

# Effects of Non-Medical Factors on Medical Care Outcomes

Himanshu Chauhan, Kate McArdle, Radhika Sundar

# Outline

## 1 Intro & Background

- Motivation
- Data
- Other Studies

## ■ Problem Defn. & Approach

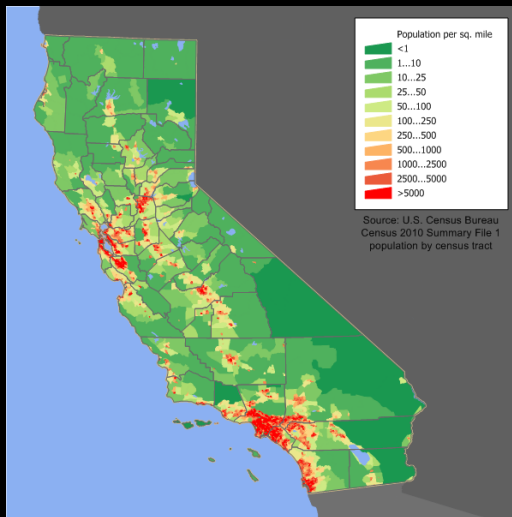
- Objectives
- Focus
- Our Approach

## ■ Results

- Insights/Inferences
- Predictive Modeling Results - Heart Failure
- Predictive Modeling Results - Cardiac Arrhythmia

## ■ Conclusion

# Motivation



# Data Source - CA Discharge Records (2009 – 2011)

hospital	diagnosis	gender	race	county	age	source	pay type	los	charge
130699	389	2	1	19		231	3	0	18032
196404	250	2	*	38	42	231	1	44	67543
190017	428	*	*	43		131	1	289	0

## ■ Demographics

- Age, Gender, Race, County, Insurance type, etc.

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- Age, Gender, Race, County, Insurance type, etc.

## ■ Diagnosis/Procedures performed

- Primary diagnosis, Principal procedure, Other diagnoses, etc.

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## ■ Demographics

- Age, Gender, Race, County, Insurance type, etc.

## ■ Diagnosis/Procedures performed

- Primary diagnosis, Principal procedure, Other diagnoses, etc.

## ■ Outcomes

- Disposition, Length of Stay, Total Charges, etc.

# Data - Challenges

hospital	diagnosis	gender	race	county	age	source	pay type	los	charge
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## ■ Masked Records

# Data - Challenges

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## ■ Missing Entries



# Data - Challenges

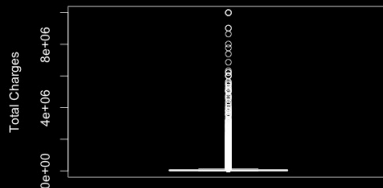
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- Highly Categorical: > 400 Hospitals,  $\approx$  13000 diagnosis codes

# Data - Challenges

hospital	diagnosis	gender	race	county	age	source	pay type	los	charge
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## ■ Large variance in Charges/Length of Stay



# Related Work

- Acute Burn Patients [Carbonell et. al. (2005)]
  - Mortality and Length of Stay
  
- Bariatric Surgery Outcomes [Peters et. al. (1996)]
  - Surgery results/recovery times
  
  
  
  
  
  
  
  
  
- In-Hospital Mortality for Severe Sepsis [Banta et. al. (2012)]

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## Records Dictated by Physicians

*Discharge status: Alive, but without permission.*

*The patient has no past history of suicides.*

*By the time he was admitted, his rapid heart had stopped and he was feeling better.*

# Problem 1: Inference/Insight Mining

- Three Counties: Los Angeles, San Francisco, Santa Clara

# Problem 1: Inference/Insight Mining

- Three Counties: Los Angeles, San Francisco, Santa Clara

Los Angeles                      Heart Failure                      Low Charges

○—————○—————○

San Francisco                      Heart Failure                      High Charges

