New Faces of Bias in Online Labor Markets

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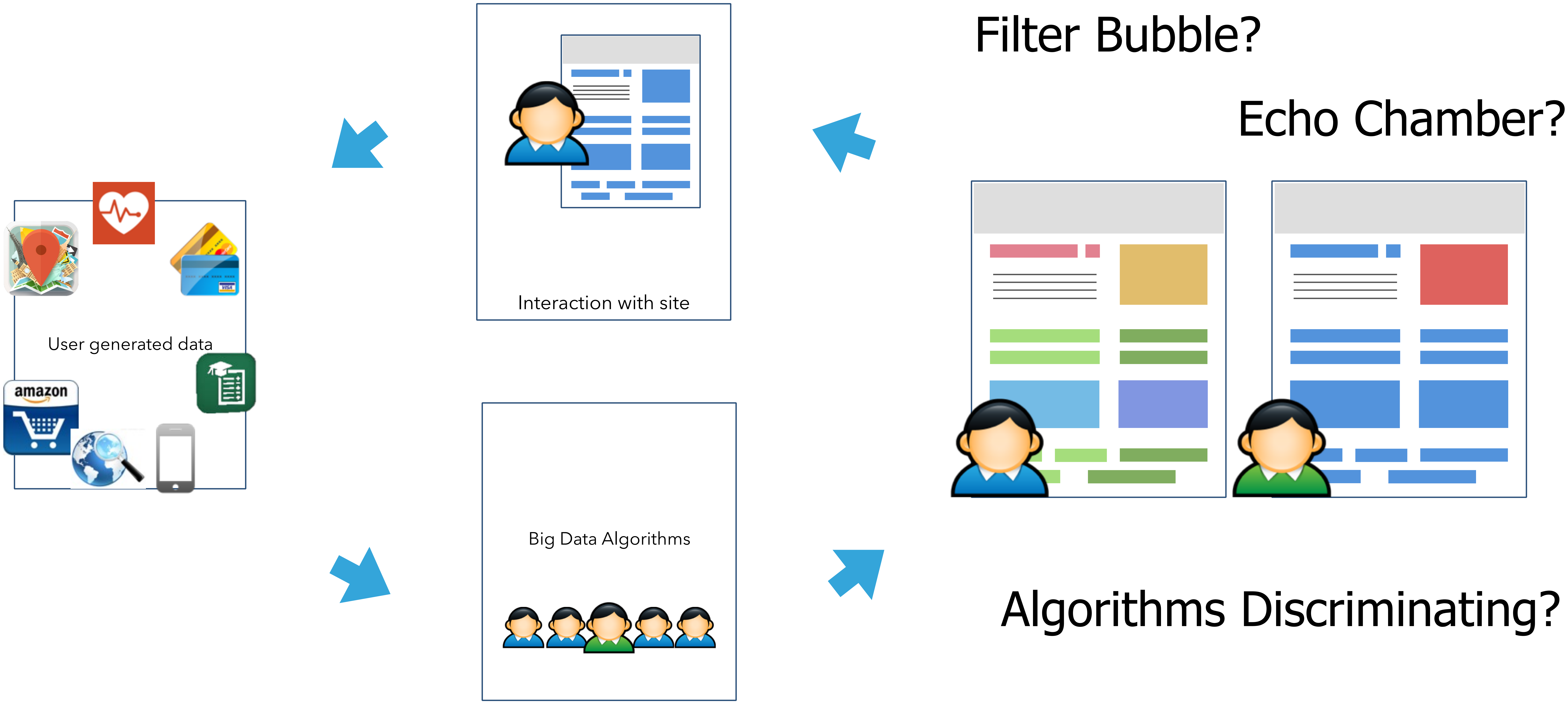
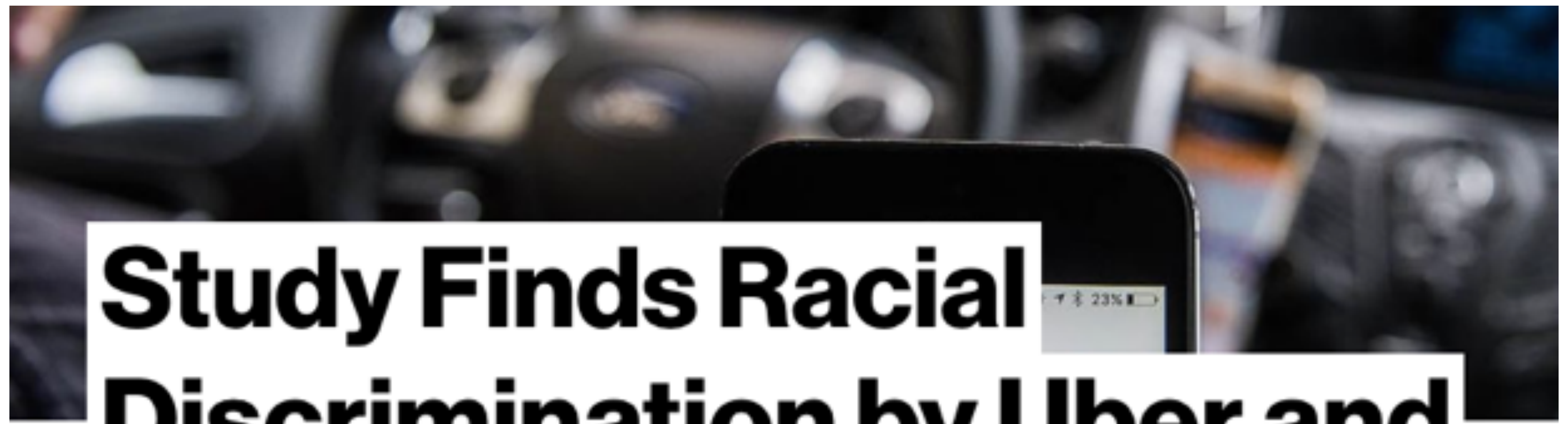
Brave New Online World



