

2024  
**SUPPLEMENTAL  
HEALTH, DI & LTC  
CONFERENCE**

The Winning  
Trifecta

# Bias and Fairness in DI Underwriting





**Dae Won Kim**

*Data Science Manager*

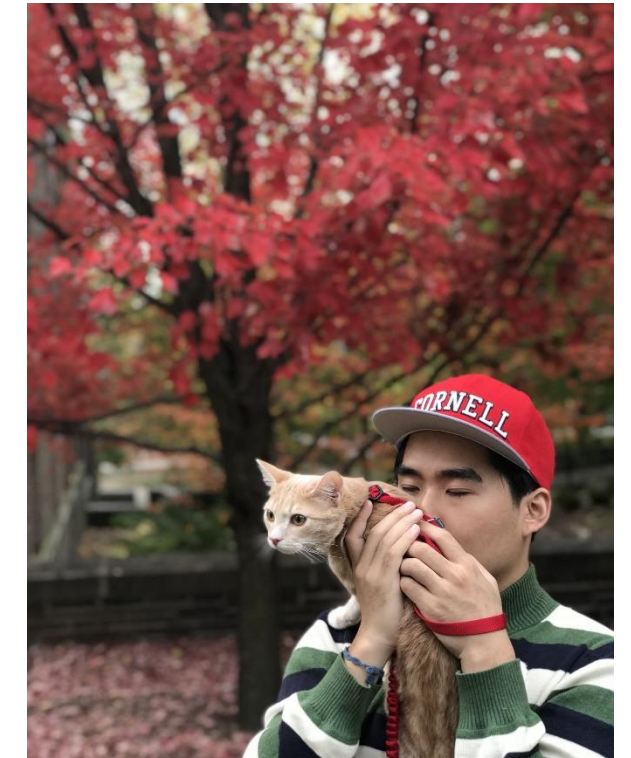
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# Who Am I: Me As A Data Point

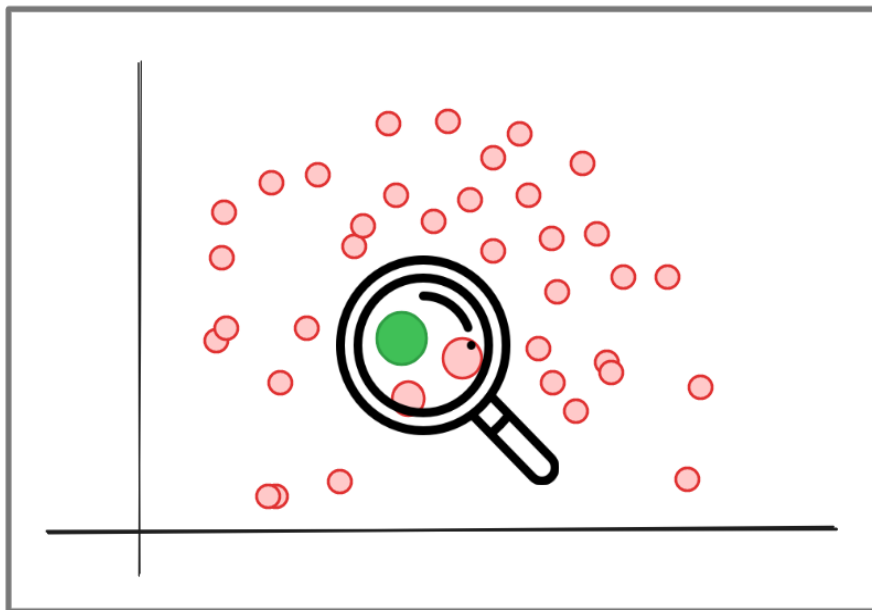
On paper:

- Data Science Manager at Munich RE
- UW AI, unstructured data specialist

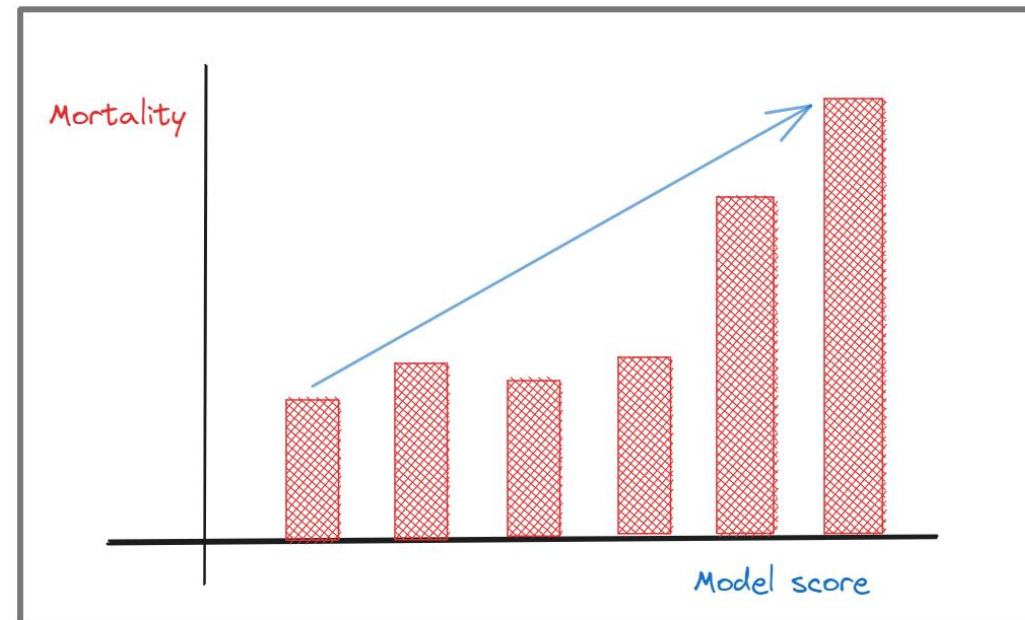




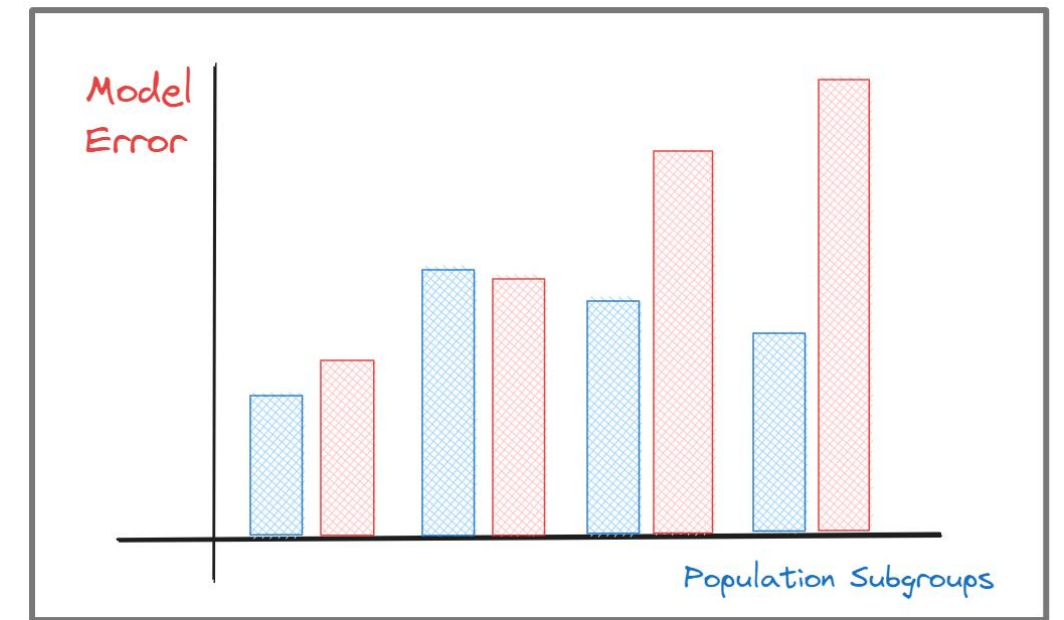
# Potential And Dangers Of AI In UW



Individualized Risk Assessment



Better Risk Segmentation



Perpetuate / Automate bias