○—————○—————○

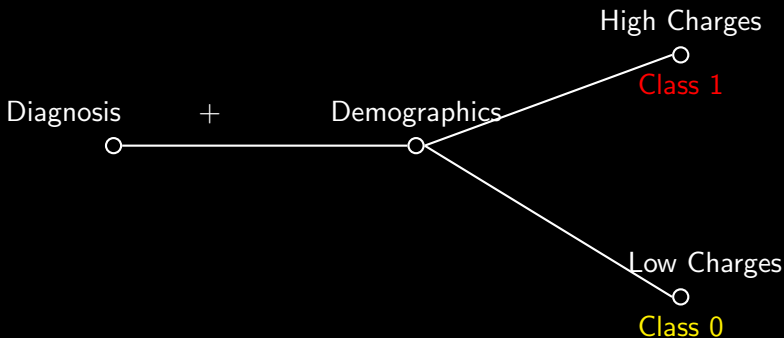
## Problem 2 - Predictions

- Predictions using demographic details
  - Charges
  - Length of Stay (LOS)



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- Predictions using demographic details
  - Charges
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# Diseases Studied

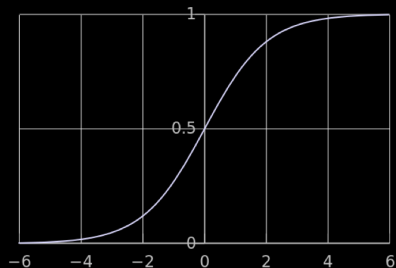
Life Threatening	Non-Life Threatening
Heart Disease	Hypertension
Cancer	Diabetes
Heart Failure	Cardiac Arrhythmia
	Mental Illness

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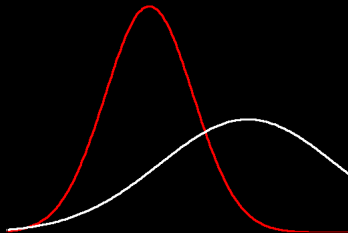
# Methods Used

## ■ Logistic Regression



# Methods Used

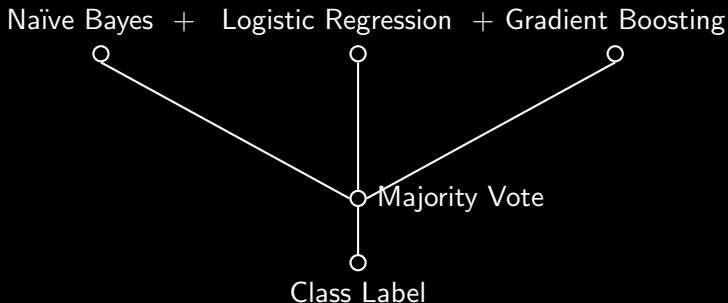
## ■ Naïve Bayes





# Methods Used

## ■ Ensemble



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- **Results**
  - Insights/Inferences
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# Results - Insights

## ■ Heart Failure Charges across Hospitals:

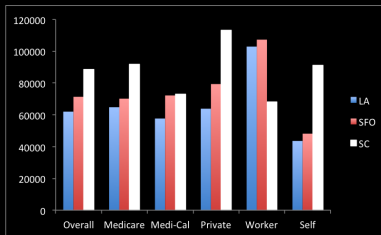
Hospital	Mean value of Charges (\$)
Overall mean	62,329
Cedars Sinai - LA	151,201
Centinela Hospital - LA	56,682
St Agnes - Bay Area	41,259

# Results - Insights

## ■ Heart Failures Per Capita

Los Angeles	Santa Clara	San Francisco
0.0074	0.0048	0.0070

## ■ Heart Failure - Insurance Payments



# Heart Failure Charge Predictions [Accuracy]

Model	% Accuracy	AUROC
Baseline	73.4	-
Demographics only	73	0.65
Naïve Bayes	79.5	0.79
Logistic Regression	79.7	0.79
Gradient Boosting	81.2	0.83
Ensemble	80.6	0.80

† AUROC : Area under ROC

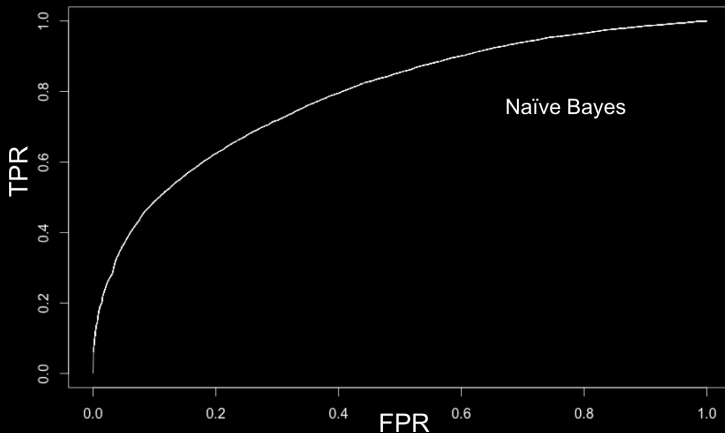
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# Heart Failure Charge Predictions [ROC Plots]

