



# Responsible AI to Benefit Society

A Survey of Use Cases and Lessons Learned

Kit Rodolfa



NOBLE



WAKE COUNTY PUBLIC SCHOOL SYSTEM



Rijkswaterstaat  
Ministerie van Infrastructuur en Milieu



Perspectives Charter Schools

Montgomery County Public Schools



WORLD BANK GROUP



ChapinHall at the University of Chicago



THE CASE FI

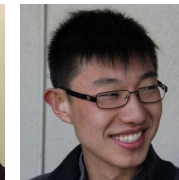
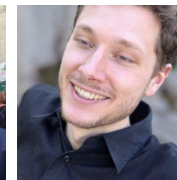
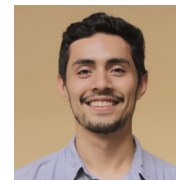
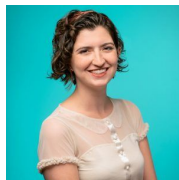
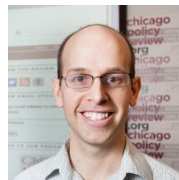
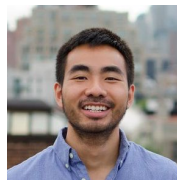
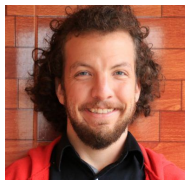
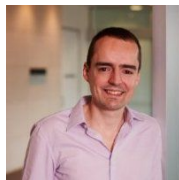
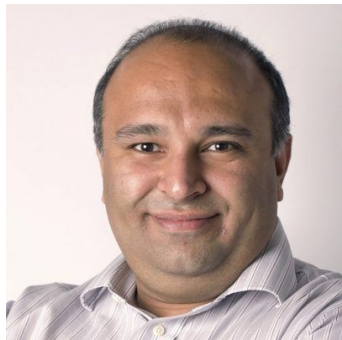


New Vision for the Ocean



More details on projects at <http://dssgfellowship.org/projects>







~275

DSSG

Fellows



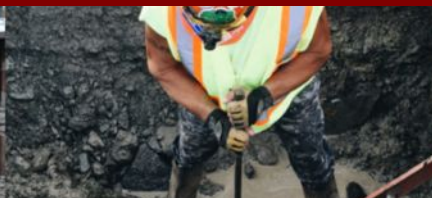






# Preventing and Reducing Water Mains breaks (Syracuse, NY)

*Using Machine Learning to Predict and Prevent Water Mains Breaks. Kumar et al KDD 2015*



240,000 main breaks/yr in US  
\$13 billion in 2010 to repair  
Expected \$30 billion by 2040  
180 breaks/yr in Syracuse, NY



# Preventing and Reducing Water Mains breaks (Syracuse, NY)

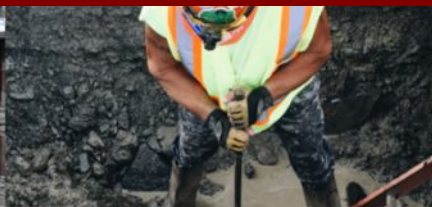
Using Machine Learning to Predict and Prevent Water Mains Breaks. Kumar et al KDD 2015





# Preventing and Reducing Water Mains breaks (Syracuse, NY)

*Using Machine Learning to Predict and Prevent Water Mains Breaks. Kumar et al KDD 2015*



64% of blocks in the top 1% of predictions were correctly predicted for last year



# LESSON 1

## Be diligent in finding relevant data

*Most data in real contexts is spread throughout the organization and much relevant data may not even be digitized*











# Manual Labeling Effort: Time Consuming & Costly



2400 blocks



Only 2018

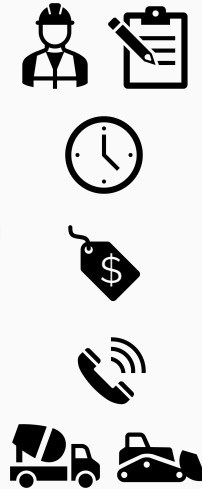






blocklot	roof_damage	roof_damage_score
----------	-------------	-------------------

1451 024	High	50-99
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# LIST OF 1000 ROWHOMES FOR INSPECTION



Address	Roof Damage score
14 Columbia Blvd.	0.9 
3939 Calvin St.	0.7 
1656 Benson St.	0.4 
374 Margaret St.	0.1 

# DARK PIXEL

What percentage of the  
pixels are darker than ?





