Automating the Status Quo

How Machine Learning Algorithms Get Biased

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Welcome
Who Are We?

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What is this about?
Automating the Status Quo
What are we talking about?

► What is machine learning?
► How does bias get introduced in machine learning models?
► Why does it matter?
► How can we not do that?
Wait, what’s machine learning actually?
Machine learning is the abstraction of a decision process into an algorithm.
For example...
Music Recommendation Model
Sarah recommends a band that Celeste might like

▶ Decision process: Sarah uses her knowledge about music to find bands that are close to Celeste’s preferences

▶ Step 1: build a map of bands you like

▶ Step 2: find a friend, build their map

▶ Step 3: match preferences
Music Recommendation Model

Breaking down a model into components

▶ **Data:** two users, a few dozen bands
▶ **Features:** genre, lyrics
▶ **Algorithm:** find band that is closest to Celeste’s current preferences, according to features
▶ **Objective function:** maximize Celeste’s musical enjoyment
▶ **Feedback loop:** use Celeste’s feedback to model to help with feature selection for future suggestions
Let’s do that again, but bigger!

Scaling models
Big Music Radio Company Recommendations

Same decision process, but at scale

- More users, more bands, more data
- More features
- More complex algorithms
- More complex objective function
- Feedback loop at scale
Now we have a common understanding of what machine learning is designed for....

Based on that, how does bias get introduced into machine learning?
So what about bias?

Let’s have a more detailed look
What is bias?
Bias introduces disparity

- Prejudice or discrimination against something, someone, or some group.
- With machine learning, algorithms can introduce bias.
- Discriminatory bias is created when data-driven decisions have unbalanced outcomes

Why?
- Machine learning is a tool
- Machine learning is not going to solve discrimination, unless we specifically build a model that does that
- As data practitioners, we are responsible for educating ourselves on how machine learning decision are affecting our society
Finding sources of bias and flawed decisions is not a scientific process that we can automate.

Bias is usually involuntary.

We are dealing with complex questions.

Decisions are subject to constraints (budget, timeline, regulations, …).

Decisions might be based on poor quality data.

We are all in this together.
It’s Easy to Introduce Bias

Feature engineering
- Subjective features
- Incomplete features
- Wrong features

Algorithm / Objective function
- Opaque “black-boxes”
- Standardized preferences

Data collection
- Incomplete data
- Biased data

Decision-making / Feedback loops
- Model outcomes have global impact

Your Model
Data selection bias
We’re here

Data collection
Incomplete data
Biased data

Your Model
Representative Data

Data should include complete information about the problem to solve

Facial-Recognition Software Might Have a Racial Bias Problem

Depending on how algorithms are trained, they could be significantly more accurate when identifying white faces than African American ones.

CLARE GARVIE AND JONATHAN FRANKLE | APR 7, 2016 | TECHNOLOGY
Learning from biased data

Word embedding

- Word embedding transforms text into vectors of words
- Characterize the “meaning” of a word using the words that are close by:
  - Paris : France = Tokyo : x
  - x = Japan

From Google News articles:

```
Gender stereotype she-he analogies

sewing-carpentry registered nurse-physician housewife-shopkeeper
nurse-surgeon interior designer-architect softball-baseball
blond-burlry feminism-conservatism cosmetics-pharmaceuticals
 giggle-chuckle vocalist-guitarist petite-lanky
 sassy-snappy diva-superstar charming-affable
volleyball-football cupcakes-pizzas lovely-brilliant
```

Source: Bolukbasi, Chang, Zou, Saligrama, Kalai (2016)
Feature selection bias
We’re here

Feature engineering
- Subjective features
- Incomplete features
- Wrong features

Your Model
Pirates will fix global warming! Can they?

Average temperatures 1820 - 2000

Number of Pirates 1820 - 2000
Risk assessments for recidivism
Are features representative of reality?

- Courts use “risk scores” at various stages of the criminal justice system
- What is an indicator of recidivism?
  - Poverty / homelessness?
  - Petty crimes?
  - Causal or correlated features? Signal or noise?
- Success at forecasting crime:
  - 60% of “High Risk” individuals were arrested within two years
  - 20% of “Violent Crimes High Risk” individuals were arrested for violent crimes within two years

Noisy features! Number of crimes increases with higher levels of poverty. But, being poor doesn’t automatically make somebody a criminal.
Feature validation
Are features representative of reality?