Class 0:  $\leq$  Mean

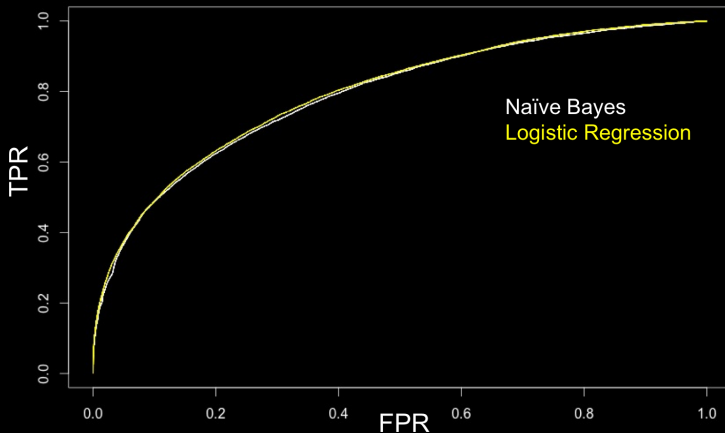
Class 1:  $>$  Mean



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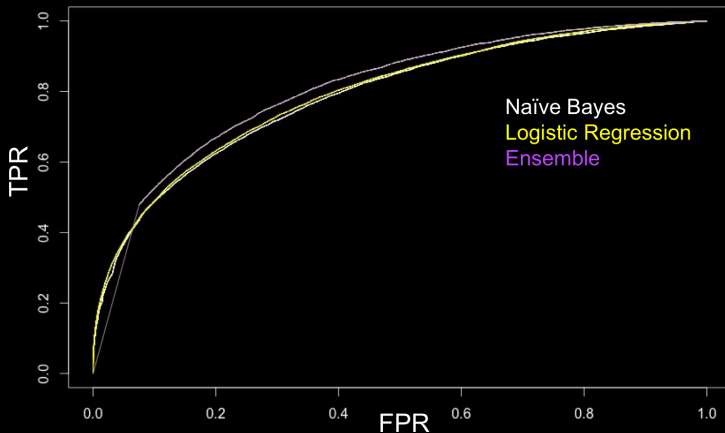
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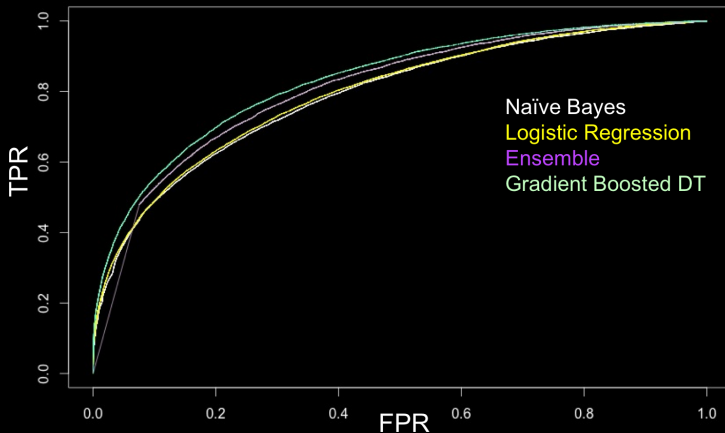
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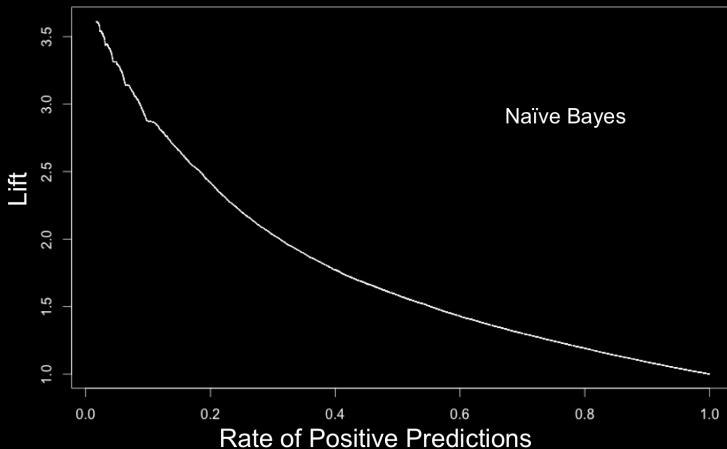