Dark Pixel

468

0

200

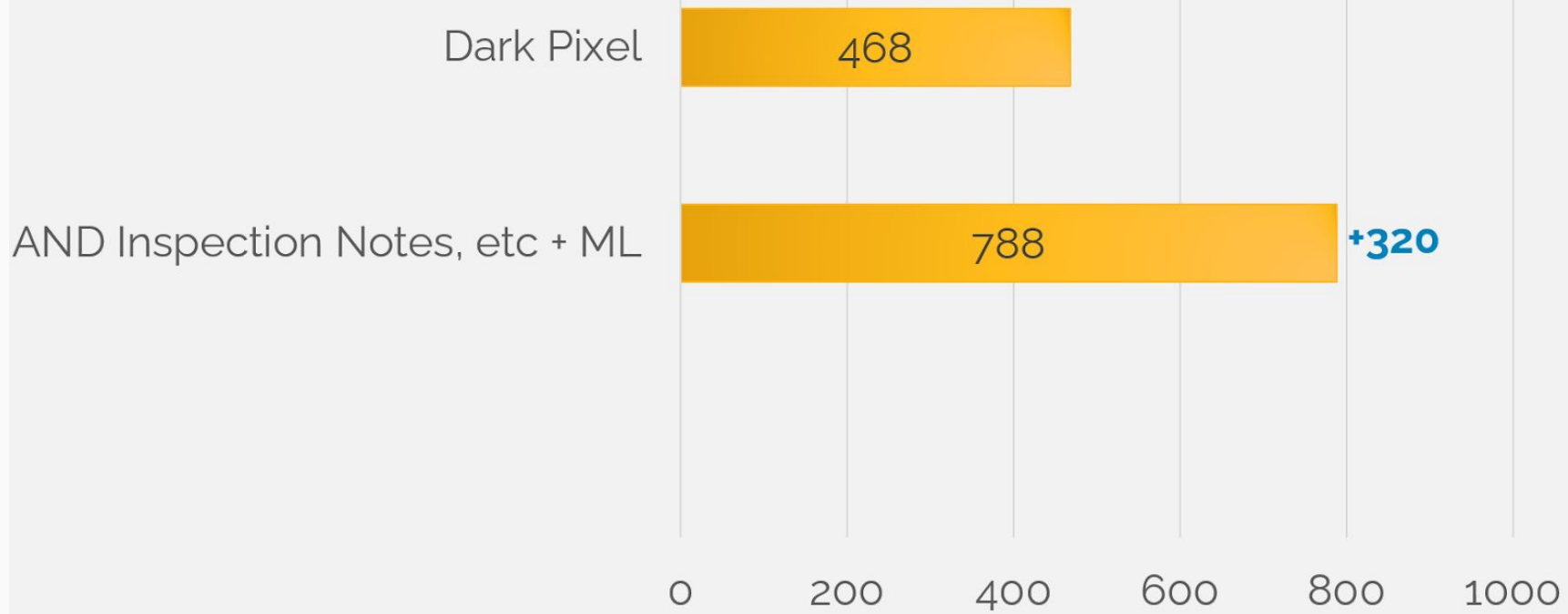
400

600

800

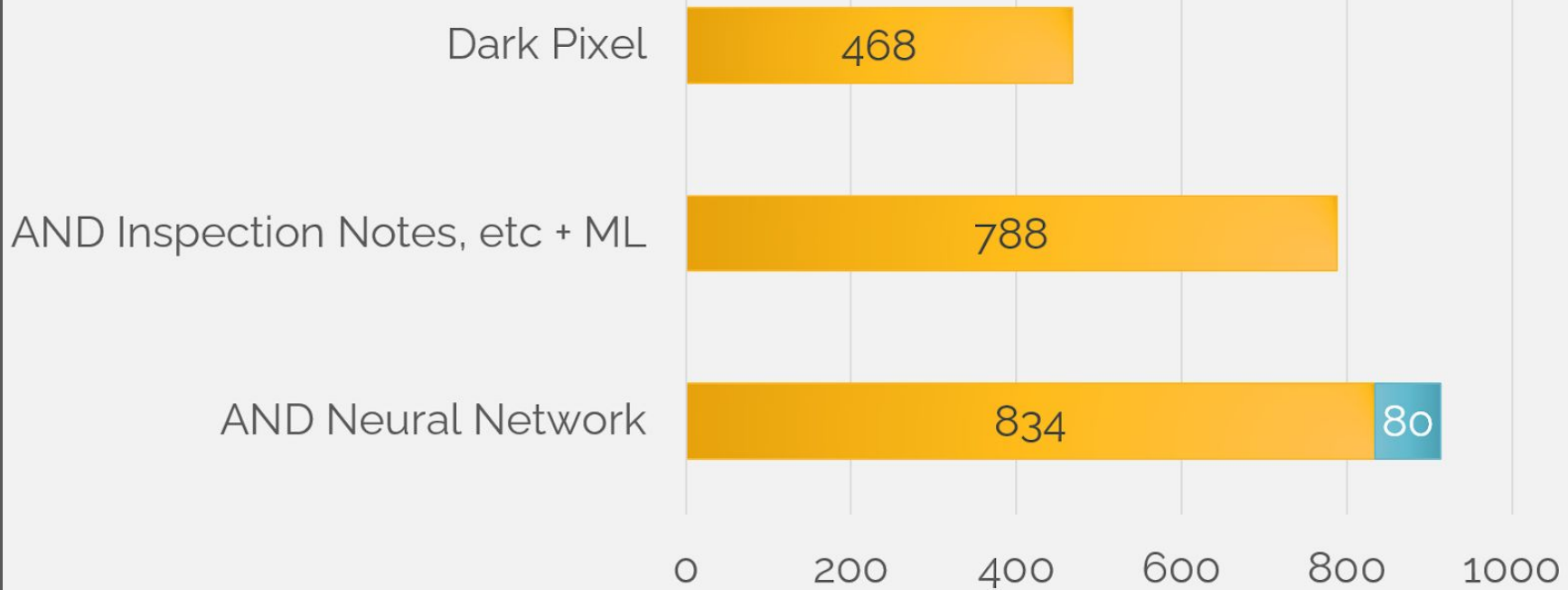
1000

MODEL PERFORMANCE



## MODEL PERFORMANCE





## MODEL PERFORMANCE

## LESSON 2

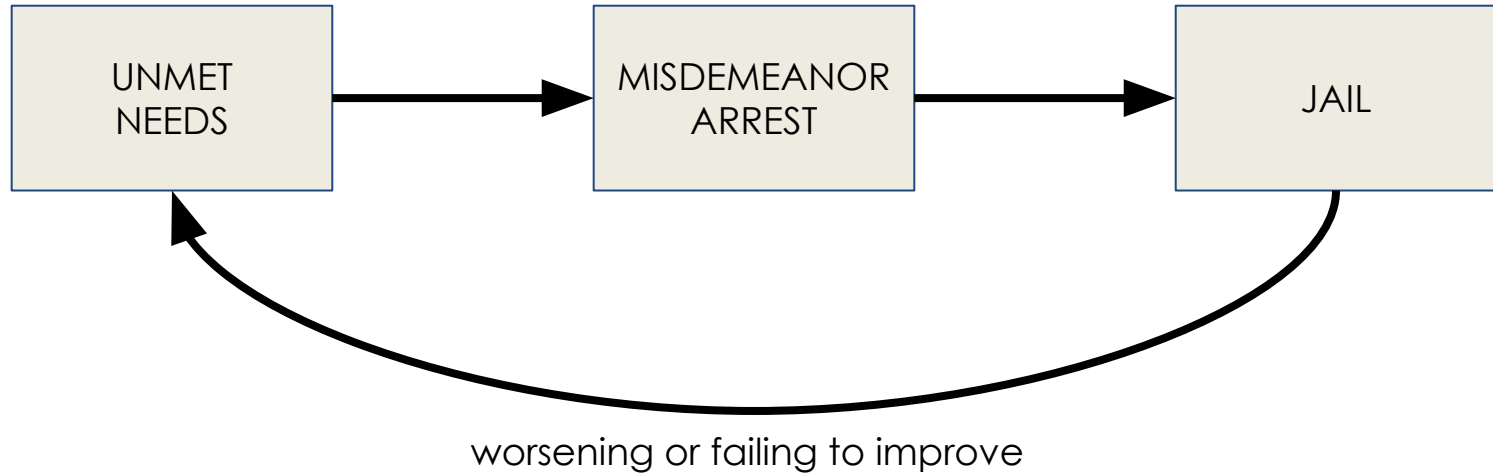
**Models will benefit from a range of data types and sources**

*Even with a seemingly straightforward vision problem, administrative data helped the model learn the nuance of the task*