Algorithms & Discrimination



Study Finds Racial Discrimination by Uber and Lyft Drivers

Researchers suggest anonym
a possible solution.

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

Study Finds Racial Discrimination by Airbnb Hosts

The New York Times

Does Airbnb Enable Racism?

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

The Washington Post
Democracy Dies in Darkness

The Intersect

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

OUTLINE

1. Freelance Marketplaces

2. Online Professional Communities

3. Job Search Sites / Resume Search services

Conclusion

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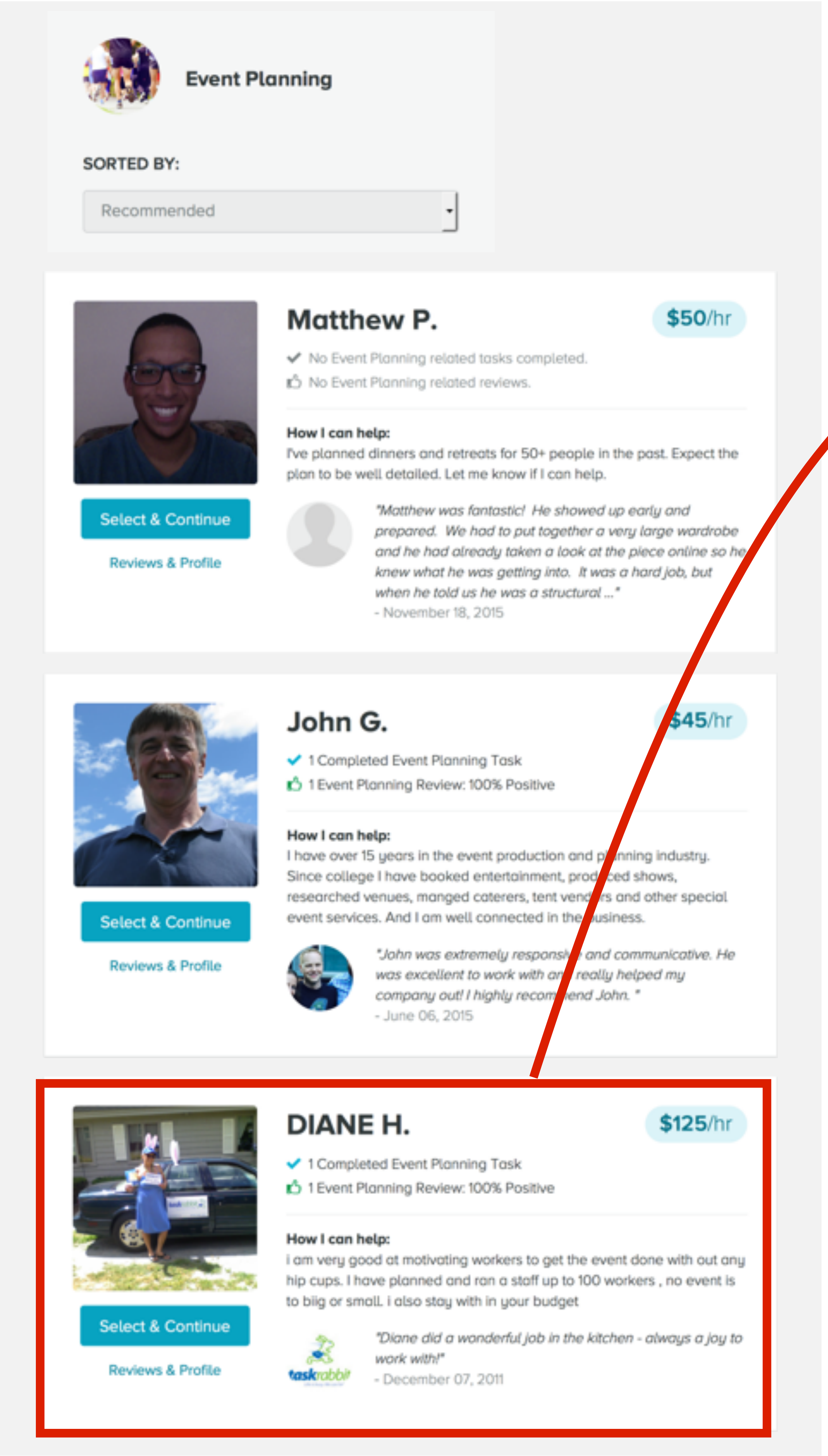
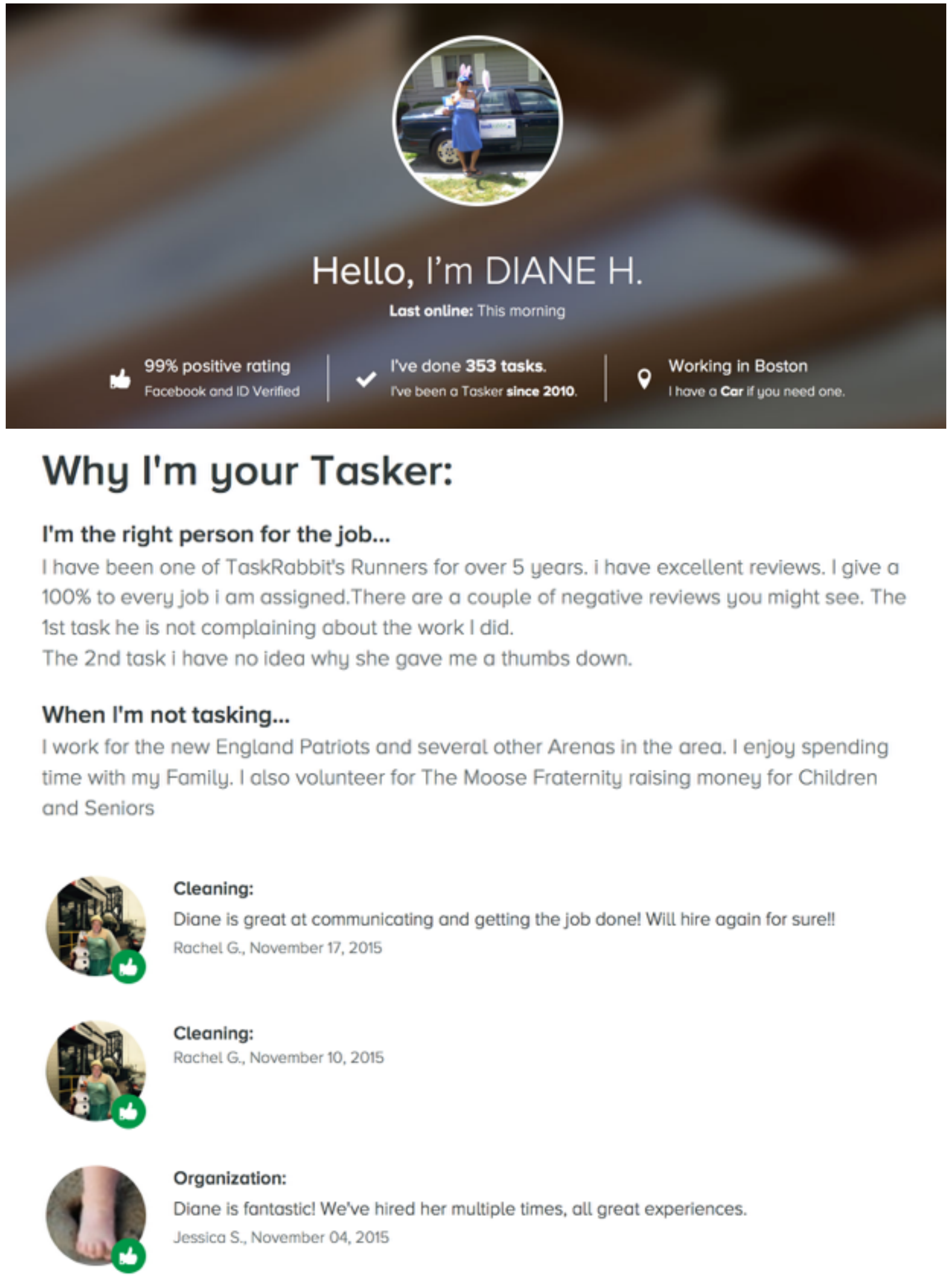
Search



