the top of the page
Fairness in Search Results

OLS regression, dependent variable: User’s Position in the Search Results

Black workers rank lower than white workers
Being a man is worse for black workers

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Significance</th>
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<tbody>
<tr>
<td>Female (Ref: male)</td>
<td>-0.468***</td>
<td>p &lt; 0.001</td>
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<tr>
<td>Asian (Ref: white)</td>
<td>0.194*</td>
<td>p &lt; 0.05</td>
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<tr>
<td>Black (Ref: white)</td>
<td>-0.428***</td>
<td>p &lt; 0.001</td>
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<tr>
<td>Asian*Female</td>
<td>0.364*</td>
<td>p &lt; 0.05</td>
</tr>
<tr>
<td>Black*Female</td>
<td>1.3***</td>
<td>p &lt; 0.001</td>
</tr>
</tbody>
</table>

*p < 0.05; **p < 0.01; ***p < 0.001
Social Feedback

We find racial and gender-based differences in

- number of reviews
- ratio of tasks evaluated
- rating score
- language of the reviews

Extent and type of inequality varies based on the site or type of job

Open questions: self-selection process, drop-out rates
1. Freelance Marketplaces

2. Online Professional Communities

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Conclusion
Investment and reputation

Online professional communities combine “community” with “reputation”
  e.g.: designers (Dribbble), software developers (GitHub), etc
effectively the online representation of a career

Building online identities and trust are a long-term investment
  reputation, trust
  customer base, history
  social ties, visibility, audience
Dribbble (yes, 3 b’s!)

Shots (60k)

Users (5k)

Teams (1000)

Views, likes, responses

followers

Invitation Email Template by Zsófia Czémán on Apr 11, 2016

This is an email template design with a custom icon.

1 Response

Roland Hideg
But big Really nice work! I love the circular too.
6 months ago | Reply | Delete | Like?

Tags
coloration mail e-mail design email template icon Invitation mail mail ui

Zsófia Czémán
Digital Product Designer | UX | UI | Illustration | Branding

 infringement

More from Zsófia Czémán

More from Zsófia Czémán

More from Zsófia Czémán

Dropbox

Simplifying the way people work together

Join us dropbox.com/jobs/design

TEAM

Brandon Land

Justin Tran
**Differences in Success**

<table>
<thead>
<tr>
<th></th>
<th># of Views</th>
<th># of Likes</th>
<th># of Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Women</strong></td>
<td>1539 (759)</td>
<td>72 (40)</td>
<td>4.1 (2)</td>
</tr>
<tr>
<td><strong>Men</strong></td>
<td>2181 (1008)</td>
<td>89 (44)</td>
<td>4.7 (2.5)</td>
</tr>
</tbody>
</table>

Cumulative Frequency

- KS test $p < 0.01$
Explaining differences

What leads to success on Dribbble? Why the differences?

1. Experience, productivity, tenure?

2. "Genderedness" of skills and designed products?

3. Difference in social network positions?
1. Experience, productivity, tenure

Gender-based differences exist

But gender is still significant if we control for them.
2. “Genderedness" of skills and products

Interfaces, Product Management Objective C, iOS dev

Calligraphy, Copy Writing, Research, Hand Lettering

Genderedness explains some of the gender effects
But not good enough at explaining success ($R^2 < 0.14$)
3. Difference in Social Network Position

Adding follower count, reciprocity, and ego density to the OLS regression

R^2 value increases from 0.1 to 0.6

# of followers and ego network density predict success

Gender is no longer significant

ERGM

Men have more followers, less reciprocal ties: bigger audience

Women have more reciprocal ties, smaller clusters: stronger ties
OUTLINE

1. Freelance Marketplaces
2. Online Professional Communities - Dribbble
3. Job Search Sites / Resume Search services

Conclusion
Job Search Sites

Job Search sites are actually tools for recruiters to find candidates.

Danger of Bias: Search Algorithm allows to filter based on many individual user characteristics.

Collected data from 3 job search sites.

Are there differences the positions of candidates in the results list based on race/gender?

Can we develop an algorithm that is “similar enough” to the ones on the site but does not take gender into account?
Discussion

New mechanisms for inequalities to emerge
   Require new measurement techniques to detect and quantify them

Open questions, next steps:
   How to mitigate inequalities? Transparency? Fair algorithms?
Accountability?
   Whose responsibility is it?
   How to regulate if the offline policies do not apply online?
Thank you!

personalization.ccs.neu.edu
ccs.neu.edu/home/ancsaaa

Balint Daroczy
David Garcia
Alan Mislove
Andras Voros
Johannes Wachs
Claudia Wagner
Christo Wilson