



Are we experimenting on people?

Data Science and AI ethics

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- Are we experimenting on people?
- What are our ethical obligations?
- How do we embed ethics into our processes?
- How do we tackle the technical challenges?



Agenda



Human Subject Research

Churn

PPC optimisation

Credit worthiness

Recommendations

Timeline ordering

Common data science projects

- Informed consent
- Respect
- Right to opt-out
- Benefits > costs
- No harm
- Provide information
- Protect privacy

Researcher obligations



Why do we need to think about this?



To avoid a dystopian future



Chukwuemeka Afigbo

@nke_ise

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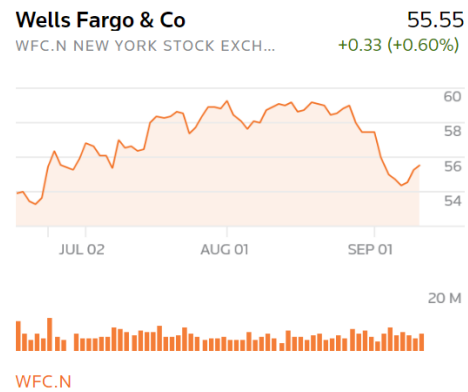
If you have ever had a problem grasping the importance of diversity in tech and its impact on society, watch this video



To not be (inadvertently) _____ist

[Tweet](#)

The \$8 million accrual is intended for roughly 625 borrowers who should have qualified for a loan modification under a program the Treasury Department set up in 2009 to help Americans who were struggling to make mortgage payments.



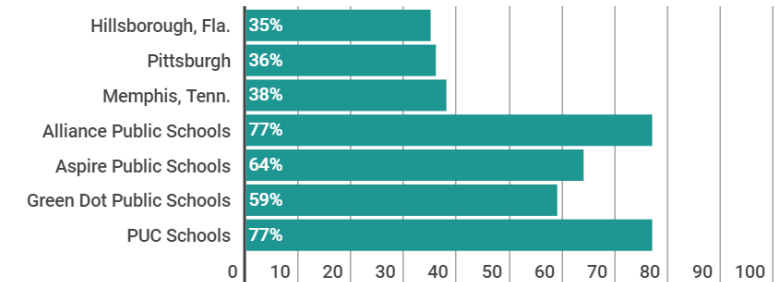
An error in Wells Fargo's underwriting tool improperly excluded those borrowers, 400 of whom eventually had their homes foreclosed upon, the bank said.

The bank also updated disclosures on issues it has discovered in auto lending, wealth management, fiduciary and custody accounts, foreign exchange trading, mortgage rate-lock extensions, "add-on" products like identity theft protection, and frozen or closed bank accounts.

Teachers' Perceptions of Evaluation Systems

In spring 2016, researchers asked teachers whether they thought the consequences tied to evaluation results are reasonable, fair, and appropriate. Consequences can include possible termination or increased compensation.

Teachers in charter schools were much more likely to believe the high-stakes consequences were fair.



SOURCE: RAND Corporation and the American Institutes for Research

EDUCATION WEEK

To avoid destroying lives

<https://money.cnn.com/2018/08/04/news/companies/wells-fargo-mortgage-modification/index.html>
<https://www.edweek.org/ew/articles/2018/06/21/an-expensive-experiment-gates-teacher-effectiveness-program-show.html>

Complete multiple tasks with one app

Switch between channels to tune the description of what's in front of the camera.



Short Text

Speaks text as soon as it appears in front of the camera



Documents

Provides audio guidance to capture a printed page, and recognizes the text, along with its original formatting



Products

Gives audio beeps to help locate barcodes and then scans them to identify products



Person

Recognizes friends and describes people around you, including their emotions



Scene

An experimental feature to describe the scene around you



Currency

Identify currency bills when paying with cash

To feel good about what we do

**How does this translate to a business
context?**

- Type I and II errors
- Change in behaviours
- Financial, medical, or political impacts

(Unintended) Consequences



- Consider and plan
- Guide implementation
- Refuse to do harmful work and/or whistleblow?
- Determine monitoring to identify potential harm

The responsibilities of the (data) scientist



- Legal
- Shareholders
- Be customer-centric?

Responsibilities of the company



What do we need to do?