Profile Information



Data

User features

Age, Education, Bio, Verified, Elite, etc

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

Search results

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

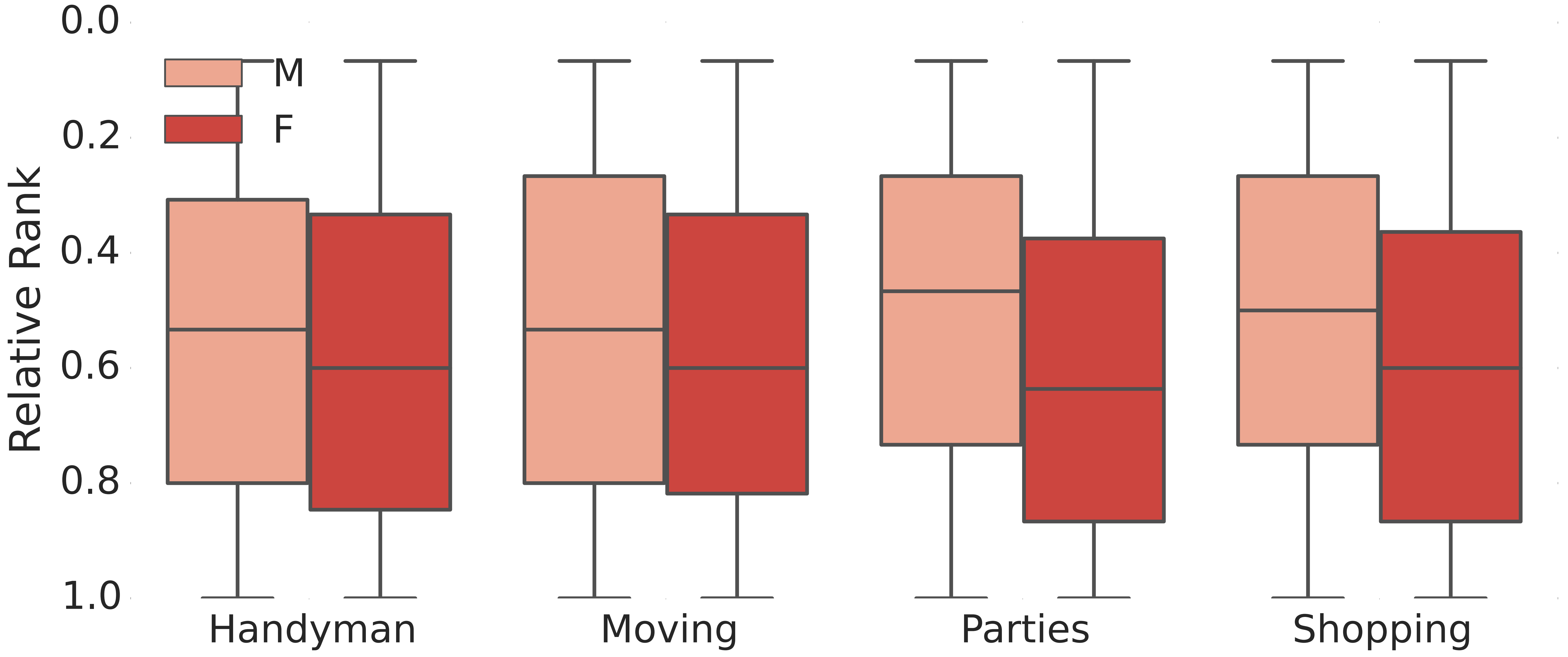
small online tasks

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

Female (Ref:male)	-0.468***
Asian (Ref:white)	0.194*
Black (Ref:white)	-0.428***
Asian*Female	0.364*
Black*Female	1.3***

*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

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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

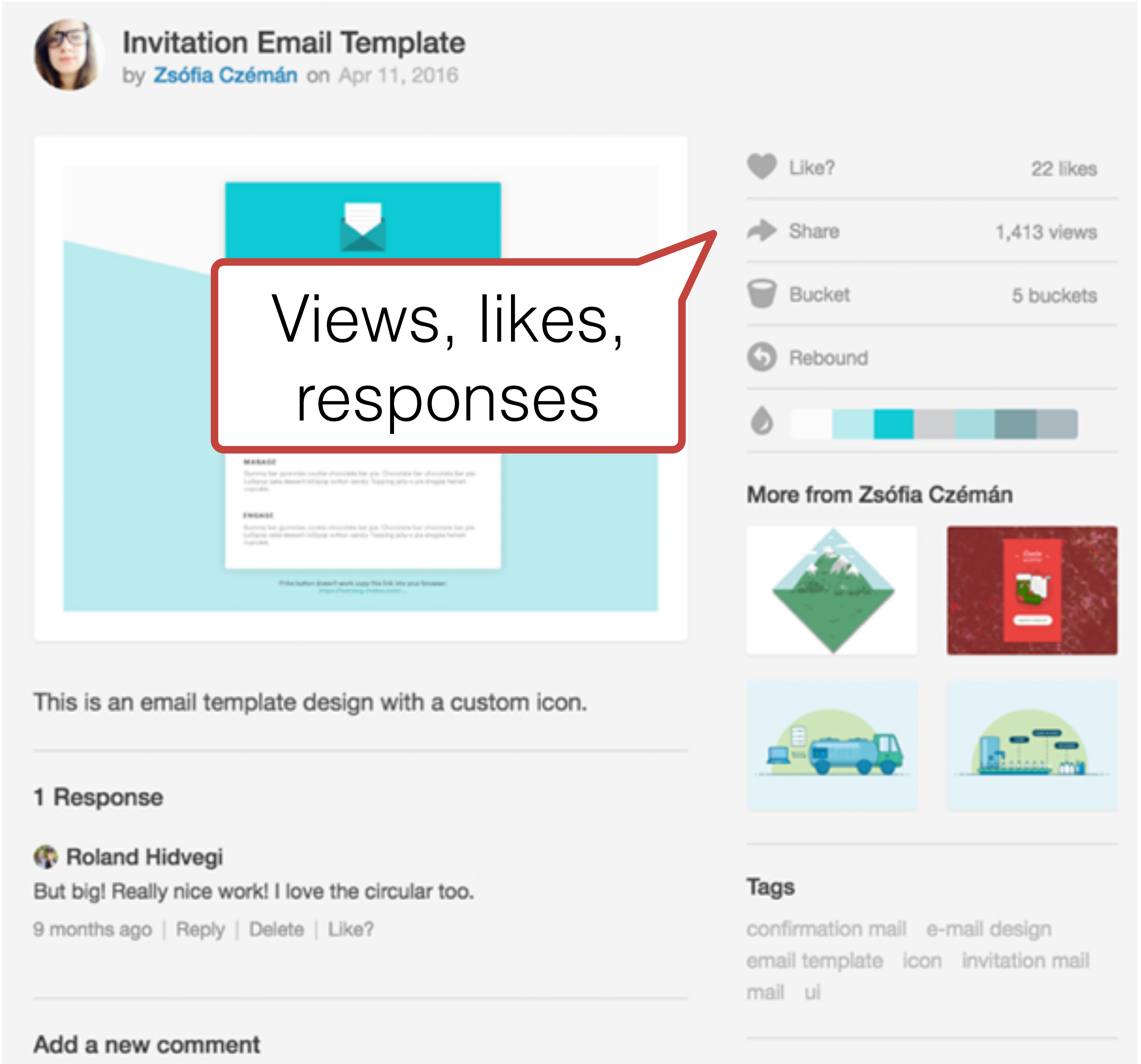
Building online identities and trust are a long-term investment

