Fixing Disparities in Health with Machine Learning

Irene Y. Chen

@irenetrampoline

Joint work with Marzyeh Ghassemi, Shalmali Joshi, David Sontag, Fredrik D. Johansson, Peter Szolovits

MIT Clinical ML
www.clinicalml.org

PROPUBLICA How Hospitals Are Failing Black Mothers

LOST MOTHERS

How Hospitals Are Failing Black Mothers

A ProPublica analysis shows that women who deliver at hospitals that disproportionately serve black mothers are at a higher risk of harm.

by Annie Waldman, Dec. 27, 2017, 8 a.m. EST

The New York Times

TheUpshot

THE NEW HEALTH CARE

A Sense of Alarm as Rural Hospitals Keep Closing

The potential health and economic consequences of a trend associated with states that have turned down Medicaid expansion.

JACC: HEART FAILURE VOL. 6, NO. 5, 2018
© 2018 BY THE AMERICAN COLLEGE OF CARDIOLOGY FOUNDATION
PUBLISHED BY ELSEVIER

EDITORIAL COMMENT

Narrowing the Disparities in Heart Failure

Treat the Event or Try to Prevent?*

Hena Patel, MD, Kim Allan Williams, Sr, MD

Congressional Research Service
Informing the legislative debate since 1914

The Growing Gap in Life Expectancy by Income: Recent Evidence and Implications for the Social Security Retirement Age

Katelin P. Isaacs
Analyst in Income Security

Sharmila Choudhury
Section Research Manager

May 12, 2017

Disparities filter into observational data

Need and Goldstein, *Cell* 2009; U.S. Food and Drug Administration, National Cancer Institute, Riley Wong for *Propublica*, 2018.

Disparities filter into observational data

Table 1. Ethnicity of participants in genome-wide association studies[a]

Race/ethnicity	Number of studies	Total participants[d]	
European only[b]	320	1 581 776	
Asian only	26	52 841	
Hispanic only	3	1019	
Native American only	2	1102	
Jewish only	2	3479	
Gambian only	1	2340	
Micronesian only	1	2346	
Mixed[c]	11	European[b,e]	92 437
		African-American	7500
		Asian	33
		Papua-New Guinean	276
		Other[f]	269

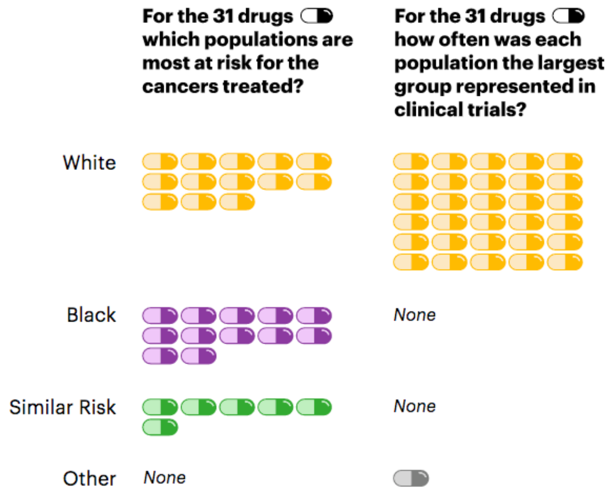
96% of participants in **GWAS studies** were of European descent

Need and Goldstein, *Cell* 2009; U.S. Food and Drug Administration, National Cancer Institute, Riley Wong for *Propublica*, 2018.

Disparities filter into observational data

Table 1. Ethnicity of participants in genome-wide association studies[a]

Race/ethnicity	Number of studies	Total participants[d]	
European only[b]	320	1 581 776	
Asian only	26	52 841	
Hispanic only	3	1019	
Native American only	2	1102	
Jewish only	2	3479	
Gambian only	1	2340	
Micronesian only	1	2346	
Mixed[c]	11	European[b,e]	92 437
		African-American	7500
		Asian	33
		Papua-New Guinean	276
		Other[f]	269



96% of participants in **GWAS studies** were of European descent

Cancer clinical drug trials do not match the populations most at risk.

