Algorithms, Privacy and Inequality

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Outline

1. Algorithmic Exclusion?
2. Sparse Data
3. Fragmented Data
4. What are the effects?
5. Provocative Conclusions

How This All Started

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Algorithmic Exclusion

When Algorithms err because data is missing due to differences in privilege

- Sparsity
- Fragmentation

In equation form (this may be lunchtime but this is MIT):

$$Y = X\beta + \epsilon$$

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Sparse Data

More general point that a broad digital footprint is a matter of privilege

- Computer Work
- Mobile Data
- Internet of Things

The idea of data deserts is neglected

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Fragmented Data

- Algorithmic data is not usually from single source
- Datasets have to be matched a
- How do you match? Cell phones..Email addresses…Names

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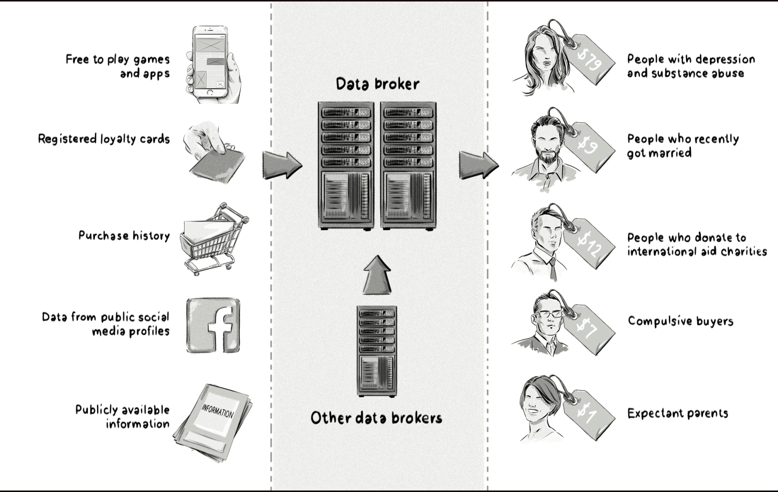
Based on Algorithms of Data Brokers



What Kind of Predictions are bought by data broker clients (Lotme)

- Age (76%)
- Gender (61%)
- Income (50%)
- Education (40%)
- Children (32%)

But how do Data Brokers Know Age and Gender?

Simple prediction task

- Data on Browsing behavior
- May tell us whether someone is a female (if I browse sanitary products)
- May tell us age (if I browse retirement homes)

We asked how good data brokers are at this

What we did

- We identified cookies from ‘pureprofile’ panel survey.
- We asked data brokers to tell whether they were male or (25-34)

Results

Data Broker	Number of Cookies	Gender Accuracy
A	1396	27.5
B	408	25.7
C	1777	35.2
D	495	56.4
E	527	48.8
F	480	47.9
G	562	46.8
H	1016	33.2
I	2336	33.6
J	14342	42.4
K	346	30.6
L	547	51.9
M	456	49.1
N	5099	62.7

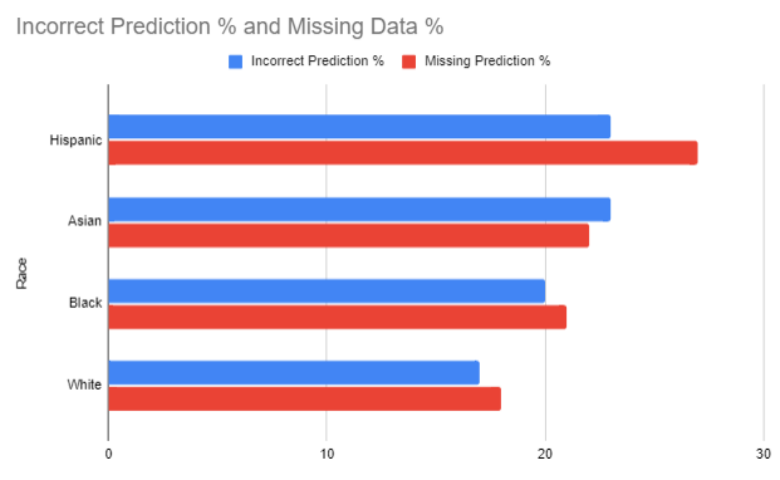
We went out and got new data on the people who were profiled

- We wanted to know if this was related to income inequality

What We Found

- Richer, more educated, home-owning people are more likely to be profiled accurately
- In particular, they are more likely to have accurate demographic information

And Race..


Incorrect Prediction % and Missing Data %
Incorrect Prediction %
Missing Prediction %
Race
Hispanic
Asian
Black
White
0
10
20
30

But should we care if people are poorly profiled by algorithms as they have missing data?

Summary

- Data is often sparse
- Data is often fragmented
- This leads to algorithmic exclusion where algorithms work poorly
- Interaction with inequality appears important outside of advertising

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Provocative Conclusion: 1

- Privacy is a ‘rich’ person’s concern
- Perhaps for low-income people data inaccuracy is a bigger concern
- Do we have the current privacy debate the right way around?

Provocative Conclusion 2

- Algorithmic transparency or auditing doesn't address this
- Instead we need to also think about data deserts in the way we think about food deserts

Thank you!

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