- reputation, trust
- customer base, history
- social ties, visibility, audience

Dribbble (yes, 3 b's!)

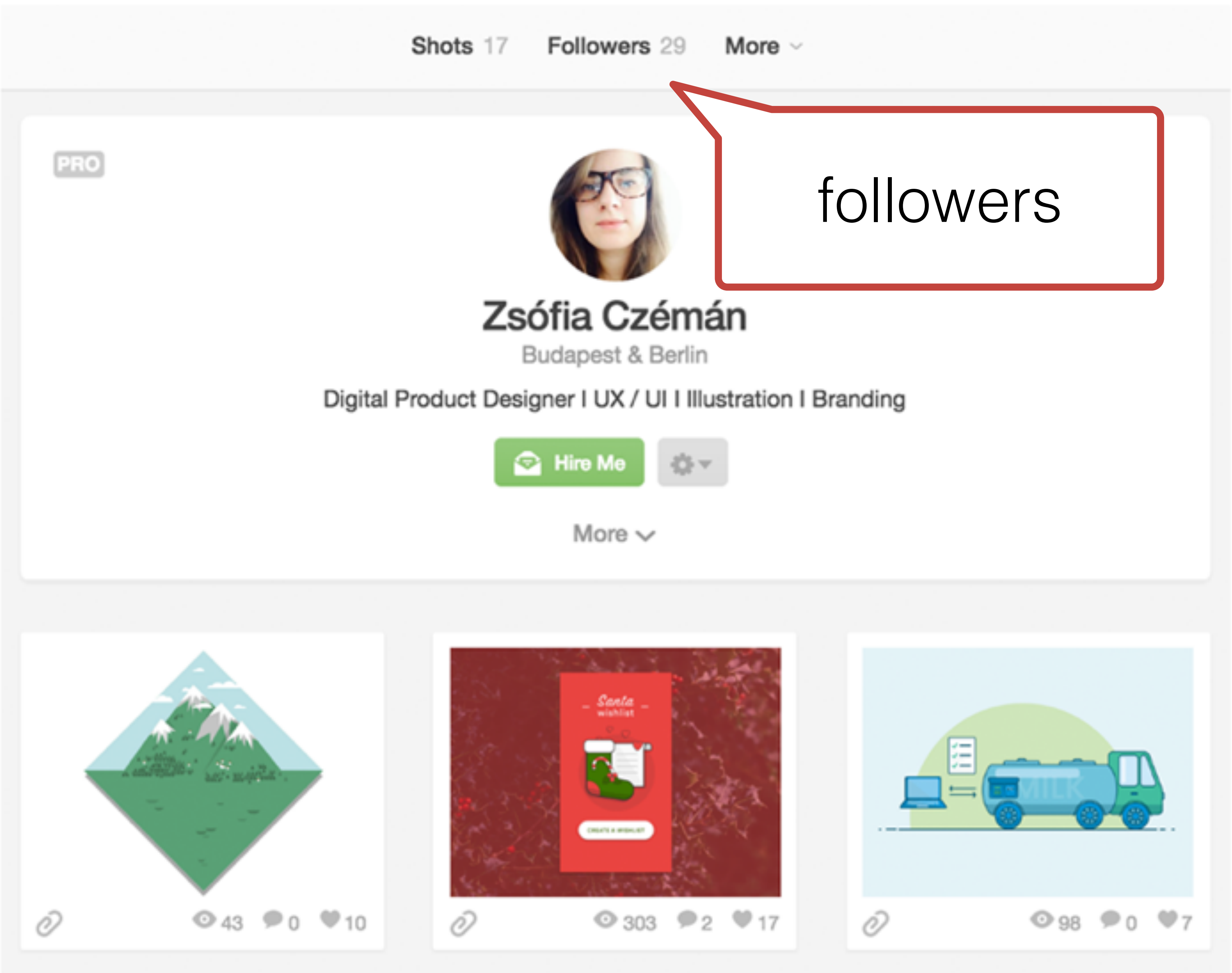
Dropbox Google Evernote Design

Shots (60k)