Need and Goldstein, *Cell* 2009; U.S. Food and Drug Administration, National Cancer Institute, Riley Wong for *Propublica*, 2018.

- **Potentially biased** observational data
- **Opaque** and **hard to certify** as “bias-free”

- **Potentially biased** observational data
- **Opaque** and **hard to certify** as “bias-free”

- **Potentially biased** observational data
- **Opaque** and **hard to certify** as “bias-free”

- Incorporate **massive datasets**
- Find latent patterns in **underserved populations**
- **Scale** quickly and widely

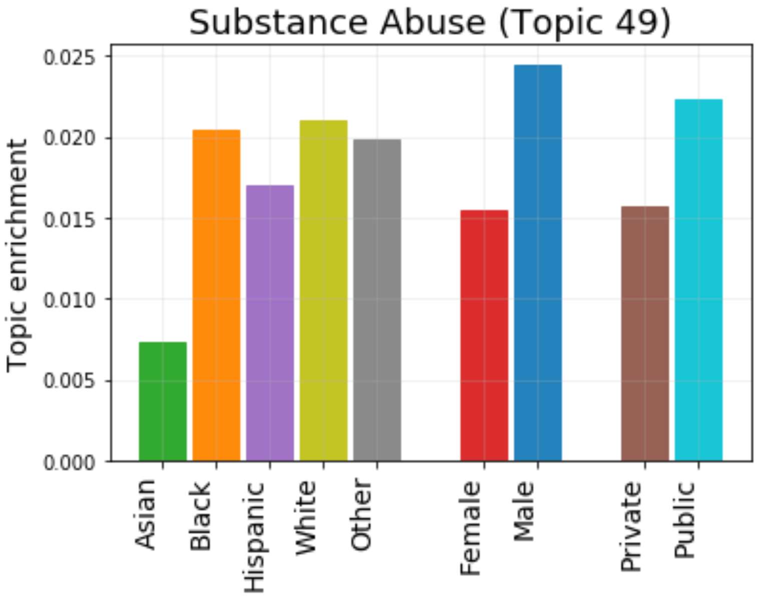
Step 1: Characterize disparities

- We can understand **unstructured psychiatric notes** through LDA topic modeling
- One salient topic, **substance abuse**, had the following key words: use, substance, abuse cocaine, mood, disorder, dependence, positive, withdrawal, last, reports, ago, day, drug

Chen, Szolovits, Ghassemi; *AMA Journal of Ethics* 2019

Step 1: Characterize disparities

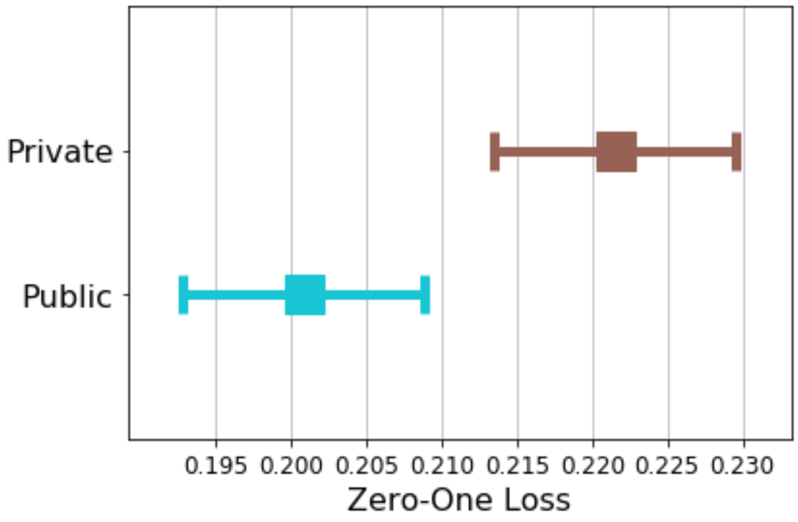
- We can understand **unstructured psychiatric notes** through LDA topic modeling
- One salient topic, **substance abuse**, had the following key words: use, substance, abuse cocaine, mood, disorder, dependence, positive, withdrawal, last, reports, ago, day, drug



