Getting Granular on Social Determinants of Health

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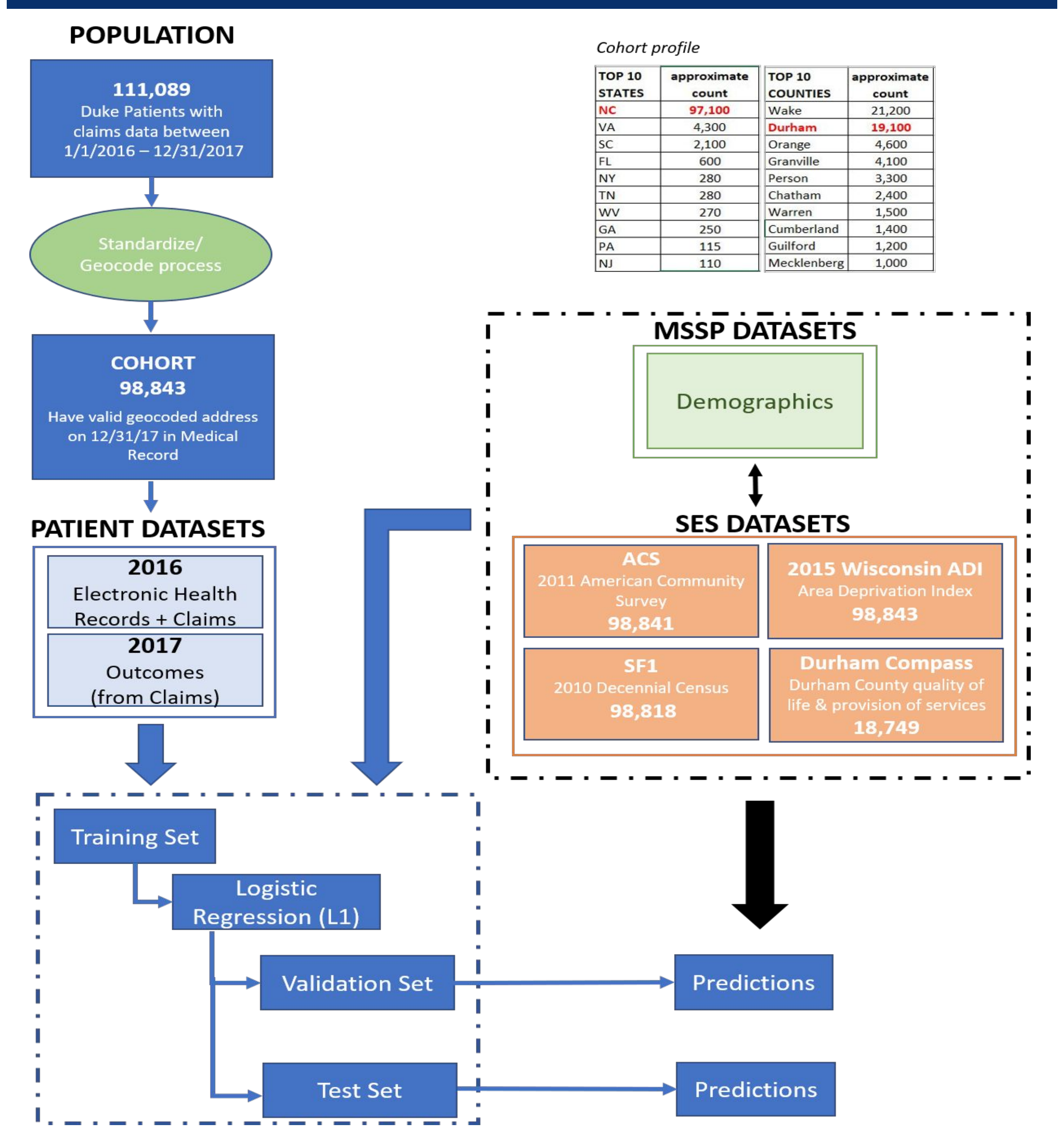
Abstract

Health outcomes data are often correlated with social end economic variables (SES). Models based on health outcome data in these situations often lead to biased predictions, even when SES data are not included in the model. Using a dataset from Duke health we show that we can predict hospital admission using electronic health records and claims data using regularized logistic regression, which yields comparable performance to state-of-the-art methods. However, these predictions are biased with respect to race. While different prediction rates are to be expected based on discrepancies in the marginal admission rate, the false positive and negative rates are different. This indicates bias is a significant concern in health data, even with simpler models.