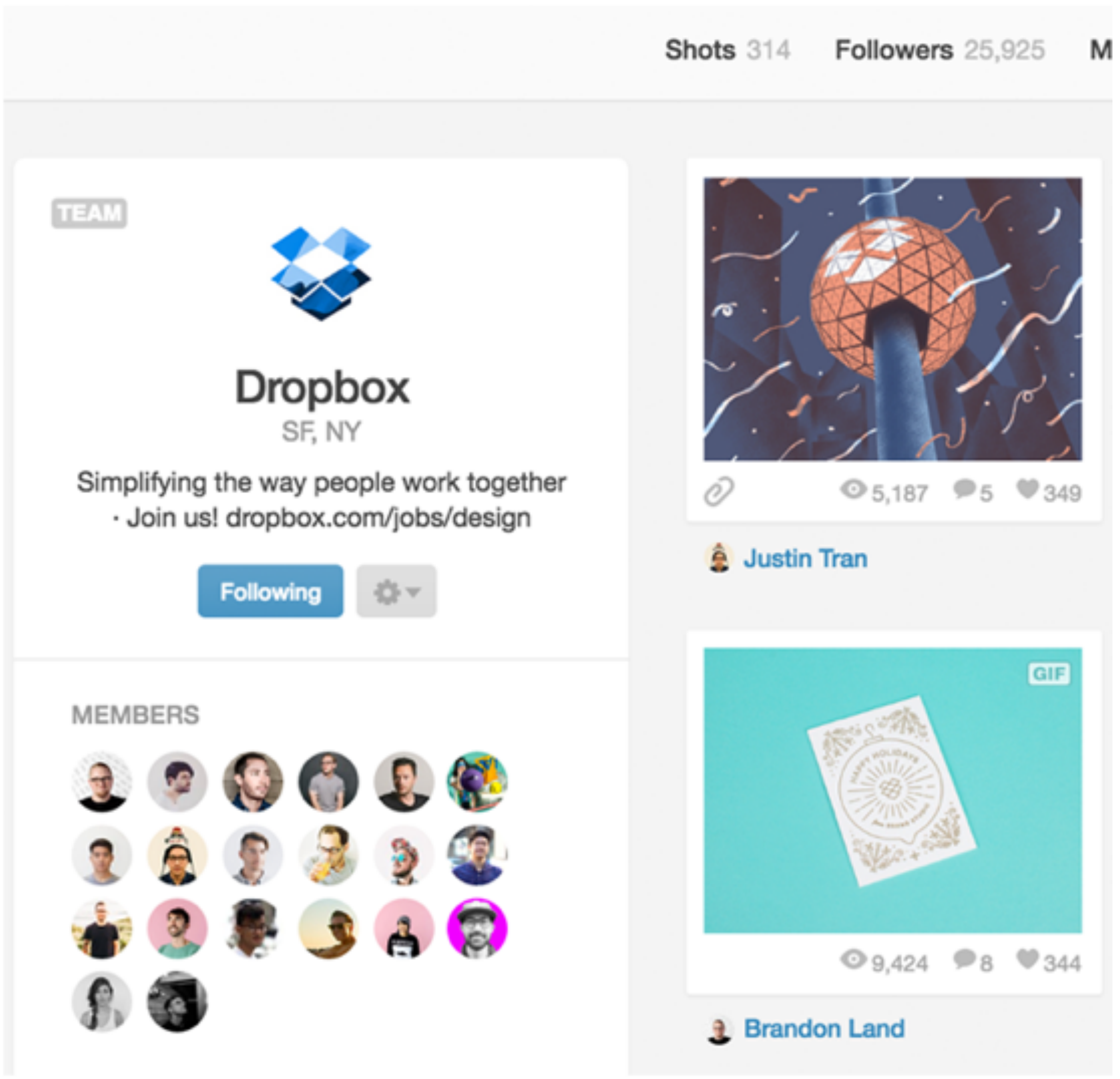
Views, likes, responses

Users (5k)