Chen, Szolovits, Ghassemi; *AMA Journal of Ethics* 2019

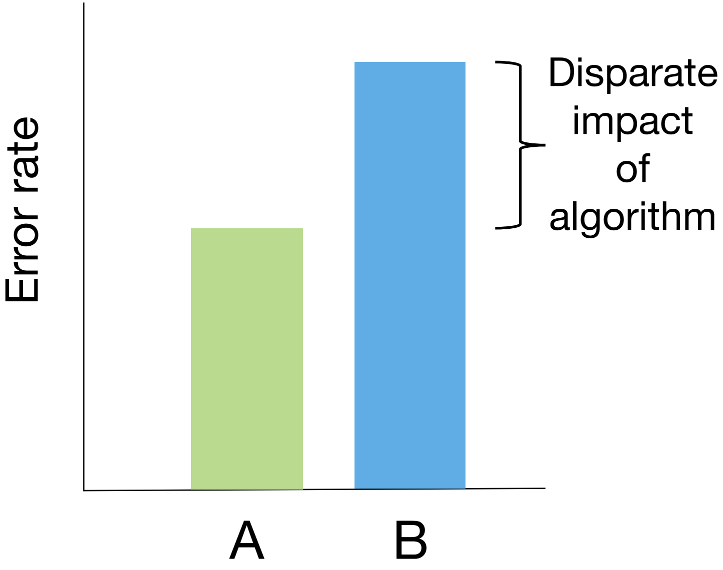
Step 1: Characterize disparities

- We can evaluate the **differences in accuracy** for a L1 Logistic Regression trained on the psychiatric notes to predict 30-day readmission
- We find algorithmic bias in **insurance type** but not race or gender



Chen, Szolovits, Ghassemi; *AMA Journal of Ethics* 2019

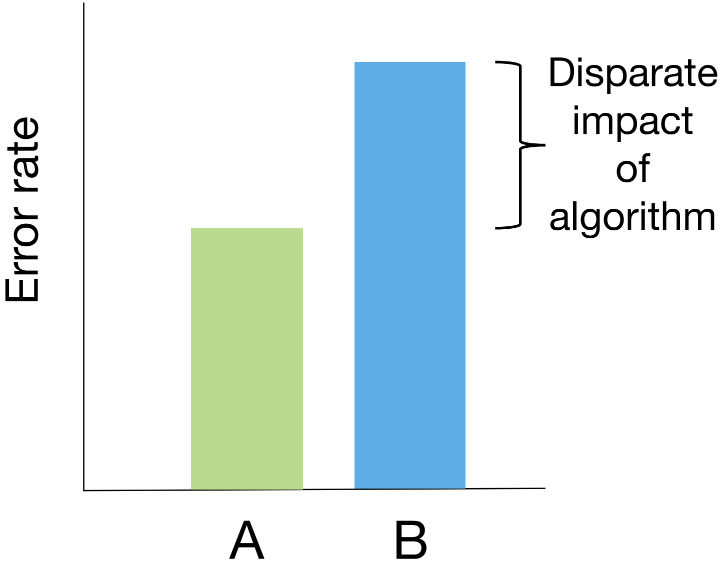
Step 2: Fix algorithmic bias



Chen, Johansson, Sontag; *NeurIPS* 2018

Step 2: Fix algorithmic bias

	Description	How to detect	How to fix
Bias	How well the model fits the data	Experiment with model complexity	Change model class
Variance	How much the sample size affects the accuracy	Fit inverse power laws to subsampling	Increase training data size
Noise	Irreducible error independent of sample size and model	Estimate Bayes error using distance metrics	Increase number of features