Data



Cohort profile

TOP 10 STATES	approximate count
NC	97,100
VA	4,300
SC	2,100
FL	600
NY	280
TN	280
WV	270
GA	250
PA	115
NJ	110

TOP 10 COUNTIES	approximate count
Wake	21,200
Durham	19,100
Orange	4,600
Granville	4,100
Person	3,300
Chatham	2,400
Warren	1,500
Cumberland	1,400
Guilford	1,200
Mecklenberg	1,000

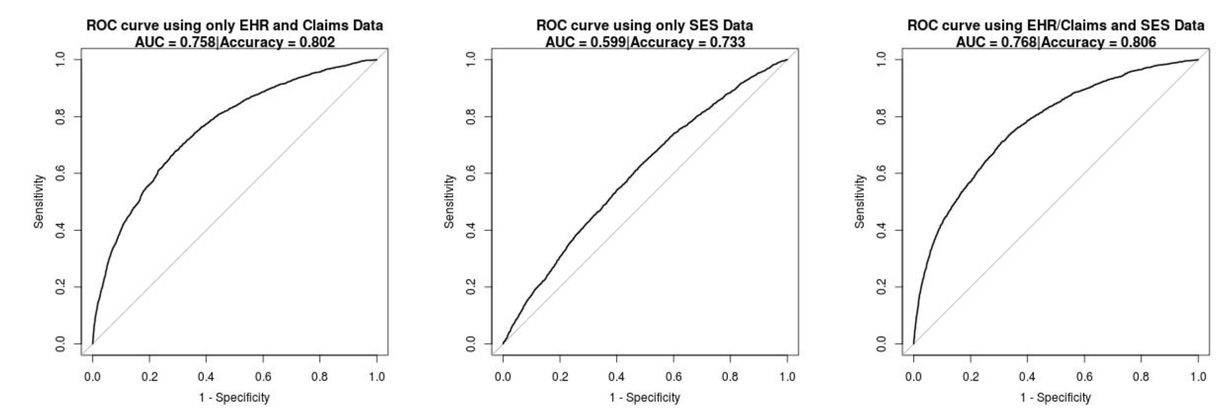
Methods

- Three logistic regression models with lasso (L1) regularization: one using 2016 EHR/Claims data, one using socioeconomic data, and one trained on both
  - Training/test/validation split of 60-20-20
  - 10 fold cross validation to determine lambda
  - Prediction cutoffs made to match the true prevalence of hospital admissions (17.8%)
  - More complex models, such as random forests and XGBoost offered little improvement over regularized logistic regression while testing
- Compare results and fairness metrics among different SES categories using the validation results of the EHR/Claims model
  - Median income and race categories were focused on in particular

Results

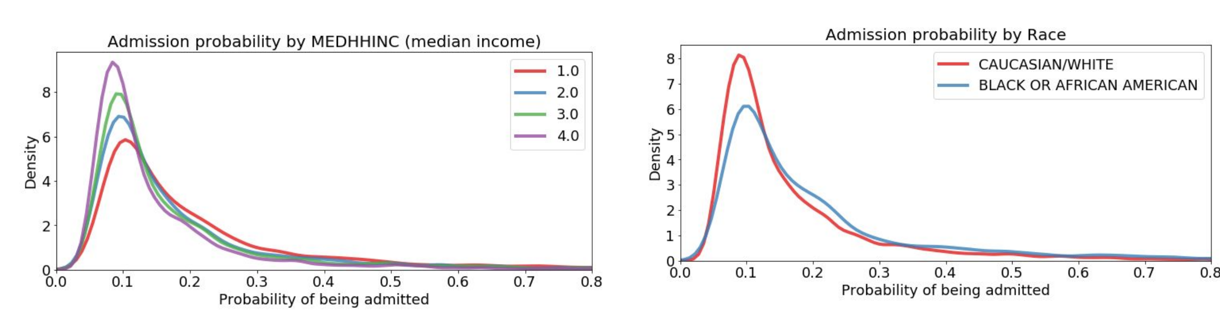
Model Performance using EHR and SES Data