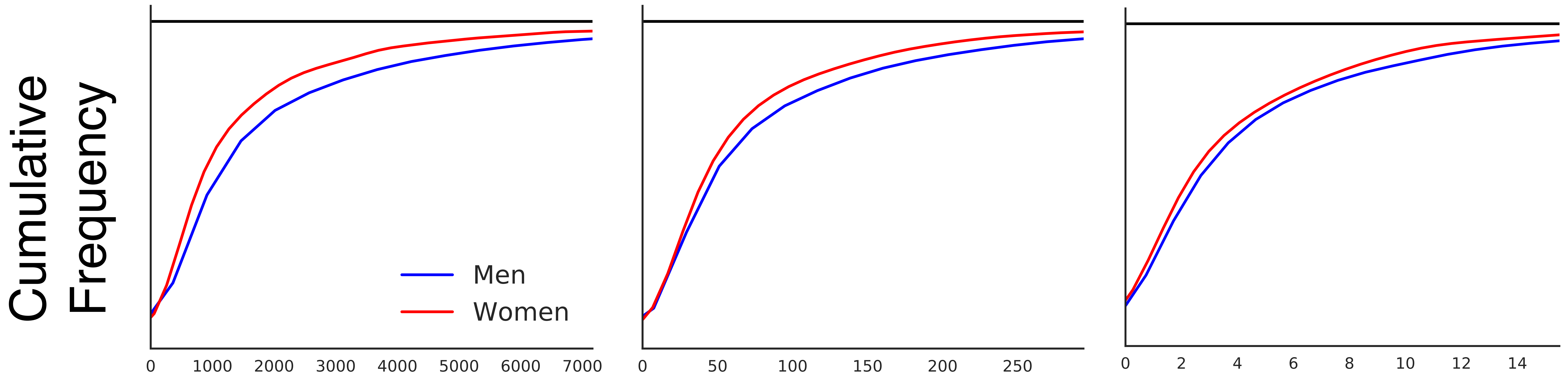
followers

Teams (1000)



Differences in Success

median (mean)	# of Views	# of Likes	# of Responses
Women	1539 (759)	72 (40)	4.1 (2)
Men	2181 (1008)	89 (44)	4.7 (2.5)



KS test $p < 0.01$ KS test $p < 0.01$ KS test $p < 0.01$

Explaining differences

What leads to success on Dribbble? Why the differences?

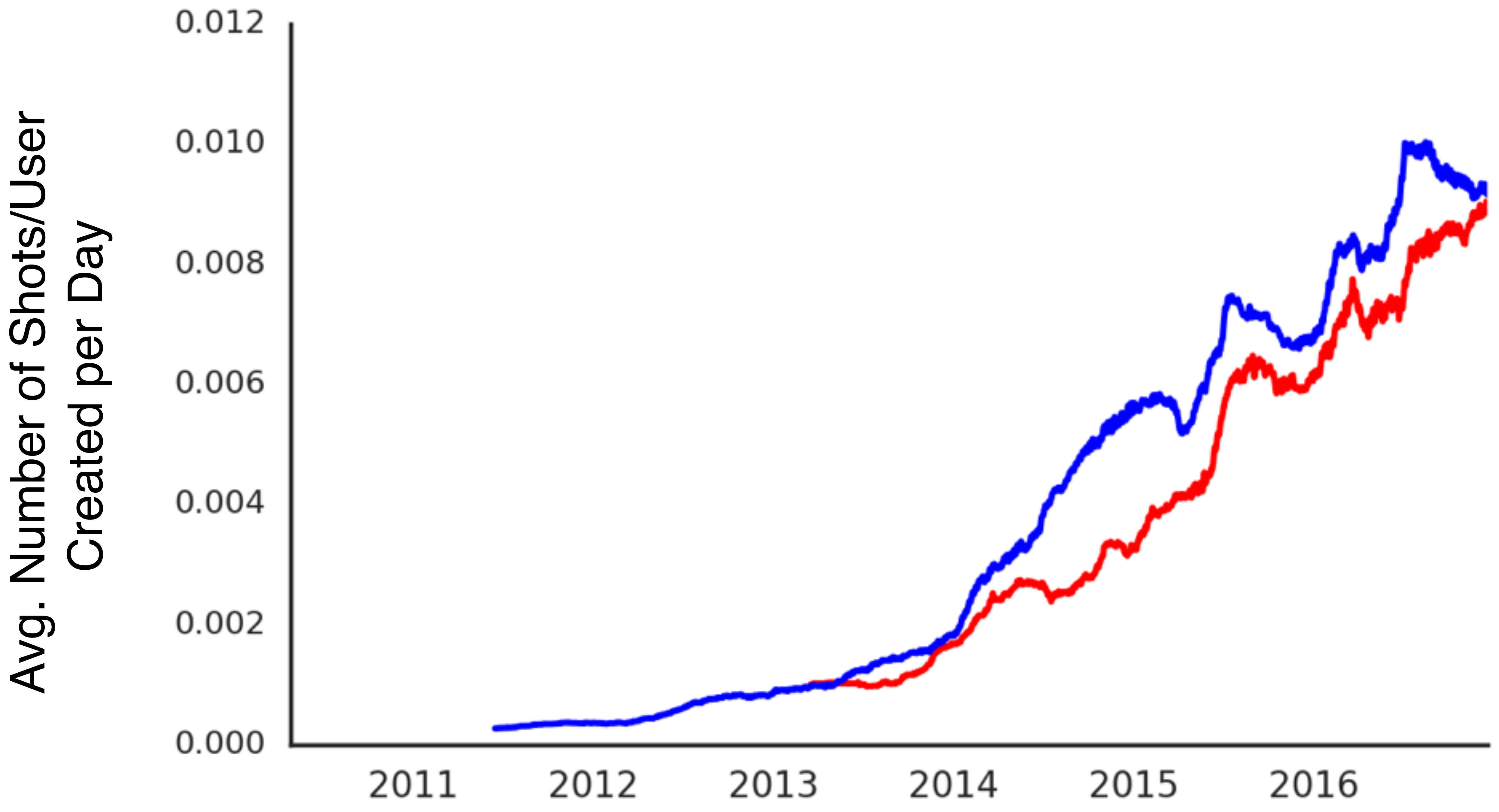
1. Experience, productivity, tenure?