# Heart Failure Charge Predictions [Lift Charts]

Class 0:  $\leq$  Mean

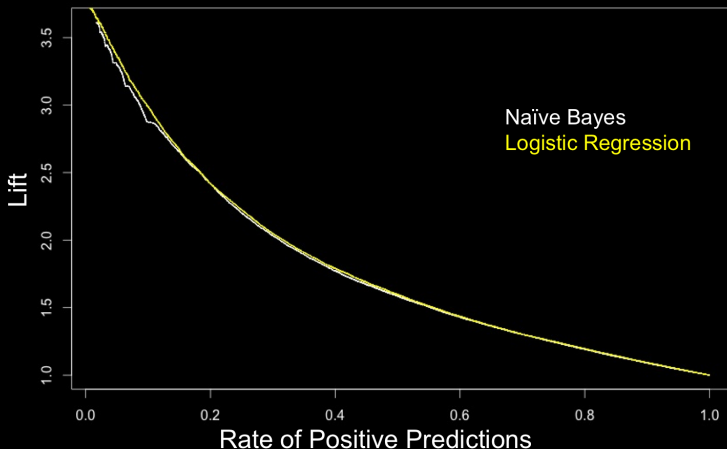
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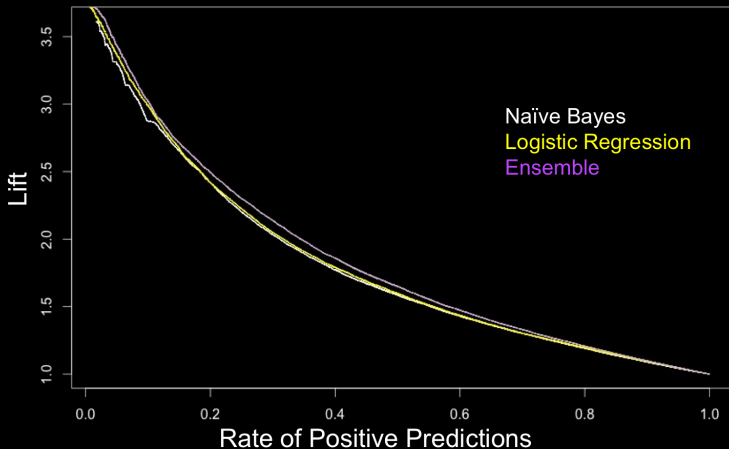
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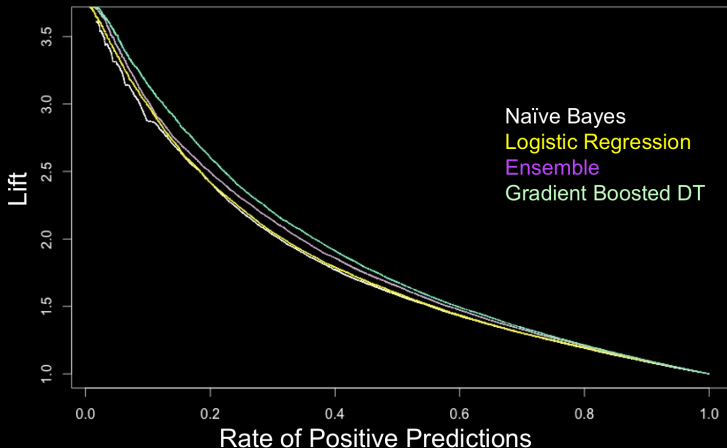
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# Heart Failure Charge Predictions [Lift Charts]

Class 0:  $\leq$  Mean

Class 1:  $>$  Mean



# Cardiac Arrhythmia Charge Predictions [Accuracy]

Model	% Accuracy	AUROC
Baseline	59.8	-
Naïve Bayes	65.5	0.70
Logistic Regression	67.9	0.69
Gradient Boosting	79.5	0.87
Ensemble	76	0.80