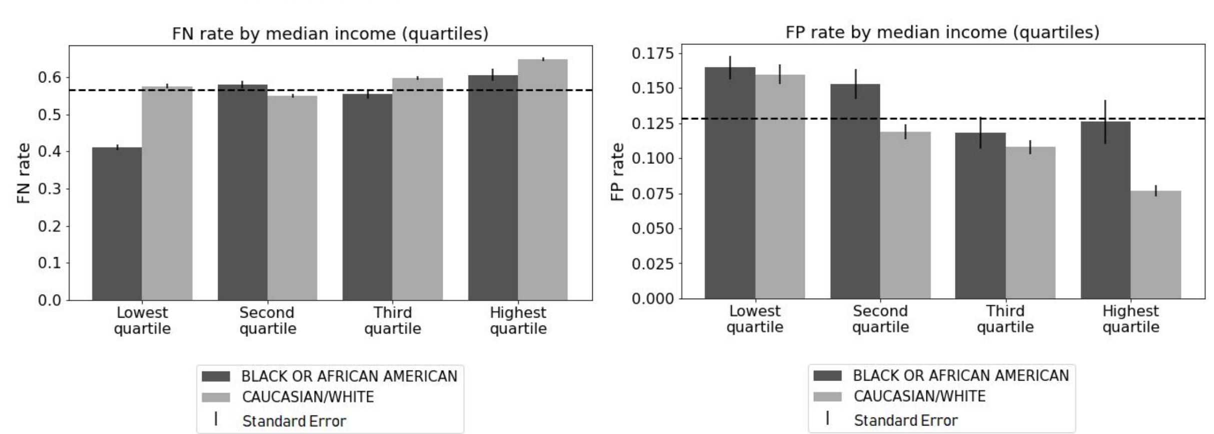
- Solely EHR/Claims data is good at predicting hospital admissions (AUC = 0.758)
- SES data on its own does contain some predictive power well above random chance
- Adding SES variables to the EHR/Claims model only allows for a slight increase in performance, indicating EHR/Claims data contains SES information



Bias in False Positive and Negative Rates

- Our model assigned a higher likelihood of being admitted to black people in comparison to white people.
- The likelihood of being classified as a future admission increased as the median income of the subject increased





Quantifying Unfairness

- Disparate impact compares the proportions of people in two groups who receive a positive prediction (admissions)
  - Model consistently overpredicts African American chances of admission, especially in the highest income quartile

	Expected Proportion	Model Disparate Impact
Caucasian/White vs Black or African American	0.85	0.73
Lowest Income Quartile	0.94	0.83
Second Income Quartile	0.99	0.88
Third Income Quartile	0.94	0.89
Highest Income Quartile	0.79	0.66

- Other metrics like equal mis-opportunity (comparison of FP rates) and equal opportunity (comparison of TP rates) are demonstrated in the above graphs

Fairness

- Bias occurs when an algorithm produces systematically erroneous results towards one group
  - In this case fairness means that admission predictions should minimize bias and thus reflect actual risk for different groups
- Variables correlated with input data will be correlated to model predictions
  - Can have strong detrimental effects when the predictive model influences policy
- Bias can also stem from oversampling different demographics: African Americans are 12 % and Asians are 5.6 %
- Fairness metrics can be used to evaluate different types of bias.
- Disparate Impact Metric:

$$\frac{\Pr(Y = 1 \mid D = Class1)}{\Pr(Y = 1 \mid D = Class2)}$$

Conclusions

- Regularized logistic regression allows us to predict unplanned admissions as well as more advanced technique.
- While SES variables are predictive, they provide little to no additional predictive power to the model, indicating SES data are associated with EHR and claims data.
- This correlation is evident as common models used for machine learning yield biased predictions with respect to SES variables

Future Work

- Split the EHR/Claims data from the demographic data in order to train and evaluate bias in a stacked model
- Evaluate performance and bias using SES data at an individual rather than aggregate level
- Apply and evaluate the efficacy/benefits of different methods to remove bias

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Student Showcase Data+ Final Poster Session

August 2, 2019, Duke University, Gross Hall