2. “Genderedness" of skills and designed products?

3. Difference in social network positions?

1. Experience, productivity, tenure

Gender-based differences exist

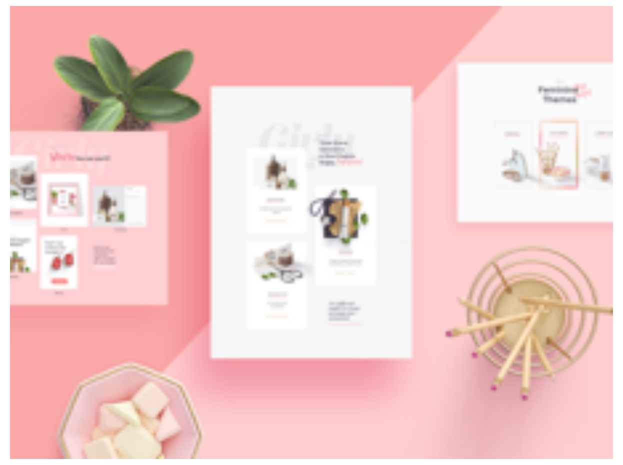


But gender is still significant if we control for them.

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 ($R^2 < 0.14$)

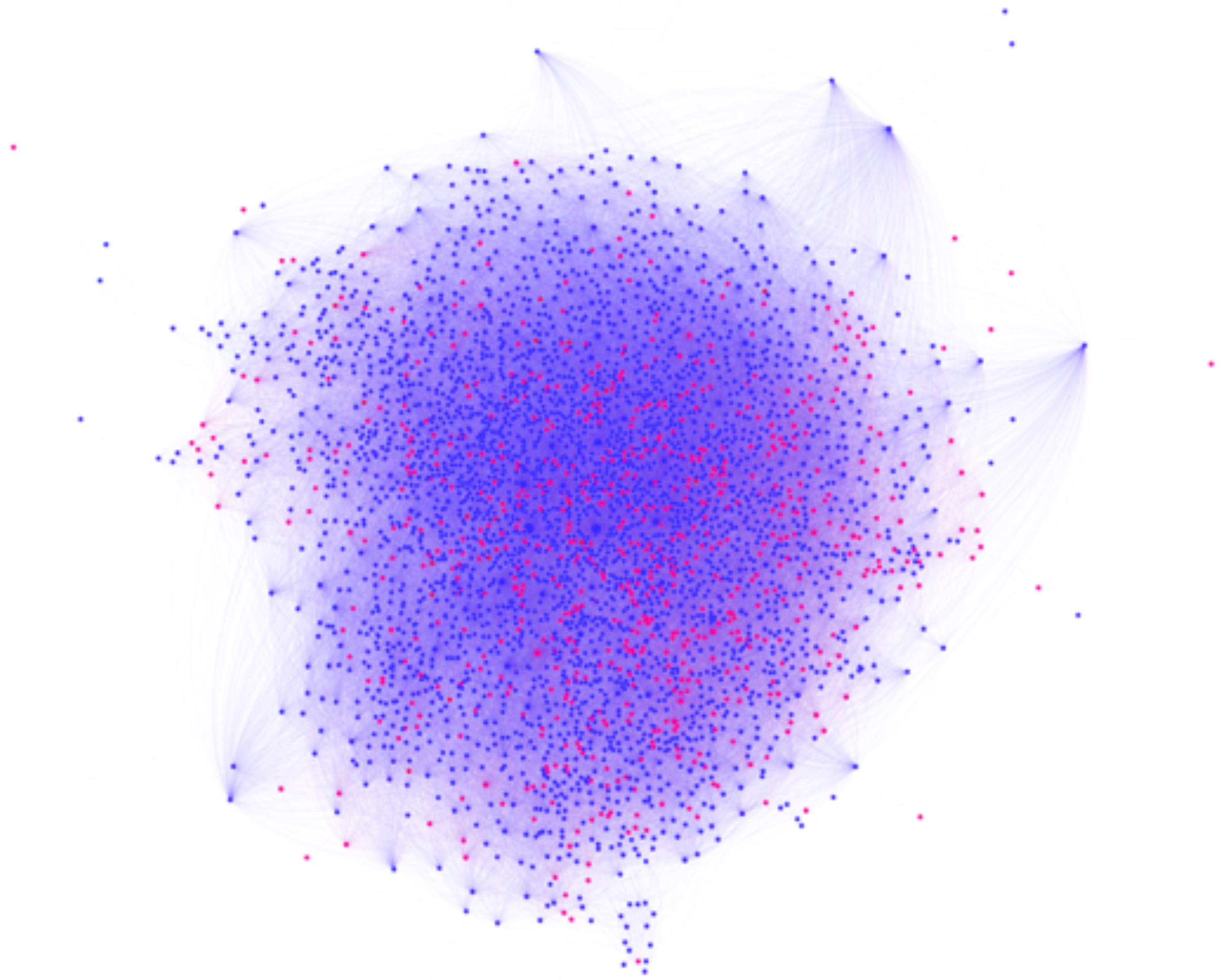
3. Difference in Social Network Position

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

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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

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