Chen, Johansson, Sontag; *NeurIPS* 2018

Step 2: Fix algorithmic bias

$$\text{Error} = Bias + Variance + Noise$$

$$\text{Unfairness} = |Error_1 - Error_2|$$

$$= |(B_1 - B_2) + (V_1 - V_2) + (N_1 - N_2)|$$

Changing model class can impact bias

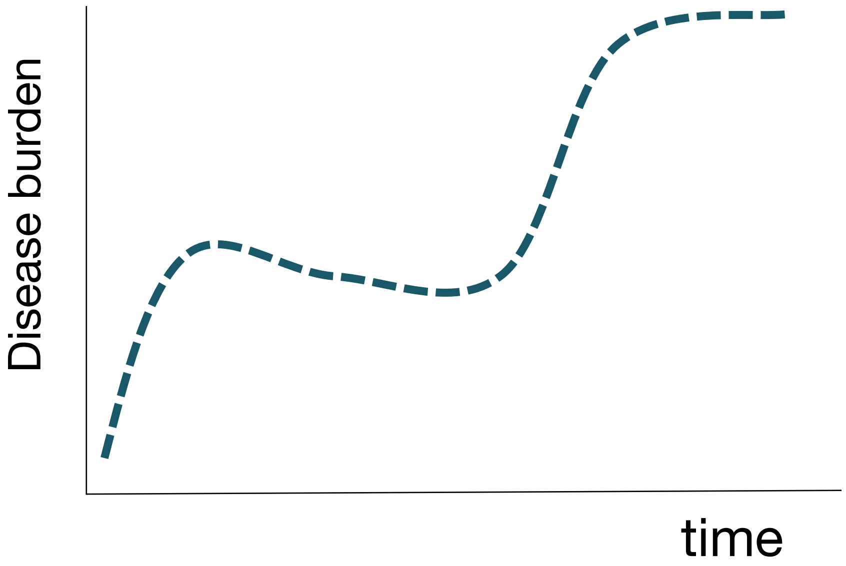
Improving sample size reduces variance

Collecting additional features can decrease noise

Chen, Johansson, Sontag; *NeurIPS* 2018

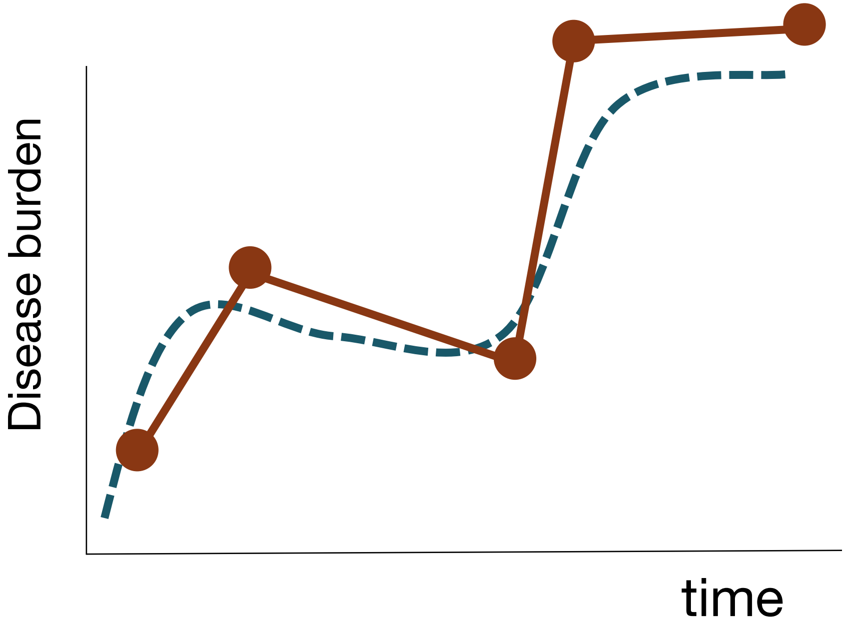