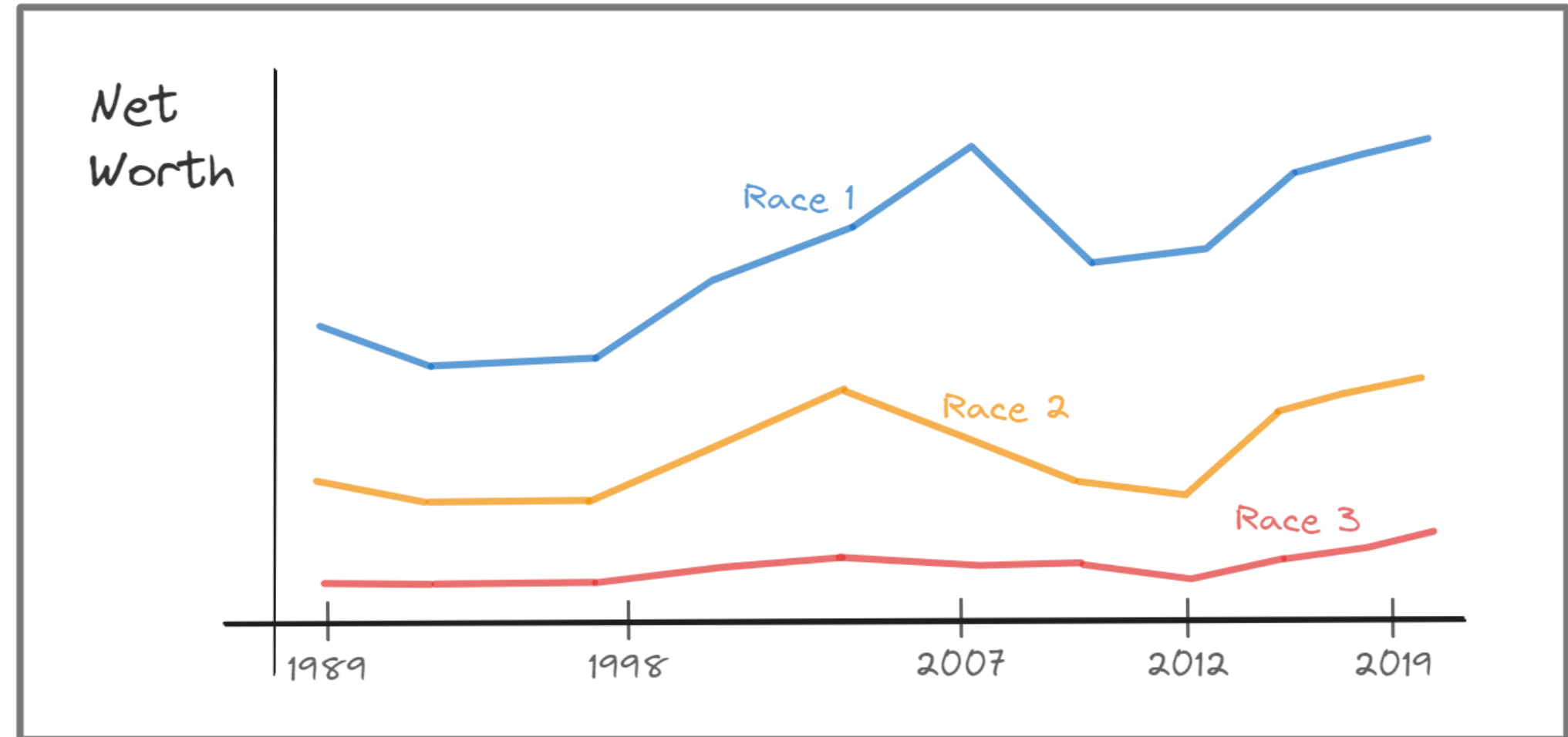
# Rapidly Evolving Regulatory Landscape



# Is Disparity In Outcome A Sign Of Bias?

Insufficient evidence of bias in model

- Modeling likely results in racial disparity
- Does this mean it's wrong to use wealth..?
- **Sources** of disparity must be **identified**