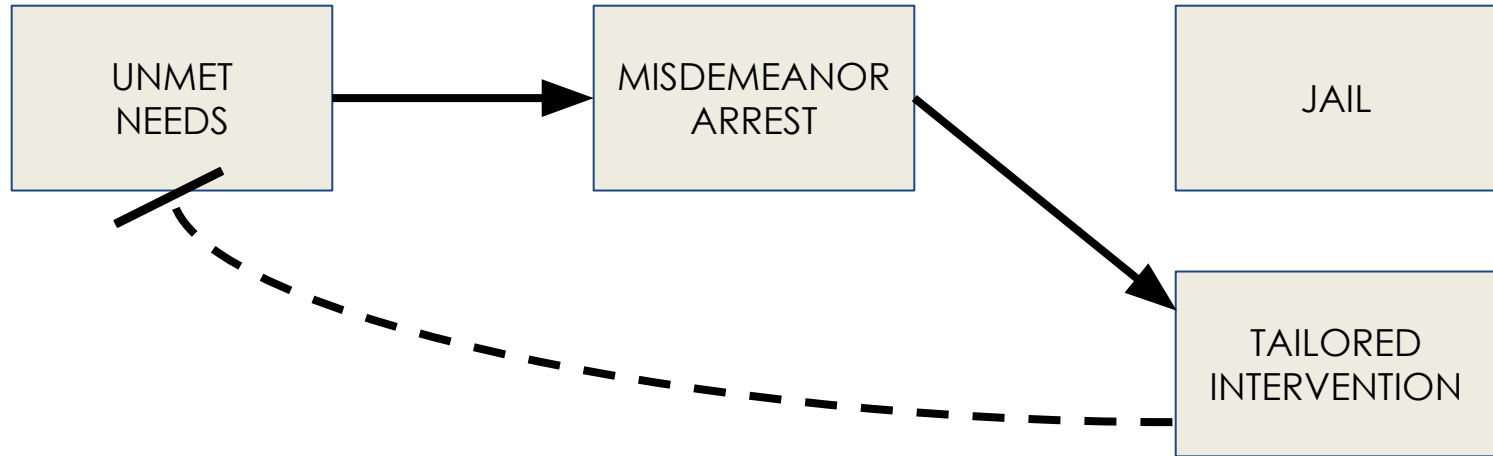




# Cycle of Incarceration



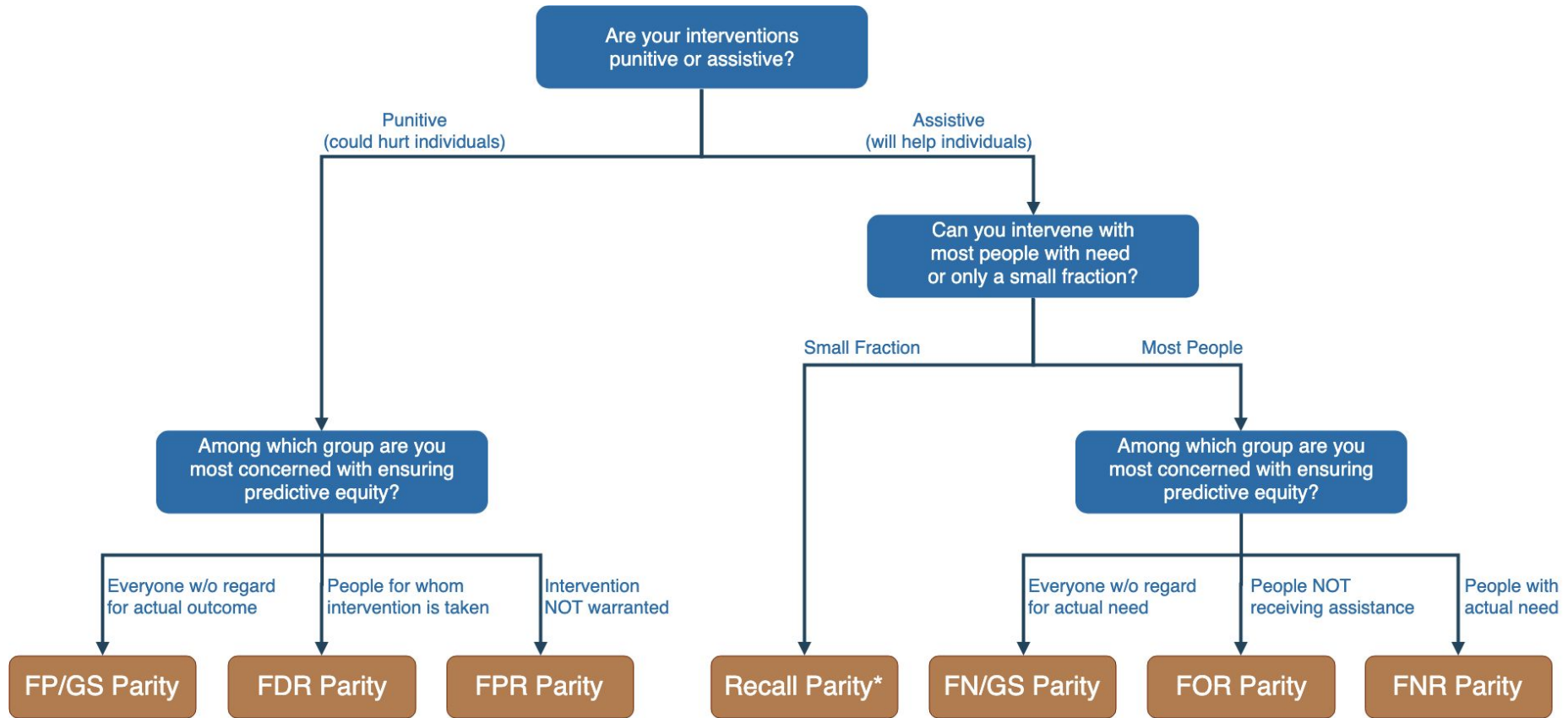
# Breaking the Cycle

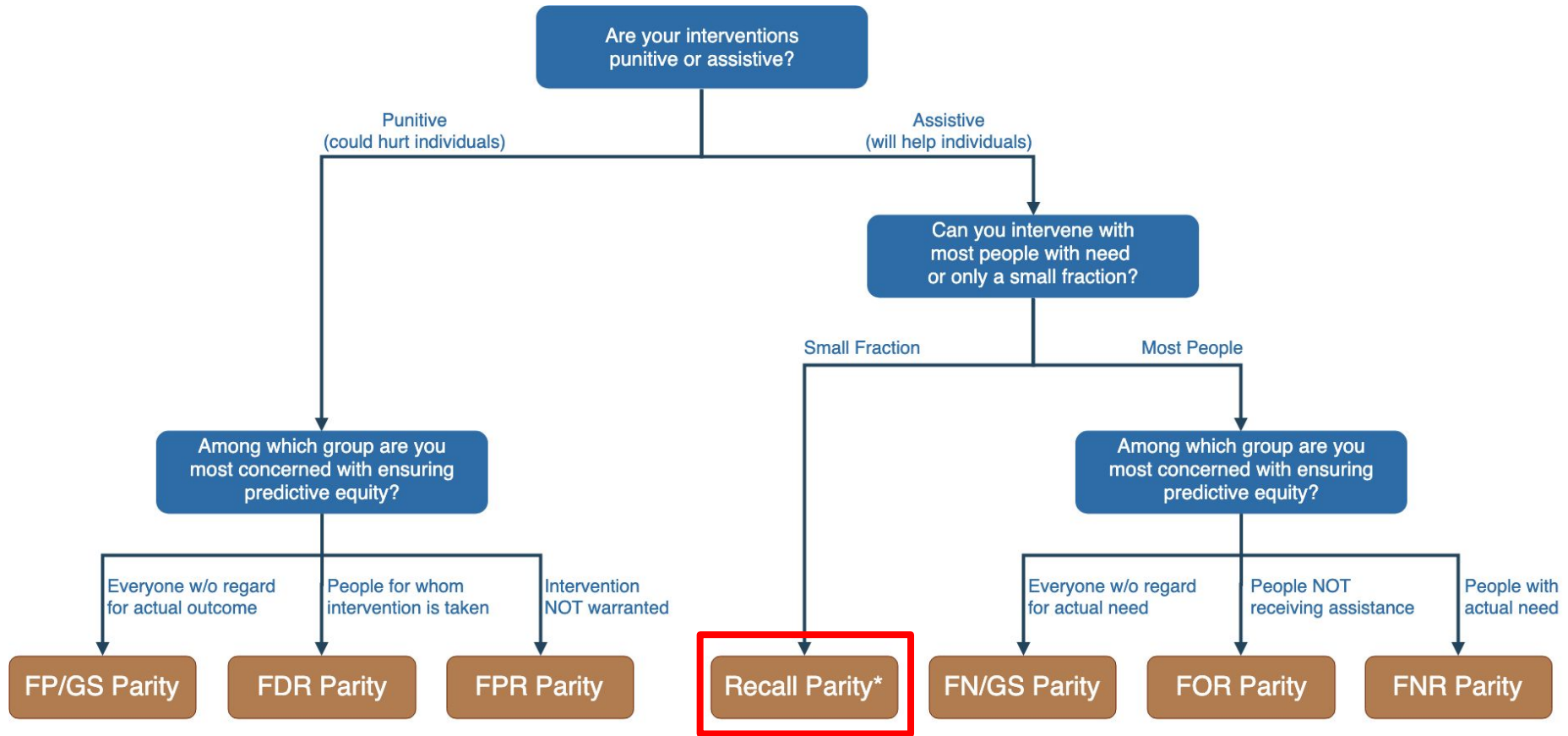


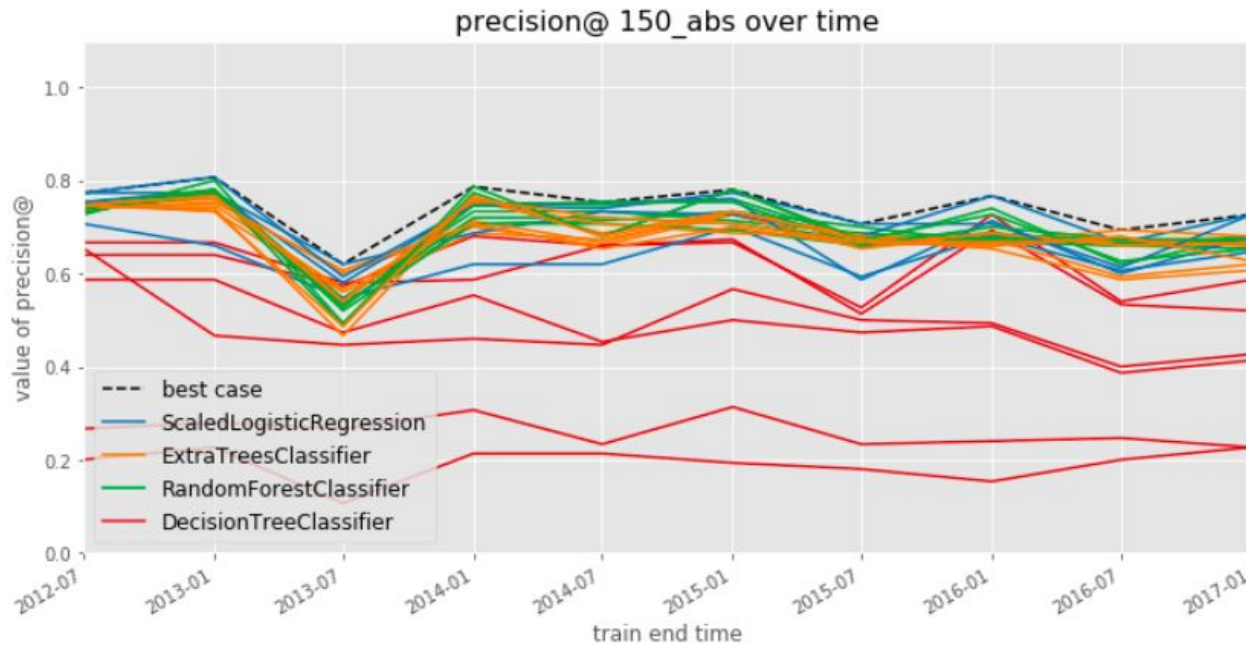
# Three Key Questions

- How do we define equity in a given policy context?
- How can we improve equity of ML models and implementation?
- How do policy makers balance trade-offs between equity, efficiency, resources?