Step 3: Model and fix systemic bias

- Lead time bias
  - Patients may enter the healthcare system at different times



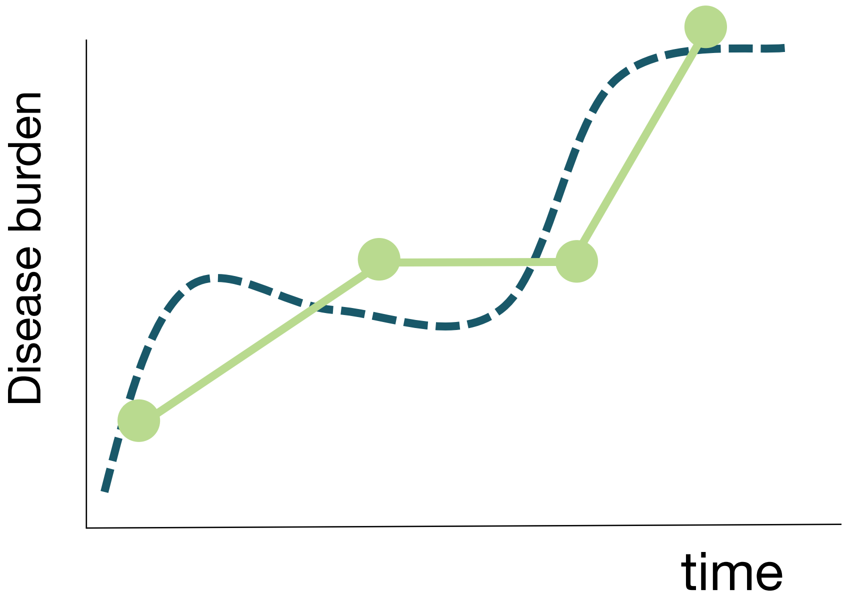
Step 3: Model and fix systemic bias

- Lead time bias
  - Patients may enter the healthcare system at different times



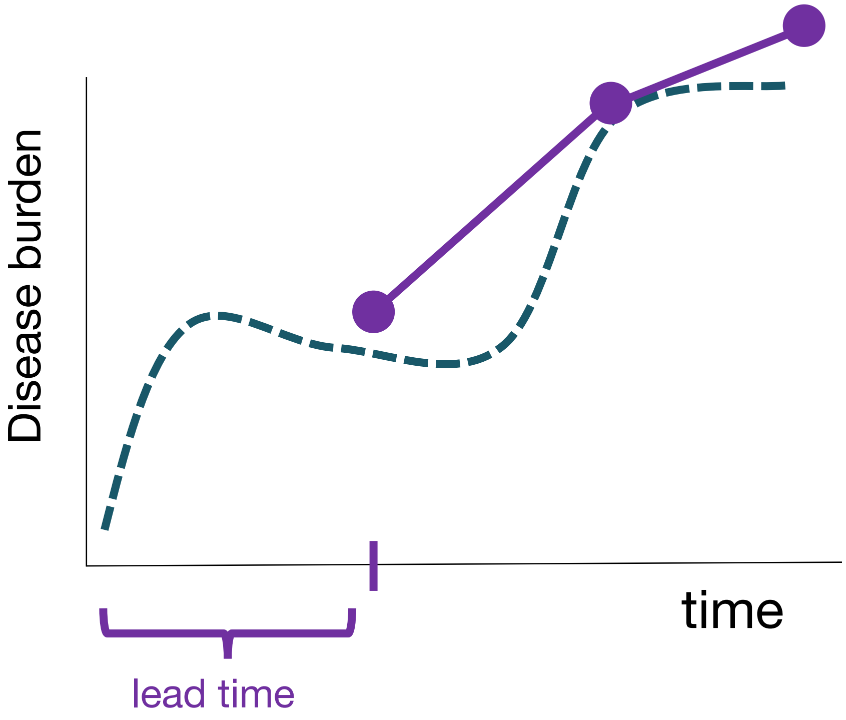
Step 3: Model and fix systemic bias

- Lead time bias
  - Patients may enter the healthcare system at different times



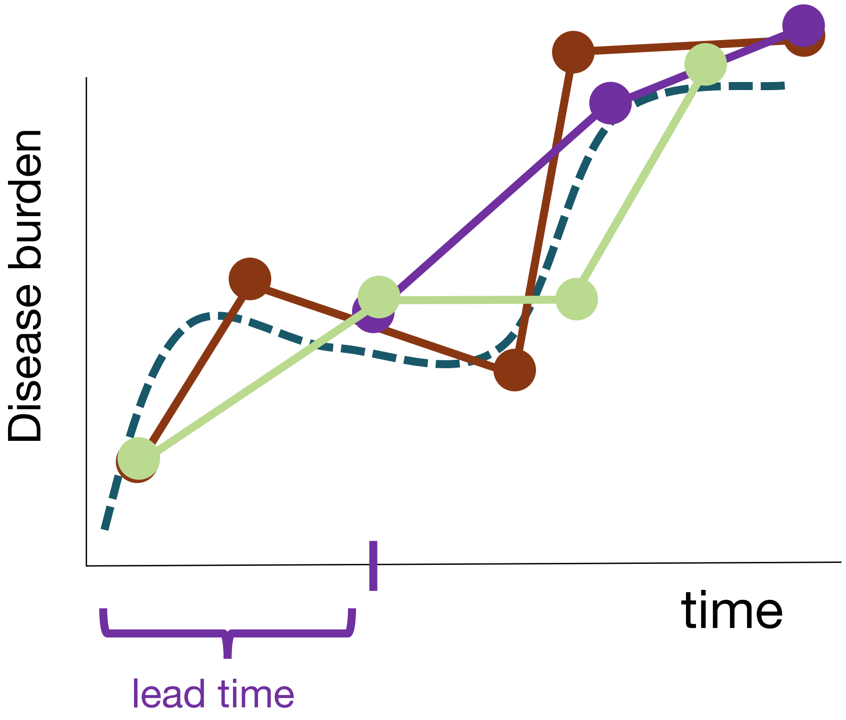