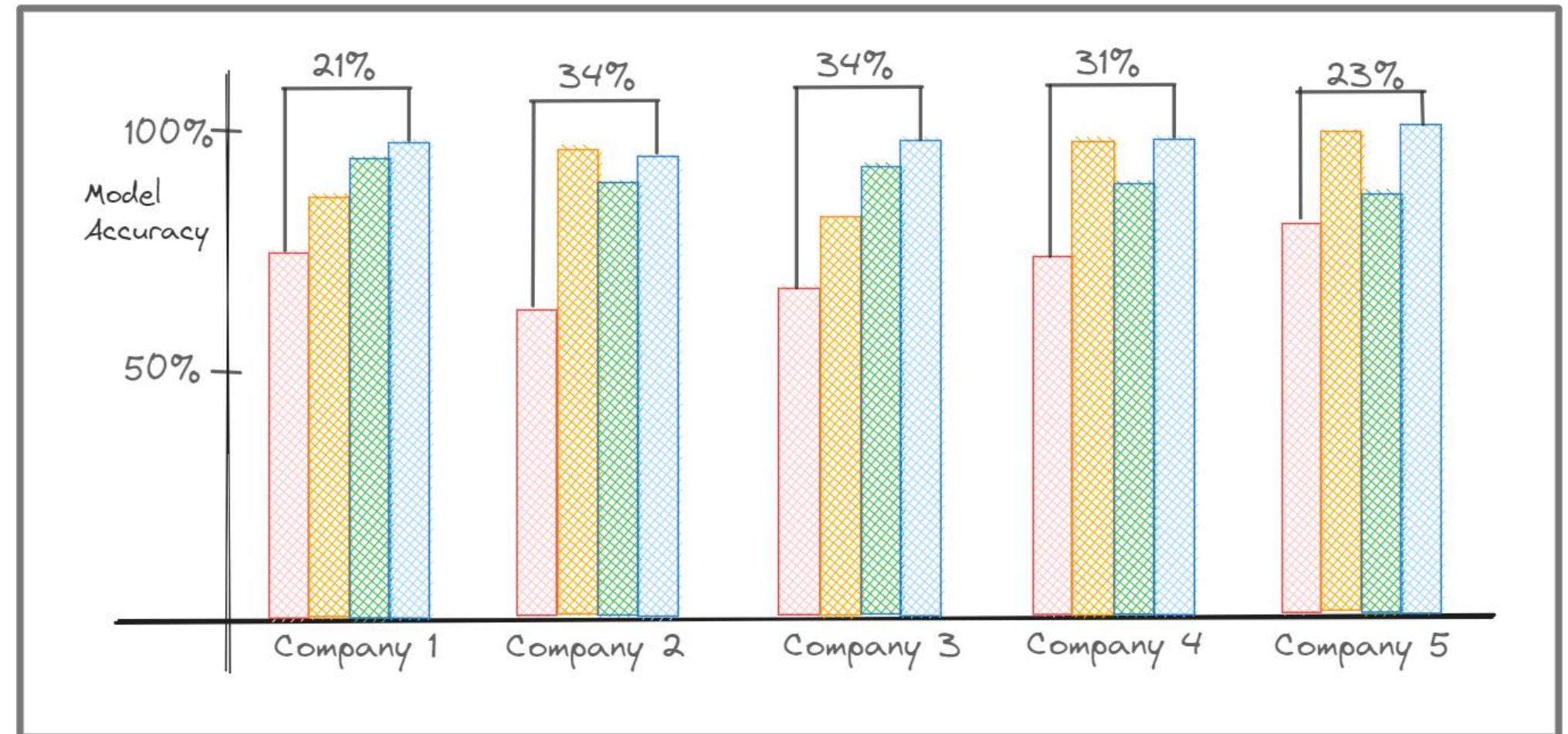


Race vs Net Worth over time

# Is Disparity In Error Rates A Sign Of Bias?

## Clearer evidence of bias

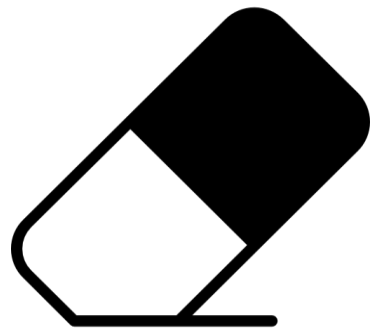
- Indicative of skew in training data or increased errors in labels for some groups
- Models will **penalize** a certain subgroup more than **expected or warranted**