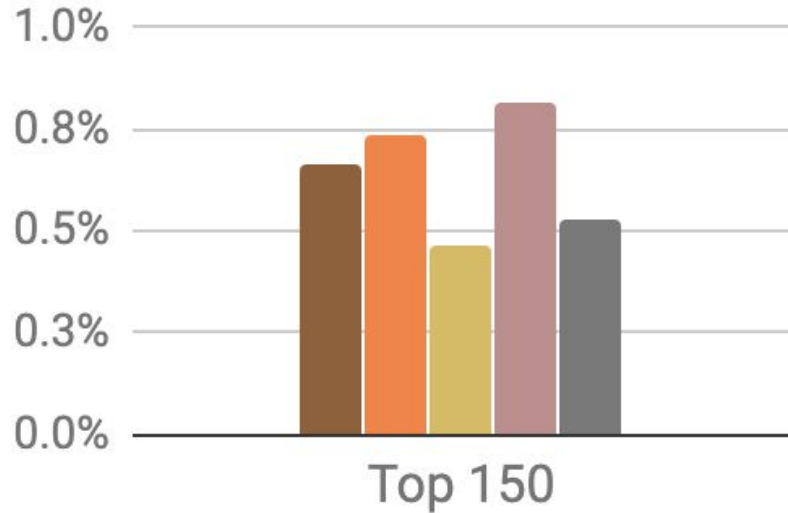


We built and selected a model to choose the 150 highest-risk individuals for intervention...



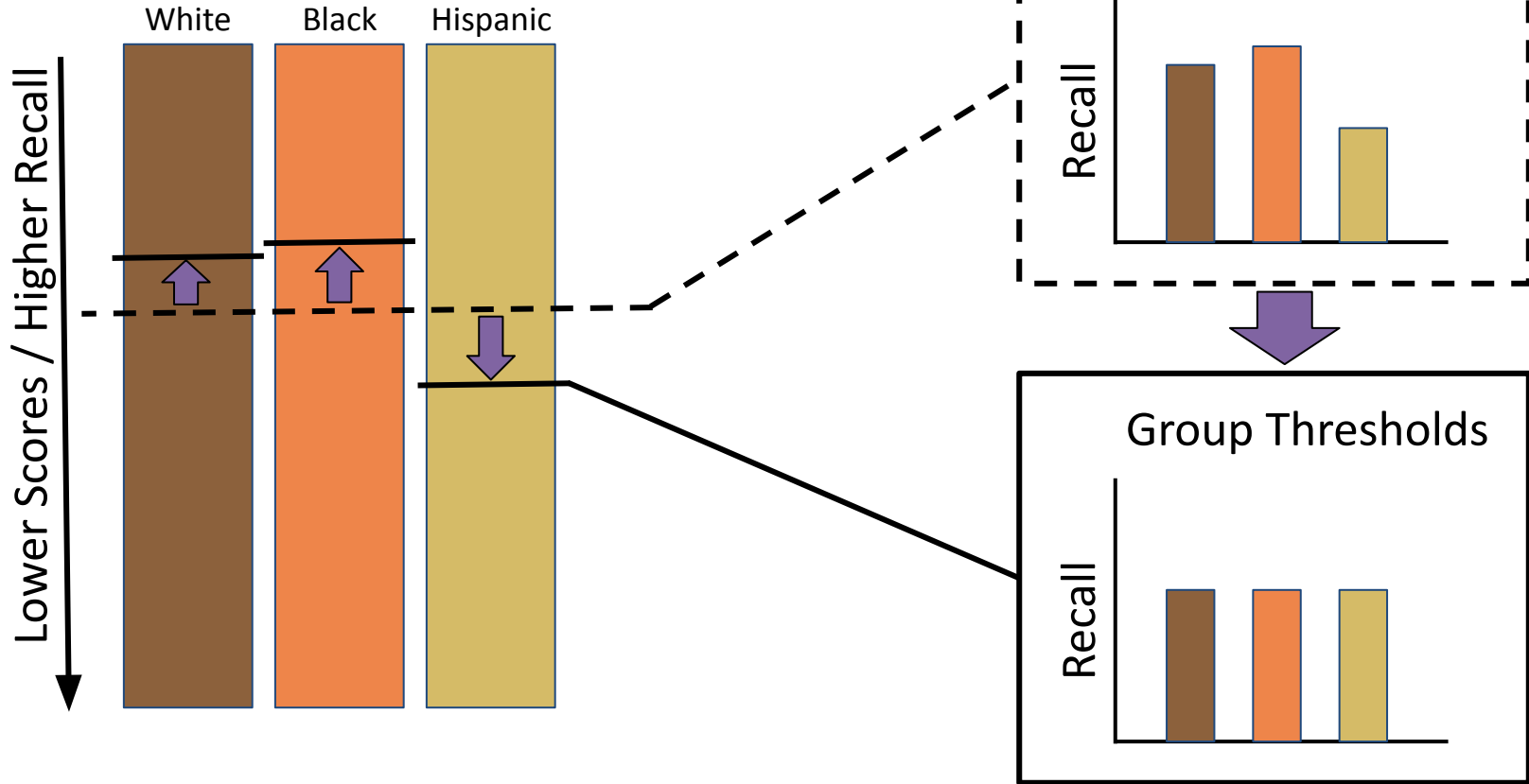
## Recall by Race/Ethnicity

White Black Hispanic  
Other Unknown

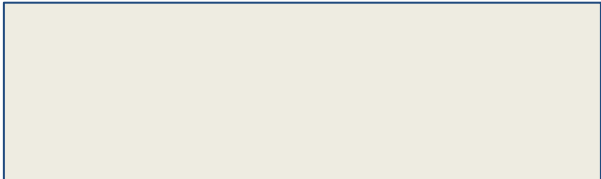
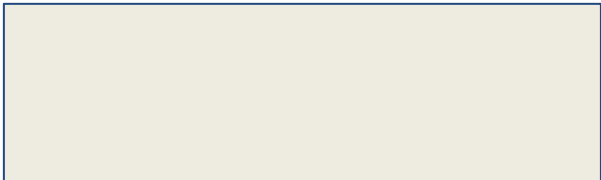
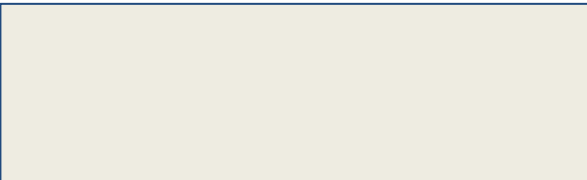
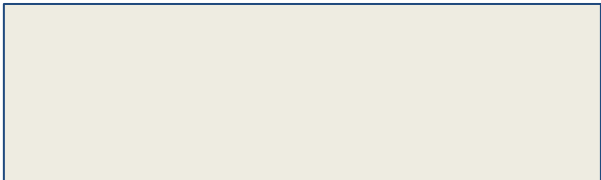
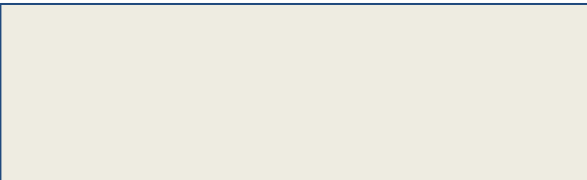


- Model was optimized for efficiency, not equity
- Top 150 highest risk reasonably balanced between black and white individuals
- However, hispanic and unknown race/ethnicity groups very underrepresented