Step 3: Model and fix systemic bias

- Lead time bias
  - Patients may enter the healthcare system at different times



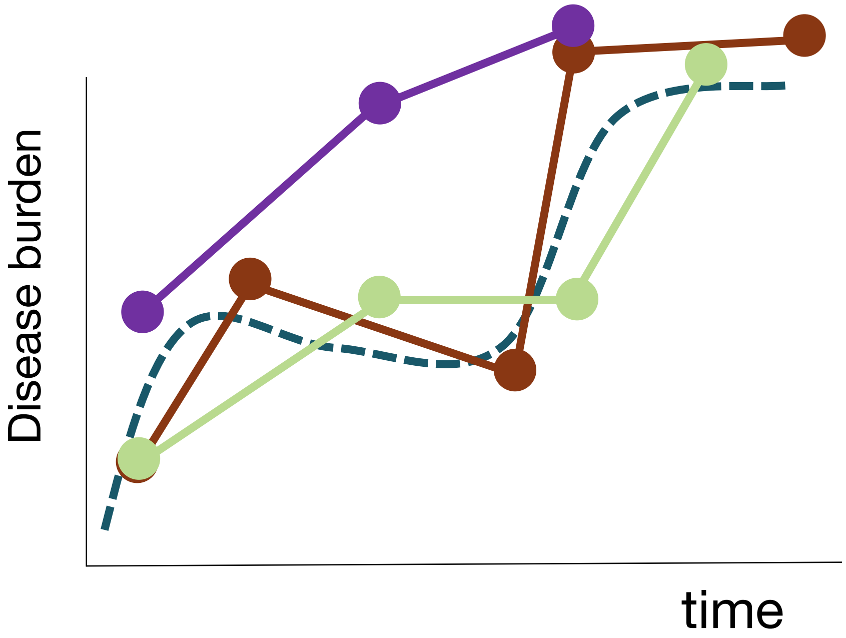
Step 3: Model and fix systemic bias

- Lead time bias
  - Patients may enter the healthcare system at different times



Step 3: Model and fix systemic bias

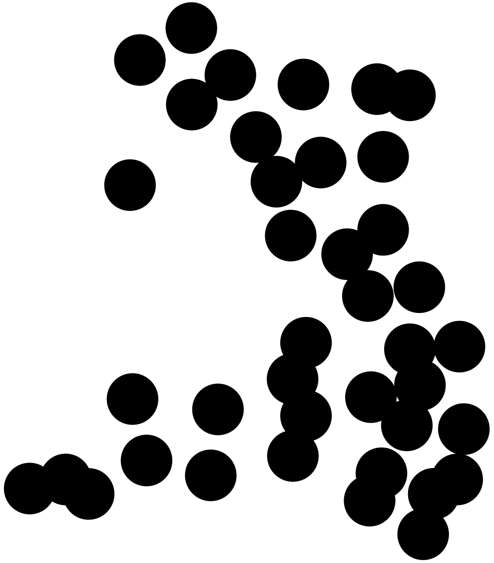
- Lead time bias
  - Patients may enter the healthcare system at different times