▶ How often is my model giving me a true answer (precision)?
  “High Risk, Reoffend” vs “High Risk, Didn’t Reoffend”

▶ Out of all true instances, how often do I get a true answer (recall)?
  “High Risk, Reoffend” vs “Low Risk, Reoffend”

<table>
<thead>
<tr>
<th></th>
<th>White</th>
<th>African American</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Risk, Didn’t Reoffend</td>
<td>24%</td>
<td>45%</td>
</tr>
<tr>
<td>Low Risk, Reoffend</td>
<td>48%</td>
<td>28%</td>
</tr>
</tbody>
</table>

Source: https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing
Feature validation
Are features representative of reality?

▶ How can we measure discrimination?

▶ Risk score should have the same effectiveness regardless of group membership:
  • “Well calibrated” (model probability reflects reality)
  • Balance for the positive class (precision)
  • Balance for the negative class (recall)

If the underlying data is unbalanced, the three conditions of fairness cannot be met simultaneously.

Source: Kleinberg, Mullainathan, Raghavan (2016)
“Inherent Trade-Offs in the Fair Determination of Risk Scores”
Feature validation
Are features representative of reality?

- When rates of arrest are unbalanced, the model is not well calibrated

Source: Kleinberg, Mullainathan, Raghavan (2016)
“Inherent Trade-Offs in the Fair Determination of Risk Scores”
Plots: https://medium.com/@AbeGong/ethics-for-powerful-algorithms-1-of-3-a060054efd84
Model bias and feedback loops

Let’s rank some universities
We’re here

Algorithm / Objective function
Opaque “Black-boxes”
Standardized preferences

Decision-making / Feedback loops
Model outcomes have global impact

Your Model
The objective function that you choose for the algorithm matters

The algorithm takes a decision and translates it into math

Biased objective function leads to a biased model
University rankings
It all started with the best of intentions

Ranking models are useful to help sort through and prioritizing a large amount of information.

In 1983, US News and World Report published their first University Ranking feature, to help students make more informed academic choices

Source: “Weapons of Math Destruction” by Cathy O’Neil
University rankings
A model is a simplified version of reality

- **Raw data**
  - N of professors / instructors
  - Research publications
  - Infrastructures
  - Classes

- **Real metrics**
  - Satisfaction
  - Personal growth
  - Career success
  - Happiness

- **Features**
  - Teacher / student ratio
  - SAT scores
  - Graduation rates
  - Employment rate
  - Reputation scores
What went wrong?
Colleges were pushed to invest in research, infrastructure, student well-being. At the same time, disparities increased

- Universities focused resources on a few programs
- Tuition and fees were left out of the equation to start
- Features are easy to cheat and subjective
- Opaque model
- Objective function too broadly defined
- Self-reinforcing algorithm
College Scorecard
Available to the public – “build your own model”

Stanford University
Stanford, CA
7,018 undergraduates

- Average Annual Cost: $14,559
- Graduation Rate: 95%
- Salary After Attending: $86,000

Santa Clara University
Santa Clara, CA
5,447 undergraduates

- Average Annual Cost: $34,556
- Graduation Rate: 85%
- Salary After Attending: $67,600

San Jose State University
San Jose, CA
26,528 undergraduates

- Average Annual Cost: $12,862
- Graduation Rate: 50%
- Salary After Attending: $53,700

https://collegescorecard.ed.gov
Bias-driven decisions

Data-driven decisions have global implications

- Data reflects the past, and the past is biased
- Model can “learn” from past data, persisting biases
- Model can create negative feedback loops, increasing biases
So what can we do?
1. Ask if the data is representative.
2. Ask if the data is biased.
3. Ask if the features are accurate proxies.
4. Ask if the goal of the model is unbiased.
5. Ask about the implications of the model results.
Learn more

- **Weapons of Math Destruction by Cathy O’Neil**
  - Engaging book full of examples about machine learning and bias
- **How to Lie with Statistics by Darrell Huff**
  - Book with insights into statistical thinking
- **Freakonomics Radio Podcast**
  - Engaging stories about economic and social science research, real world biases, etc.
- **Data & Society research institute**
  - Blog, reports, and talks about big data and society
- **ProPublica Machine Bias series**
  - Investigative journalists focusing on machine bias
Thank You

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