# Mitigating Disparities



# Menu of Options

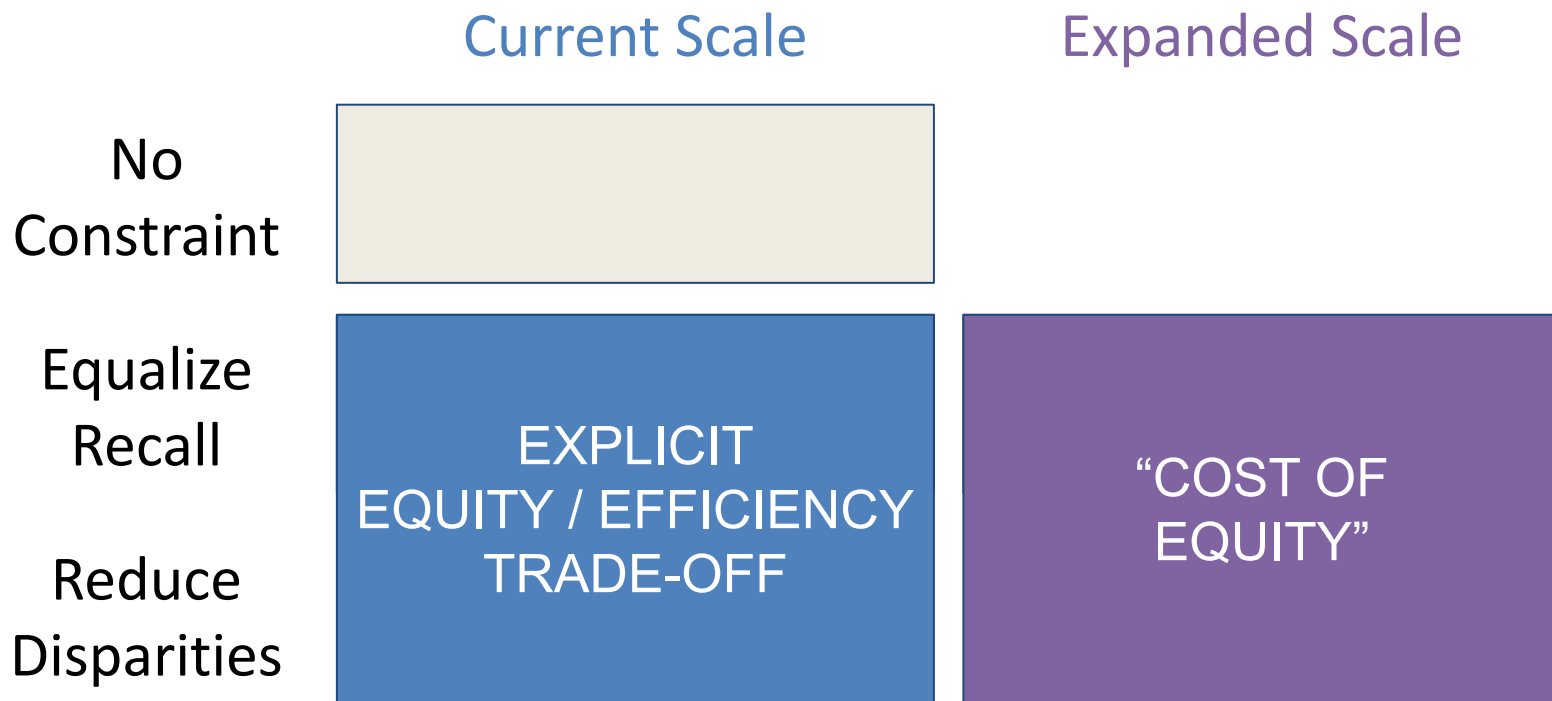
	Current Scale	Expanded Scale
No Constraint		
Equalize Recall		
Reduce Disparities		



# Menu of Options

	Current Scale	Expanded Scale
No Constraint	BASE MODEL	
Equalize Recall		
Reduce Disparities		

# Menu of Options

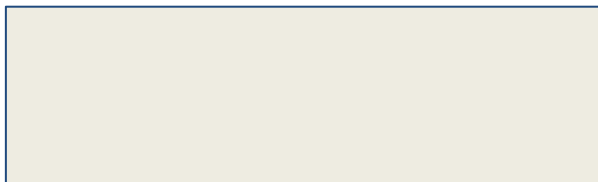


# Menu of Options

Current Scale

Expanded Scale

No  
Constraint



Equalize  
Recall

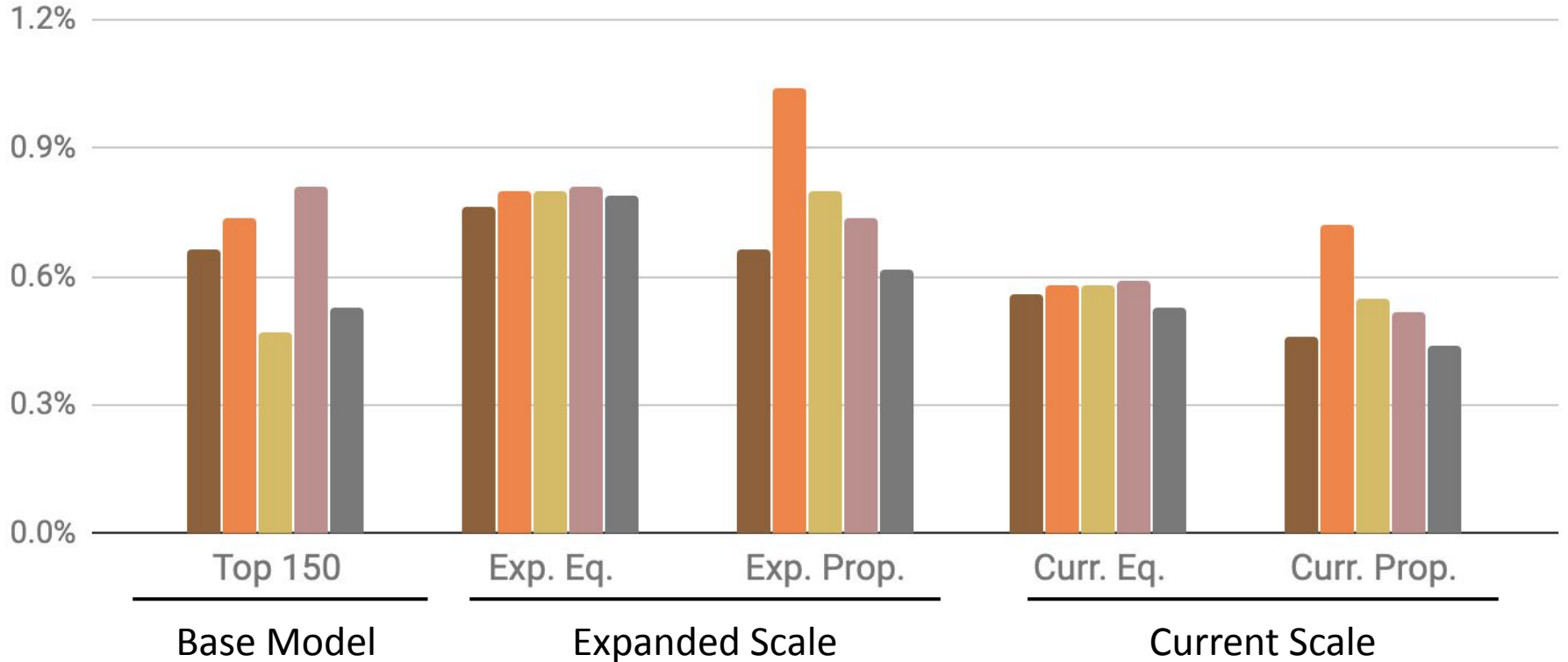
IMPROVE OUTCOMES AT SAME  
RATE ACROSS GROUPS