Skin Color vs Facial recognition software



# Closer Look: Proxy Discrimination



Difficult to remove



Cannot easily decide  
"Good" vs "Bad" proxy



Costs in performance  
and profit



Impractical



# Case Study: Gender Disparity In Referral Rates



## 1. Identify

- Monitoring picked up **refer gap between genders**
- Females +8% higher for extended periods
- Persistent YTD gap of 3+%



## 2. Investigate

- Identifying the cause:
- Are there disparities in input data? (disclosures, third party)
- Are final outcomes different between male vs females? (inherent risk)
- Are there differences in identified risk factors for each gender?
- At which stage does the disparity increase / decrease?



## 3. Report

- Females have more claims
- Referral per claim same for both
- Program actually lessens gap
- Multiple data sources help



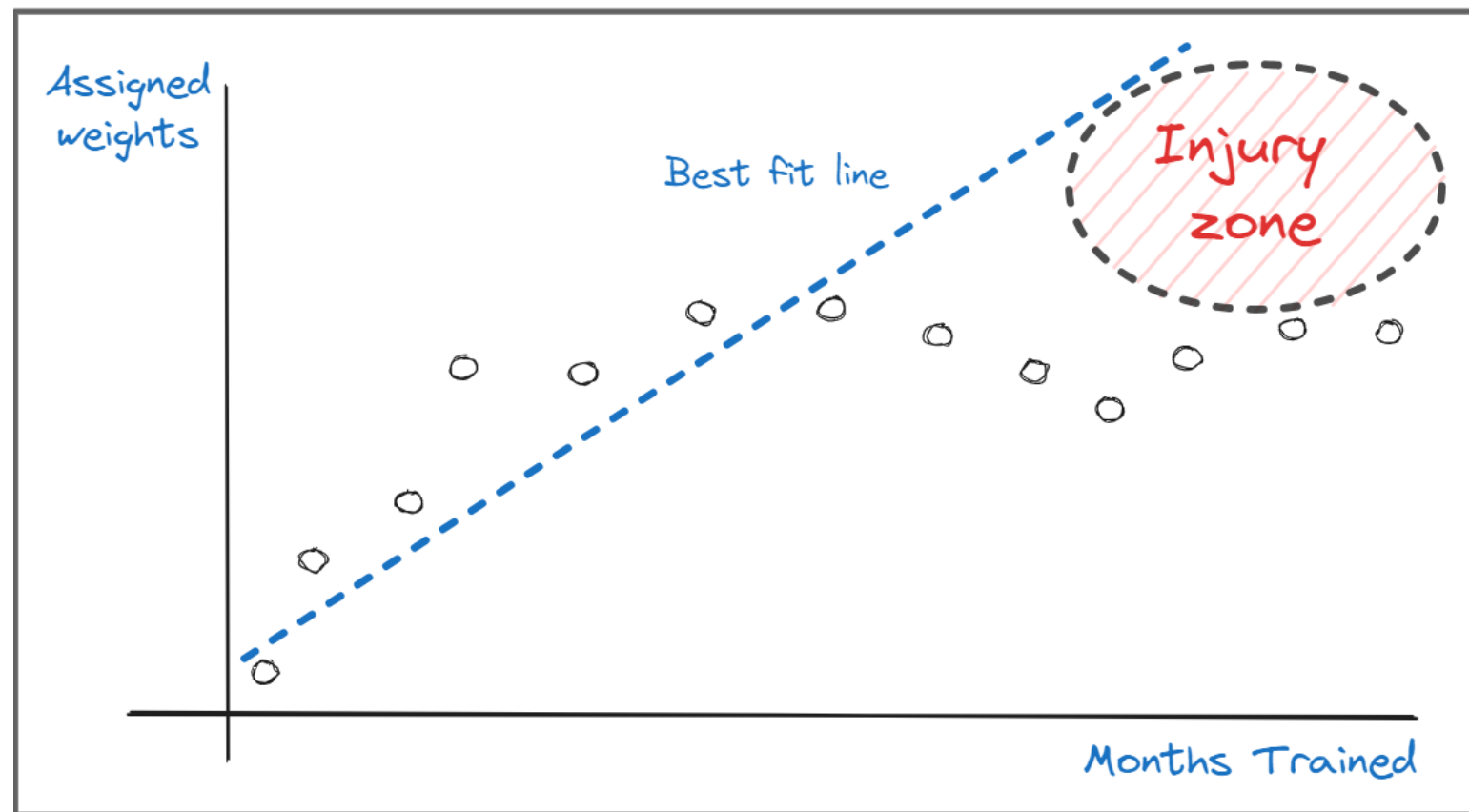
## 4. Takeaways

- Monitoring & reporting **infrastructure** is highly important
- Disparity in outcome **does not** signify bias in program
- **Varied sources** of data is crucial for mitigation
- Strong need for **uncertainty** modeling