Step 3: Model and fix systemic bias

- Lead time bias
  - Patients may enter the healthcare system at different times
- Subtyping
  - Diseases can manifest in many ways

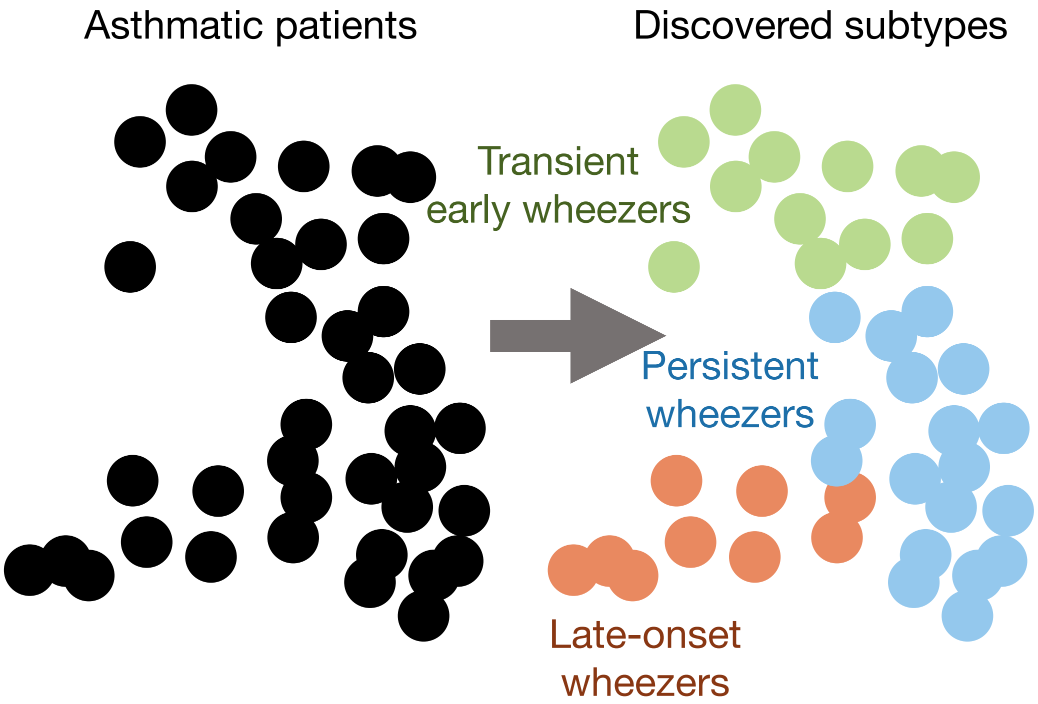
Asthmatic patients



Deliu et al; *Pulmonary Therapy* 2016

Step 3: Model and fix systemic bias

- Lead time bias
  - Patients may enter the healthcare system at different times
- Subtyping
  - Diseases can manifest in many ways



Deliu et al; *Pulmonary Therapy* 2016

Challenge to the community

1. **Expand beyond mathematical definitions.** Consider historical and systemic causes to define and fix health disparities.

Challenge to the community

1. **Expand beyond mathematical definitions.** Consider historical and systemic causes to define and fix health disparities.
2. **Seek and promote different perspectives.** Interdisciplinary work and a more diverse research community bring more people to the table.

Challenge to the community

1. **Expand beyond mathematical definitions.** Consider historical and systemic causes to define and fix health disparities.
2. **Seek and promote different perspectives.** Interdisciplinary work and a more diverse research community bring more people to the table.
3. **Aim for higher fruit.** Short-term clinical prediction is only the first step in improving the healthcare system.