Reduce  
Disparities

IMPROVE OUTCOMES FASTER FOR GROUPS  
WITH HIGHER UNDERLYING PREVALENCE

# Recall by Race/Ethnicity Group

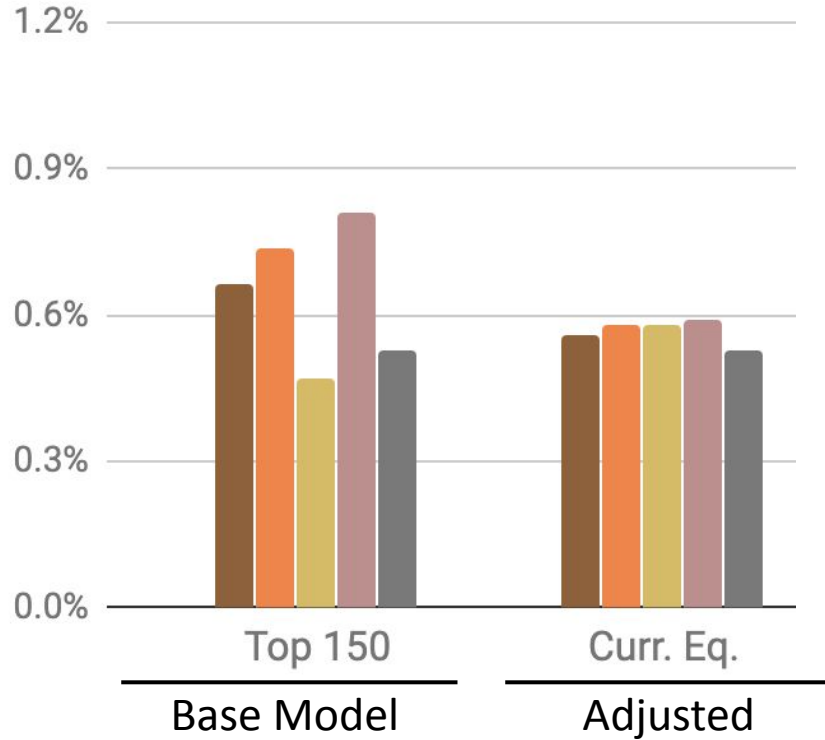
White Black Hispanic Other Unknown



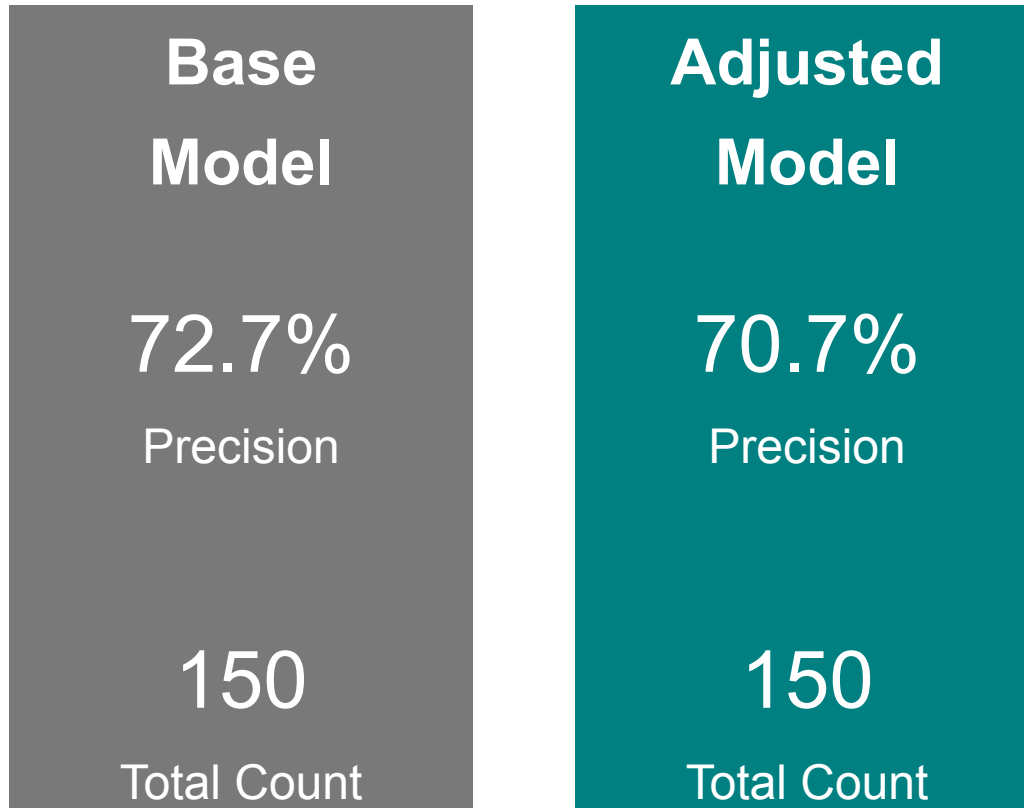


## Recall by Race/Ethnicity Group

■ White ■ Black ■ Hispanic ■ Other ■ Unknown



# Little Fairness/Accuracy Trade-Off



# Little Equity/Efficiency Trade-Off at Current Scale

**Top 150**

**72.7%**

Precision

**150**

Total Count

**Equal  
Recall**

**70.7%**

Precision

**150**

Total Count

**Proportional  
Recall**

**70.7%**

Precision

**150**

Total Count

# LESSON 3

**ML Fairness can be achieved (if it is an explicit goal)**

*In many cases, we've seen little or no trade-off in accuracy when improving fairness, but it needs to be thoughtfully defined, measured, and optimized*





# Preventing Lead Poisoning in Children (Chicago, IL)

*Predictive Modeling for Public Health: Preventing Childhood Lead Poisoning. Potash et al. KDD 2015*

*Validation of a Machine Learning Prediction Model of Childhood Lead Poisoning. Potash et al. JAMA 2020*



**Children in at least 4 million U.S. households are exposed to high levels of lead (CDC Report)**



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Impaired Attention

Hearing Loss

Lower IQ

Lack of Motor Skills

Learning Disability

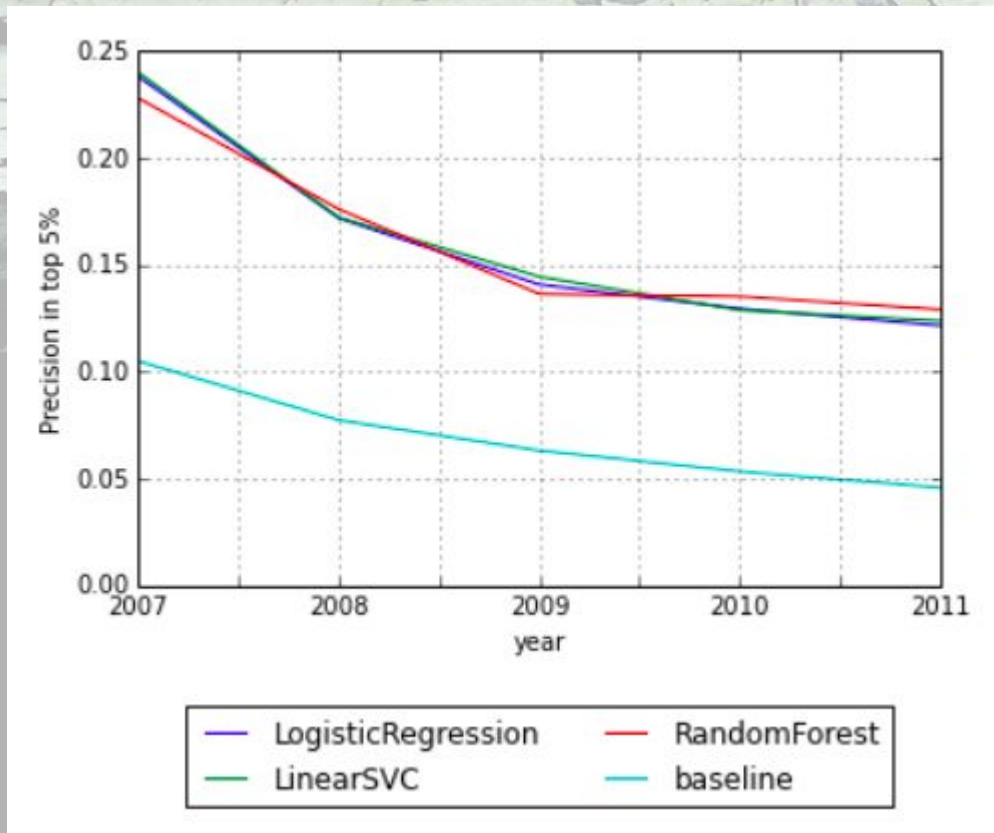
Memory Problems



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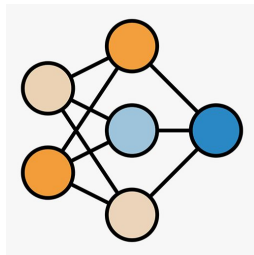
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**Historical  
Data**