# How AI Processes Become Biased

## Toy example #1: model bias

- Optimal lifting weight vs Time
- Linear model on non-linear truth
- Produces harm + suboptimal program



## Toy example #2: data bias

- High prevalence Asians in 20s pre-covid in Long Island City
- Data has race, age, citizenship for rent credit in LIC apartments
- If not retrained, model continues to favor Asians in their 20s
- Significant demographic changes post-covid, produces disparity of error

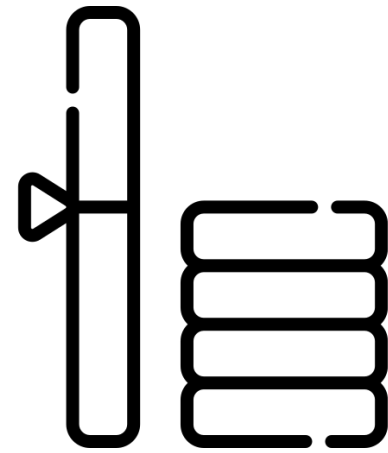




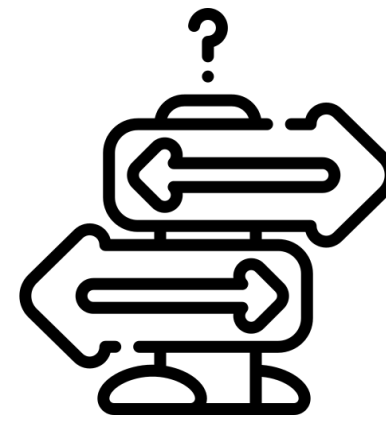
# How AI Processes Become Biased



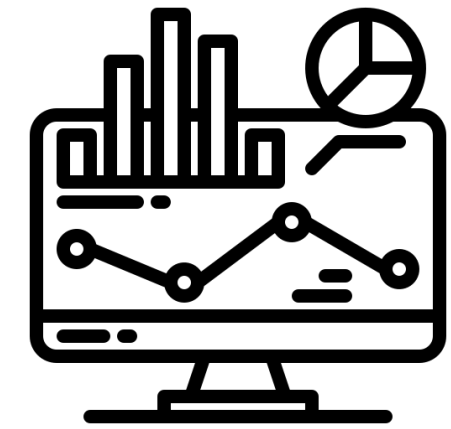
Imbalanced data &  
Lack of retraining



Models with  
severe limitations



No uncertainty  
considerations / modeling



Lack of monitoring /  
reporting infrastructure

# Building Governance In Data Science Development

## 1. Build a rich dataset

- Data represents target population
- Models contextualize an individual
- Replenish, update, and prune training data

## 2. Implement robust data science practices

- Model uncertainty
- Use flexible ML models
- Monitor fairness metrics
- Easy-to-understand visuals & analysis

