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S01 Session 1: Morality in the Machine: Ethics and the Rise of AI in the Insurance Industry
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SOCIETY OF ACTUARIES
Antitrust Compliance Guidelines

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The United States antitrust laws aim to protect consumers by preserving the free economy and prohibiting anti-competitive business practices; they promote competition. There are both state and federal antitrust laws, although state antitrust laws closely follow federal law. The Sherman Act, is the primary U.S. antitrust law pertaining to association activities. The Sherman Act prohibits every contract, combination or conspiracy that places an unreasonable restraint on trade. There are, however, some activities that are illegal under all circumstances, such as price fixing, market allocation and collusive bidding.

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- **Do not** discuss prices for services or products or anything else that might affect prices
- **Do not** discuss what you or other entities plan to do in a particular geographic or product markets or with particular customers.
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About me: broadcasting to actuarial science to data science

• Attended Univ. of Michigan; left school to pursue radio broadcasting career
• News anchor, reporter, and morning show host in Detroit
• Returned to school to finish degree at Eastern Michigan
• At Delta Dental of Michigan, Ohio, and Indiana since 2010
• Master of Science in Business Analytics at Carnegie Mellon University, expected graduation May 2021
  • Studying Machine Learning, Optimization, and data-driven leadership
  • Especially interested in questions of fairness and bias in machine learning
Foundations: what we mean when we say “Artificial Intelligence” and “Machine Learning”
Are “AI” and “ML” just buzzwords?

These terms are popular in marketing materials, but what do they really mean?
“Artificial Intelligence” is a slippery term

I like Andrew Moore’s definition of Artificial Intelligence because it points out that the definition of “AI” is subjective and changes over time.

“Artificial intelligence is the science and engineering of making computers behave in ways that, until recently, we thought required human intelligence.”
- Andrew Moore, Google Cloud (former dean of CMU School of Computer Science)

What counts as “AI” has changed over time

**ELIZA:**
Primitive “chatbot” with simple logic

**“Hey, Siri...”**
AI built on deep machine learning

**Deep Blue:**
“Rule based” system on a massive scale
Who writes the code for these AI programs?

“Hey Siri, find pictures of cats” + Magic? = Kitty!

Tasks like computer speech recognition improved significantly when technology moved from rules-based programs to AI built on machine learning.
Today’s AI is built on machine learning

The leap from Deep Blue to AlphaGo represents a revolution in deep learning.
Definition: In Machine Learning, programs “learn” from data

“Machine learning is the study of computer algorithms that allow computer programs to automatically improve through experience.”

- Tom Mitchell, founding Chair of the Machine Learning Department, Carnegie Mellon University


(Thanks to Prof. Zachary C. Lipton of Carnegie Mellon University for recommending these definitions of AI and ML.)
(Supervised) machine learning is much like regression, with extremely expressive functional forms.

A simplified view of supervised learning

- Training Data
- Fitting
- Prediction
- Validation
- Final Model

Loss minimization
Key idea:
To understand ethical concerns in ML and AI, remember that ML models are highly dependent on their training data.
Applications of Machine Learning and the ethical questions they invite
AI is all around us
Human Resources

Can Artificial Intelligence Make The Hiring Process More Fair?

Amazon scraps secret AI recruiting tool that showed bias against women
J. Dastin, "Amazon scraps secret AI recruiting tool that showed bias against women," Reuters, 9 October 2018.
AI is all around us

Autonomous Vehicles
AI & ML in insurance
Auto Insurance

- Telematic Data
- Crash Damage Recognition
AI & ML in insurance

Health Insurance

Biometric Data

Fraud Detection
AI & ML in insurance
Across insurance lines

- Product Design
- Marketing
- Claims Processing
Hopes that computer algorithms are “automatically fair” are naïve

Moritz Hardt (UC Berkeley), leading ML fairness researcher:

Machine learning acts as a social mirror, reflecting and sometimes amplifying society’s inequities.

M. Hardt, "How big data is unfair," Medium, 14 September 2014.
Key idea:
Algorithms aren’t automatically fair. It is the difficult task of machine learning practitioners to identify and correct algorithmic bias.
Unintentional bias example: Hiring AI favored men, resisting correction efforts

“The algorithm) penalized resumes that included the word ‘women’s,’ as in ‘women’s chess club captain.’”

“They literally wanted it to be an engine where I’m going to give you 100 resumes, it will spit out the top five, and we’ll hire those.”

Amazon scraps secret AI recruiting tool that showed bias against women

J. Dastin, "Amazon scraps secret AI recruiting tool that showed bias against women," Reuters, 9 October 2018.
What happened?
Past imbalance led to unwanted bias in new model

The model was trained on historical hiring data, and past hiring had favored men.