**ML Model**



**Schedule  
Inspection**



**Inspect &  
Remediate**

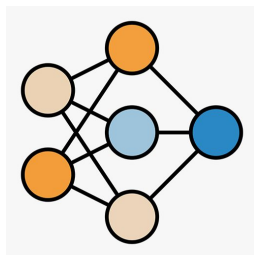
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**Historical  
Data**



**ML Model**



**Schedule  
Inspection**



**Inspect &  
Remediate**

# LESSON 4

## Fairness is a system property

*Even with fair model outputs, the implementation matters and it is important to consider how the system as a whole works together to achieve its goals*

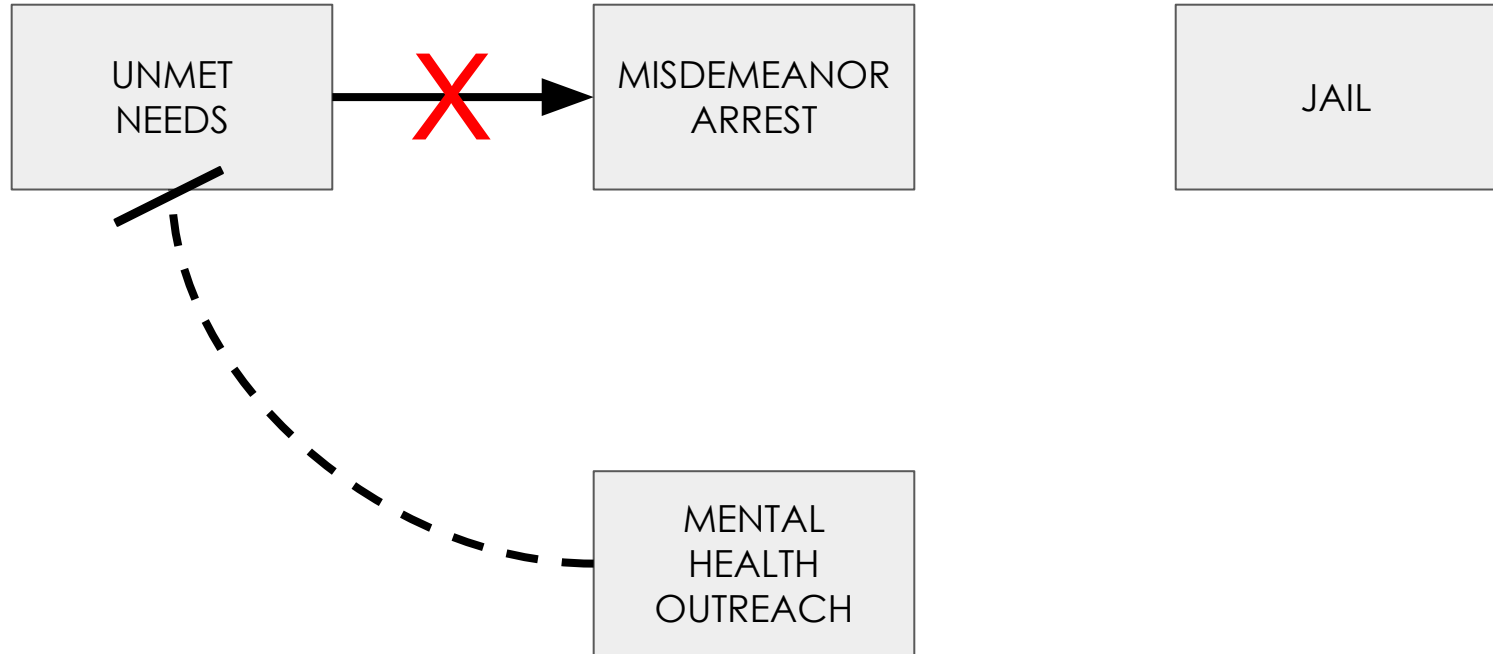


# Cycle of Incarceration





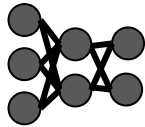
# Breaking the Cycle



Released From Jail  
In Past 3 Years

...With History of  
Mental Health  
Needs

Model



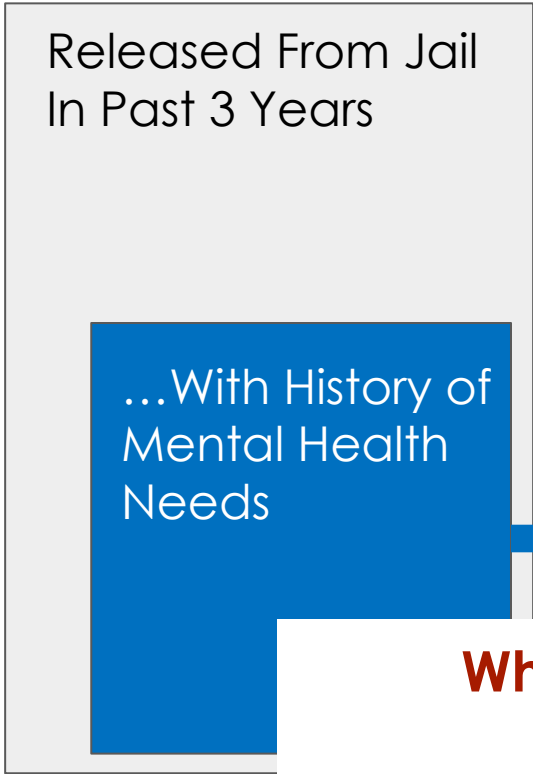
Return to Jail Risk

ID	SCORE
27	0.95
13	0.93
1	0.89
93	0.89
53	0.82
23	0.75
59	0.72
64	0.65
20	0.61
18	0.59
46	0.52
82	0.48
49	0.37
56	0.22
17	0.12