## 3. Build & optimize governance

- Transparency in bias considerations
- Sign-off on methods, monitors & reports
- Clear division of mitigation duties
- Automating governance to minimize bureaucracy

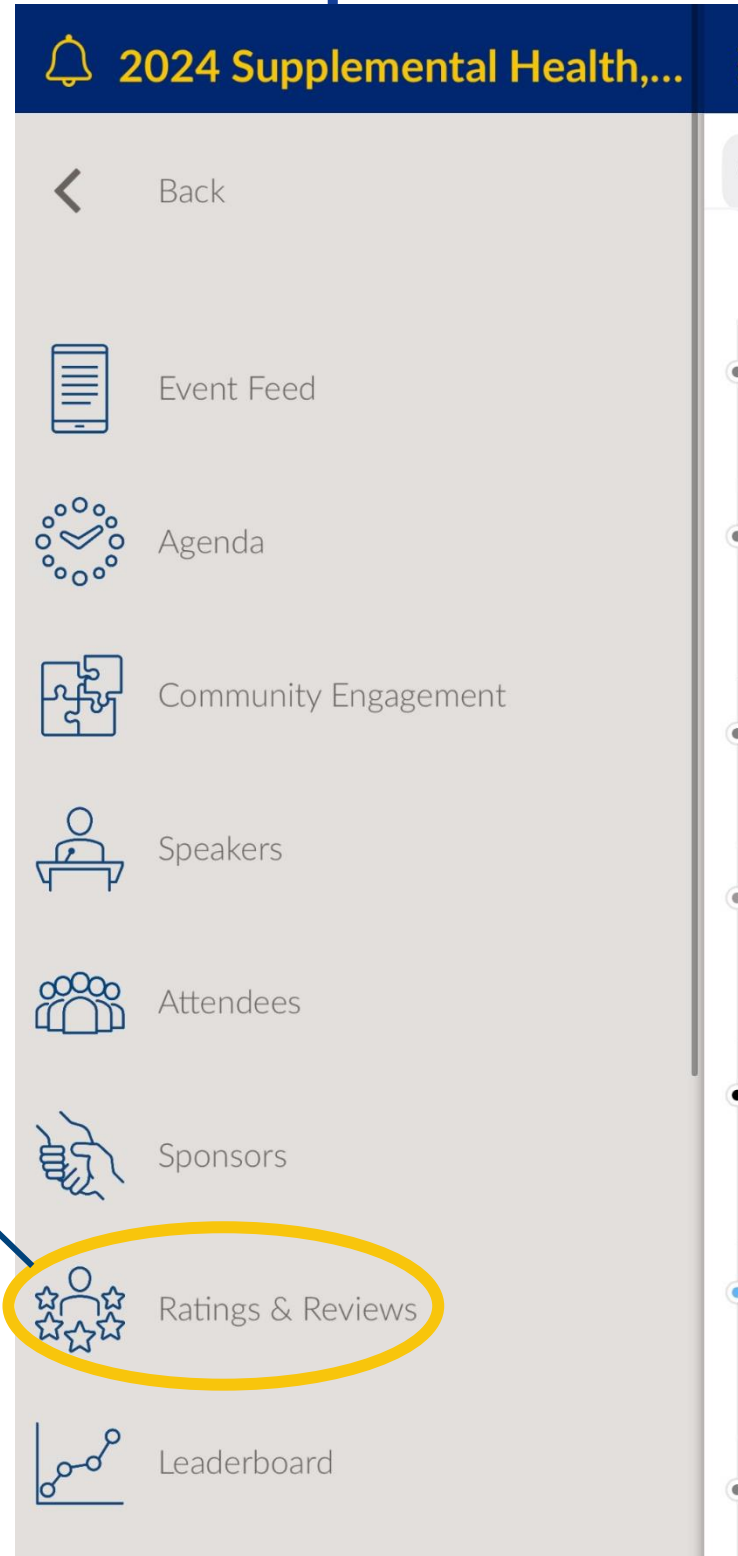
## 4. Minimize impact of bias

- **Place intervention** where the penalties occur
- Conduct end-to-end analysis of program, not just models
- Use models to triage rather than fully automate