- Communicate about ethics internally
- Run workshops to help understand implications scu.edu/ethics-in-technology-practice
- Share stories about what data scientists fail to be ethical

Education



- Initial impact assessments
- Plans and checklists
- Test strategies and harnesses
- ainowinstitute.org/aiareport2018.pdf
- www.gov.uk/government/publications/data-ethics-framework/data-ethics-framework

Frameworks



- **group unaware** - same cutoff points / decision boundary
- **group thresholds** - different cutoff points to allow different volumes in
- **demographic parity** - different cutoff points to end up with distribution like overall demographics
- **equal opportunity** - the same true positive rate holds across groups
- **equal accuracy** - the same overall accuracy rate holds across groups

5 concepts of fairness

- Legal and contractual requirements
- Anonymisation and maintaining privacy
- Consultation processes

Data





Show me the tech!

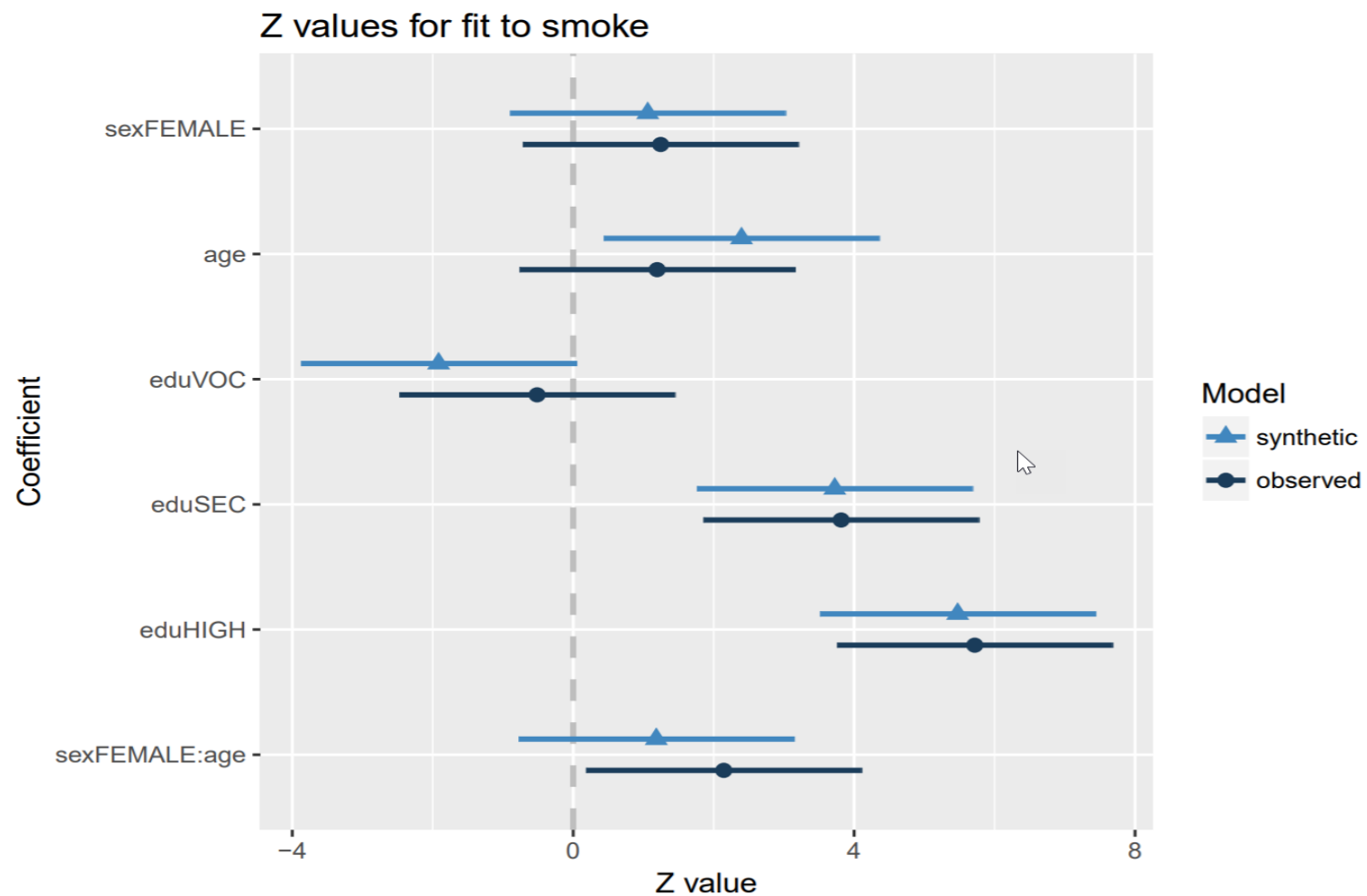


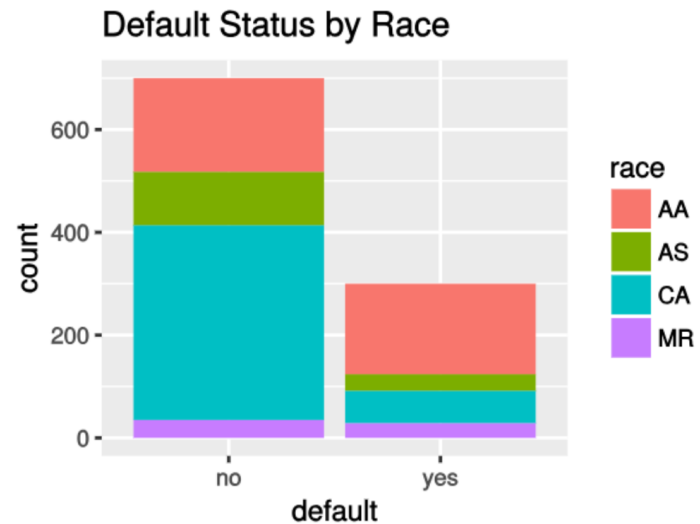
Figure 1: Comparison of intervals for fit `f8` and original data.

Synthetic data

As you can see in the histogram below, the majority of our data set is Caucasian (**CA**) at 44.2%, closely followed by African American (**AA**) at 35.8%, and then Asian American (**AS**) at 13.6% and Hispanic or Mixed Race (**MR**) at 6.4%.

```
In [8]: table(credit$race, credit$default) / 10  
  
ggplot(credit, aes(default)) + geom_bar(aes(fill = race)) + ggtitle("Default Status by Race")
```

	no	yes
AA	18.2	17.6
AS	10.4	3.2
CA	37.9	6.3
MR	3.5	2.9



EDA

- Functions for fairness concepts
- Analysis by groups
- Pen portrait / "Typical" entries

Testing



Testing

FairML: Auditing Black-Box Predictive Models

FairML is a python toolbox auditing the machine learning models for bias.



Description

Predictive models are increasingly being deployed for the purpose of determining access to services such as credit, insurance, and employment. Despite societal gains in efficiency and productivity through deployment of these models, potential systemic flaws have not been fully addressed, particularly the potential for unintentional discrimination. This discrimination could be on the basis of race, gender, religion, sexual orientation, or other characteristics. This project addresses the question: how can an analyst determine the relative significance of the inputs to a black-box predictive model in order to assess the model's fairness (or discriminatory extent)?