Mental  
Health  
Outreach

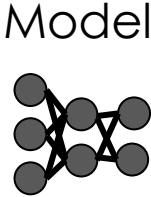


Return to  
Jail



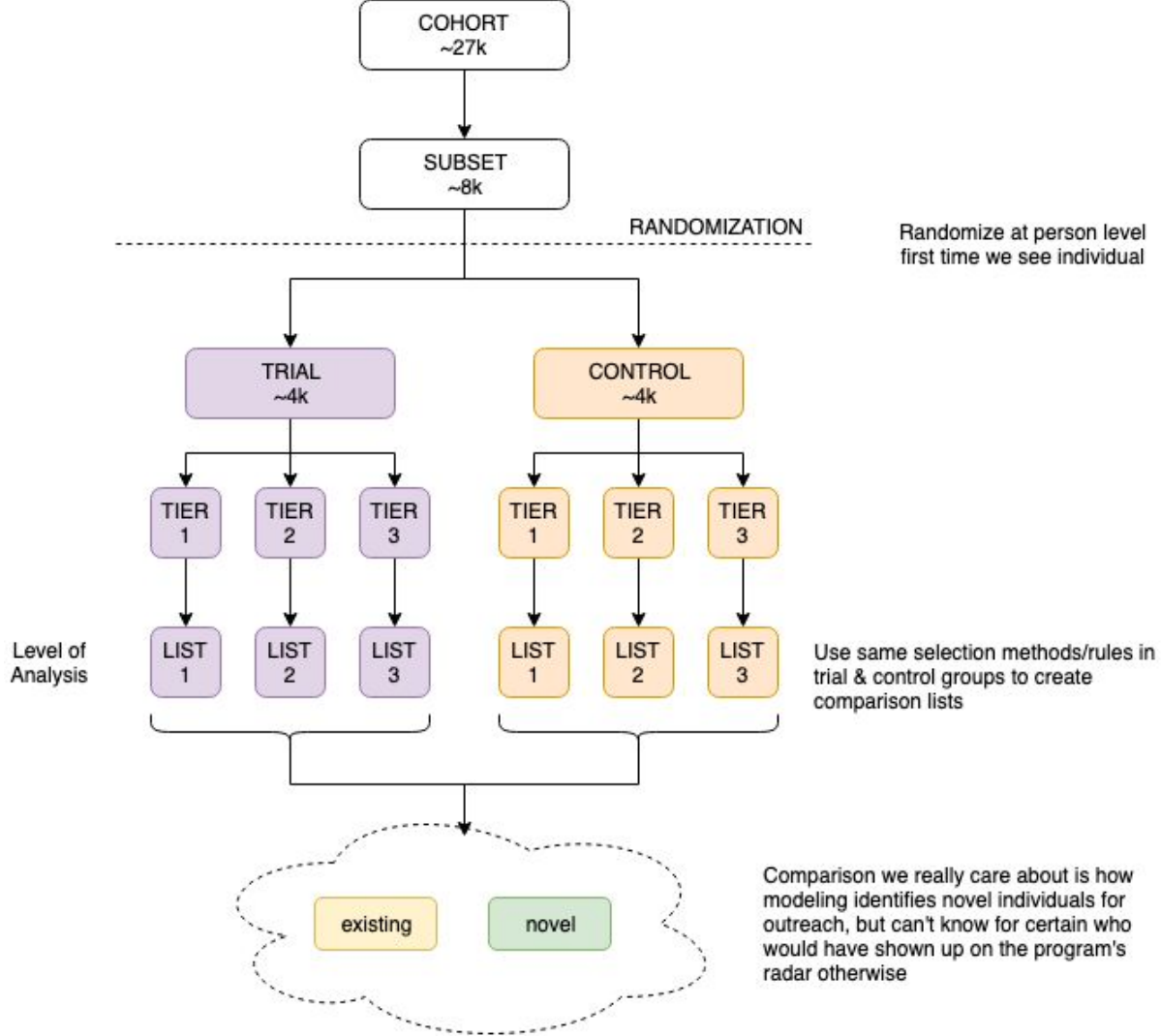
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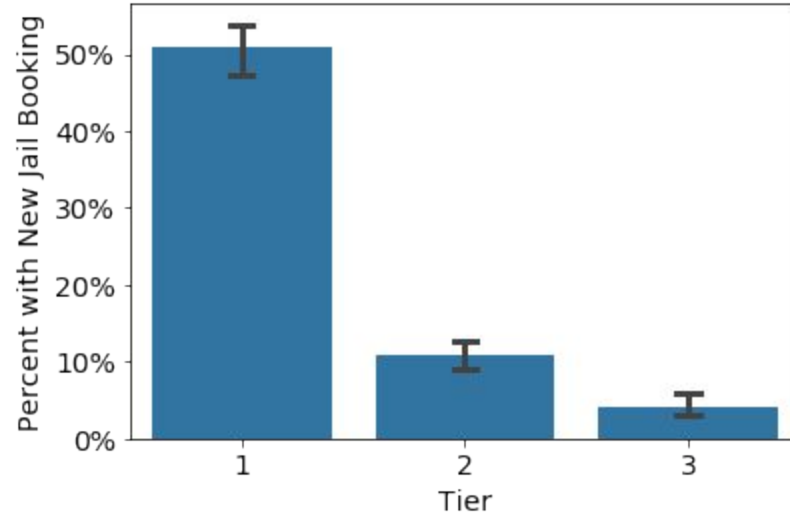


**What would you want to learn  
through a field trial?**

17	0.12
----	------

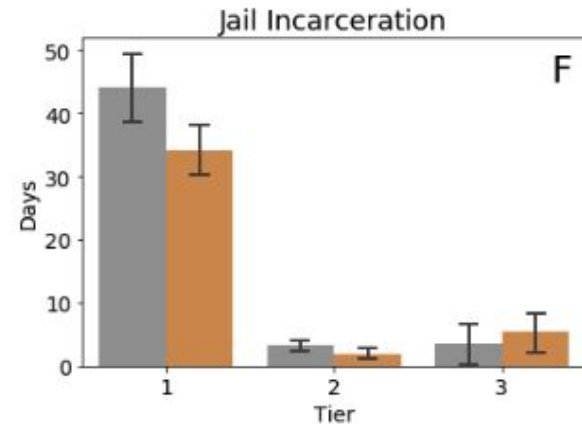
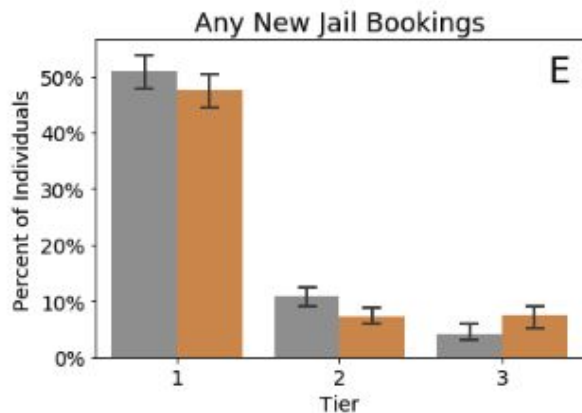
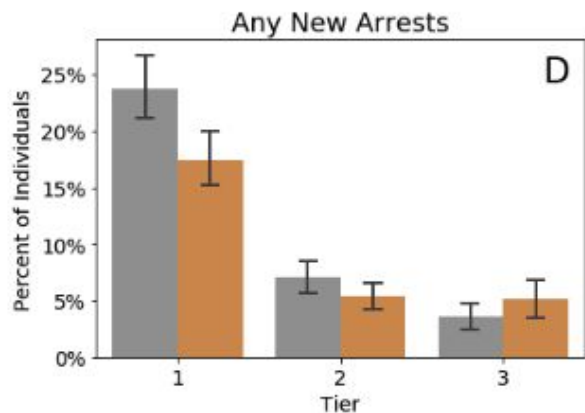
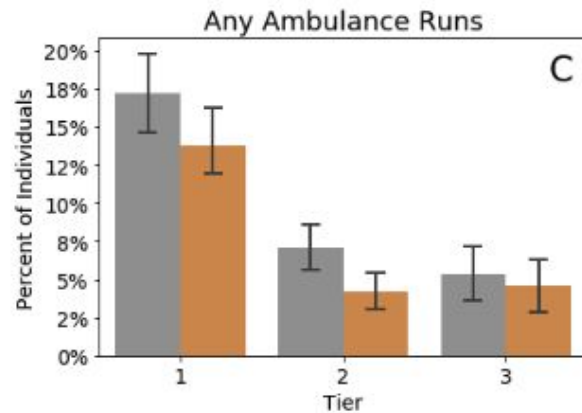
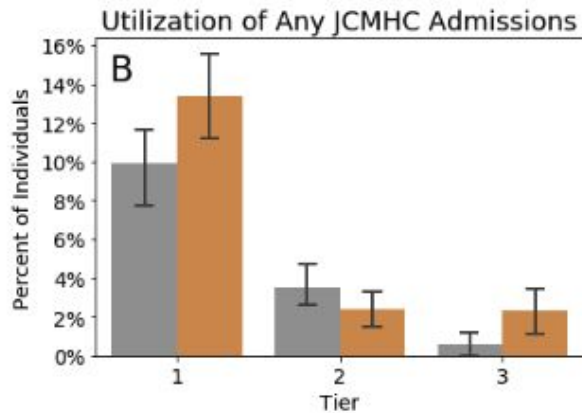
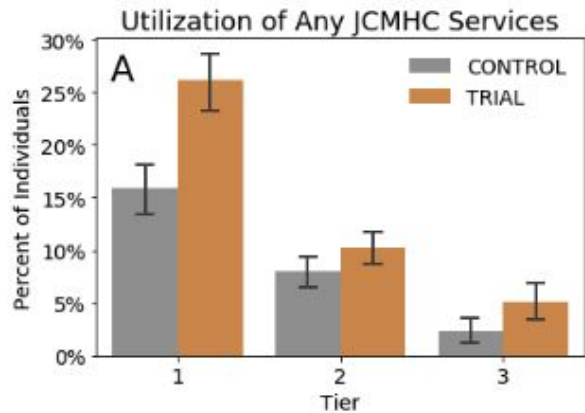


# Q1: Is the Model Predictive?





# Q2: Does Model+Intervention Affect Outcomes? For Whom?



# LESSON 5

## Think beyond A/B tests for field trials

*Field validation is critical before deployment, but should go beyond simply asking if the model is predictive – how will it be used? what assumptions should you test?*



# Recap

- Be diligent in finding relevant data
- Models will benefit from a range of data types
- ML Fairness can be achieved (if it's an explicit goal)...
- ... but it is a property of the entire system, not just the model's predictions
- Think beyond A/B tests for field validation

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