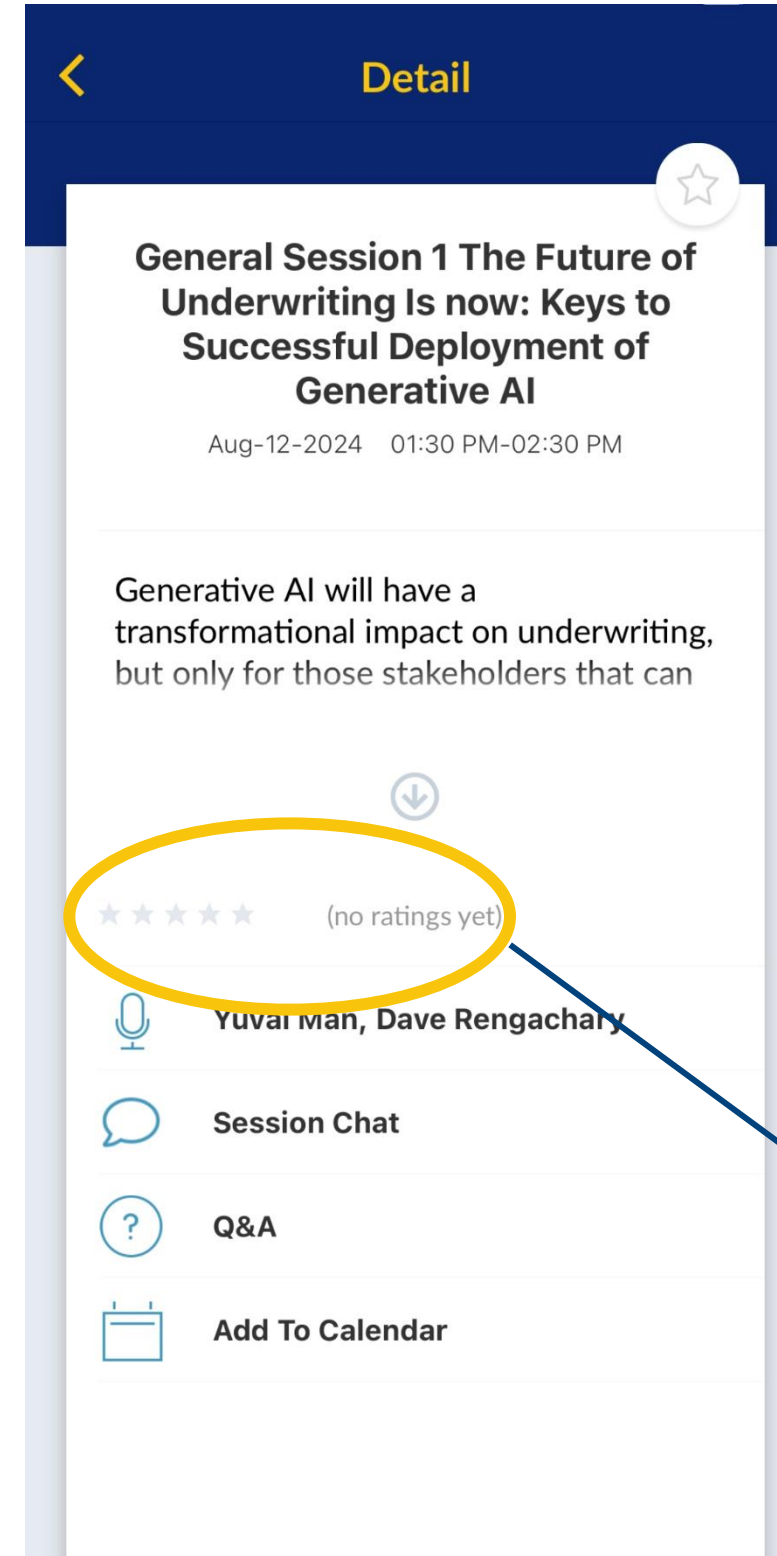


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## Module Option



## Agenda Option



# Thank You