We present FairML, an end-to-end toolbox for auditing predictive models by quantifying the relative significance of the model's inputs. FairML leverages model compression and four input ranking algorithms to quantify a model's relative predictive dependence on its inputs. The relative significance of the inputs to a predictive model can then be used to assess the fairness (or discriminatory extent) of such a model. With FairML, analysts can more easily audit cumbersome predictive models that are difficult to interpret.s of black-box algorithms and corresponding input data.

DATAPOINT EDITOR

PERFORMANCE + FAIRNESS

FEATURES

Set Ground Truth

Ground Truth Feature

over_50k

What is this?

Select the feature to set as a ground true label for all loaded examples in order to in order to investigate model performance. [More](#)

Cost Ratio

1

Why do I need a cost ratio?

Necessary to optimize the classification threshold.
1.00 = false positives and false negatives are equally as costly
4.00 = false positives are 4 times more costly than false negatives
0.25 = false negatives are 4 times more costly than false positives. [More](#)

Compare Slices + Fairness Metrics

Slice by

sex

What does slicing do?

Investigate performance for the groups of examples with each unique value of the selected feature.

Slice by (secondary)

<none>

Specify a second feature to slice the data by.

Optimize sliced thresholds for:

What am I optimizing for? [More](#)

Group unaware

Demographic parity

Equal opportunity

Equal accuracy

Group thresholds

Explore Performance

Male

0.41

	Predicted Yes	Predicted No	Total
Actual Yes	19.5% (66)	9.1% (31)	28.6% (97)
Actual No	8.6% (29)	62.8% (213)	71.4% (242)
Total	28.0% (95)	72.0% (244)	

Female

0.37

[illegible]

Testing

- Protected characteristics
- Spot checks and counter factuals

Monitoring



- Adversarial behaviours
- Robustness
- Retro-engineering
- Lessons from security – Red and Blue Teams?

Security



@theStephLocke

bit.ly/ethicaldatasciencelinks

Thanks!