Image by Han Huang, Reuters Graphics
Bias persisted even as gender was hidden

Past Hiring Decisions (Favored Males)

New Applicants (Gender Censored)

Hiring Model

New Hiring Decisions (Still Favor Males)
Bias persisted even as gender was hidden

Past Hiring Decisions (Favored Males)

Hiring Model

New Applicants (Gender Censored)

New Hiring Decisions (Still Favor Males)

Are we sure?
Traits like gender and race can leak into the model through correlated features

Known as “redundant encoding,” sensitive attributes are encoded in the model via proxies or other relationships.

Actuaries will be familiar with strong proxies like 5-digit ZIP Code. There are many other, more subtle examples.

Principal: No fairness through unawareness [1]

Efforts to remove redundant encoding can be ineffective and even harmful to protected groups. [2]

Example: Program to control healthcare costs unintentionally included racial bias

Z. Obermeyer, et al. "Dissecting racial bias in an algorithm used to manage the health of populations."
Example: Program to control healthcare costs unintentionally included racial bias

- Risk scores used for high-risk care management program

- Researchers found enhanced care was disproportionately offered to White patients compared to similarly sick Black patients

- The source of bias was subtle. We’ll revisit this later on.

Key idea:

Machine learning bias is rarely caused by malicious actors. It is almost always unintentional and therefore is a concern for all practitioners.
How do we define fairness?

The tension among competing definitions and the impossibility of satisfying them all.
Individual Measures of Fairness

“Treat similar individuals similarly” [1]

Challenges:

• Definitions of “similar” are highly task dependent [2]
• Breaks down at decision boundaries [3]

Group-based Fairness Measures

1. “Statistical Parity”
   - Example: admitting the same proportion of male applicants as female applicants to a college program.

2. “Error Rate Balance”
   - Example: ensuring the same rate of “false positive” results across racial or gender groups

3. “Predictive Parity”
   - Example: Accuracy of predictions are equal across groups

Challenge:
   - It is impossible to achieve all three in the cases we usually care about! (Proven by Alexandra Chouldechova of CMU)

Example: Courtroom algorithm accused of racial bias

Computer generated risk assessments were used to set bail, and for sentencing guidelines.

Machine Bias
There’s software used across the country to predict future criminals. And it’s biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica
May 23, 2016

Investigators: White defendants given lower risk scores

“Scores for white defendants were skewed toward lower-risk categories. Scores for black defendants were not.”

Source: ProPublica analysis of data from Broward County, Fla.

Investigators claim secret algorithm hides bias

Proprietary algorithm on 137 factors

Survey questions

Criminal records

Demographic information (not race)

Risk Score
Similarly, could a health risk score hide bias?

Is your model fair?
That can be a hard question to answer.
Whether an algorithm is unfair can be subjective

• ProPublica used “error rate balance” to accuse the COMPAS algorithm of racial bias.
• The makers of COMPAS used “predictive parity” to defend their algorithm as unbiased [1]

Who is right?
It depends on your definition of “fairness.”

Key idea:

Machine learning fairness has no universal definition that applies to all situations. Attempts to satisfy all definitions of fairness are futile.
So what do we do about machine learning fairness?
Actuaries are used to dealing with these issues

• Actuarial justification or maximal predictive accuracy vs. public policy goals or societal values

• Discussion around ACA age cost curve is a good illustration of this tension
Actuaries are used to dealing with these issues

Actuarial practice evolves to reflect societal values and public policy goals, like abolishing the use of race in mortality tables.

Study offers example of combatting algorithmic bias

• Fundamental problem causing the bias was the choice of label.
• Model predicted healthcare expenditure, which turned out to be a biased proxy for underlying health status.
• Diagnosing the problem was possible because the algorithm manufacturer cooperated with researchers.

Study offers example of combatting algorithmic bias

• A new label was developed: a basket of health outcomes and cost outcomes

• Measurable racial bias in model scoring was reduced by 84%

How do machine learning practitioners avoid unintended bias?

• First step: Awareness

Obliviousness to the problem is the first risk factor to overcome!
Seeking outside help to avoid algorithmic bias

• Fair ML conferences and publications
• Fairness audits offered as services from consulting companies
• Open source software packages with built-in fairness testing assistance
Without endorsing any specific product or service, a search will turn up a wealth of research and resources.
Key Idea:
Machine learning fairness is a challenging issue, and it may be wise to consult outside resources for help.
Concluding thoughts

The actuarial profession has a valuable role to play in the field of algorithmic fairness research and its related public policy debates.
Questions?

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