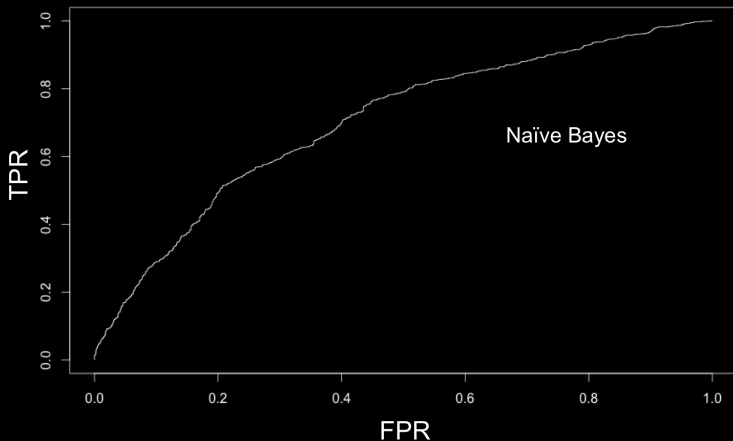
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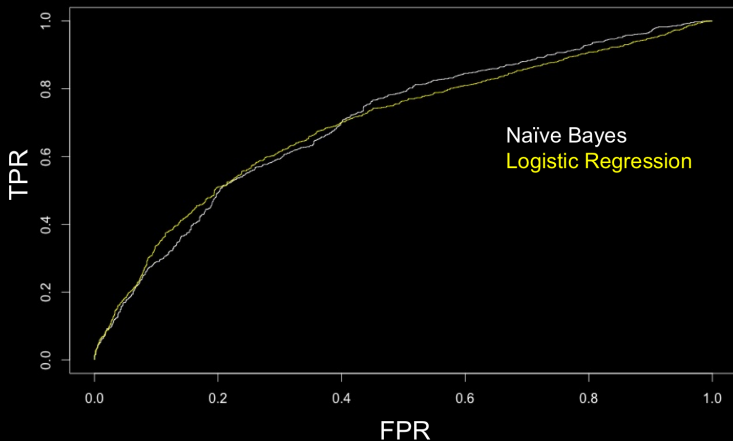
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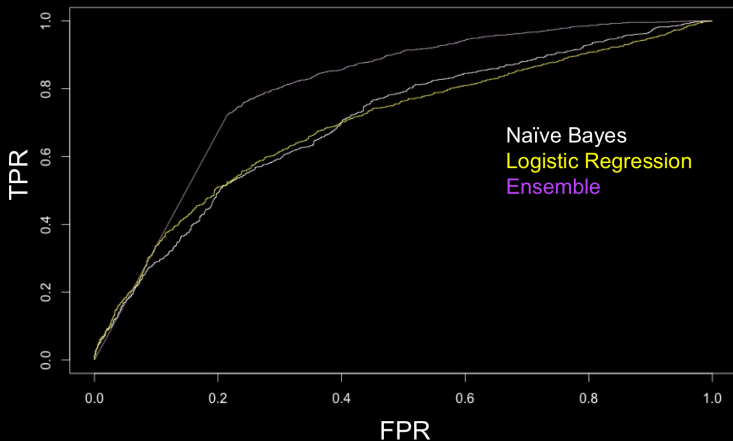




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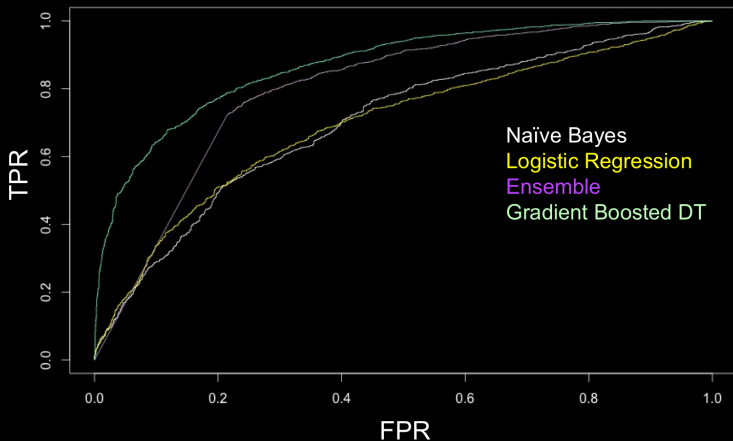
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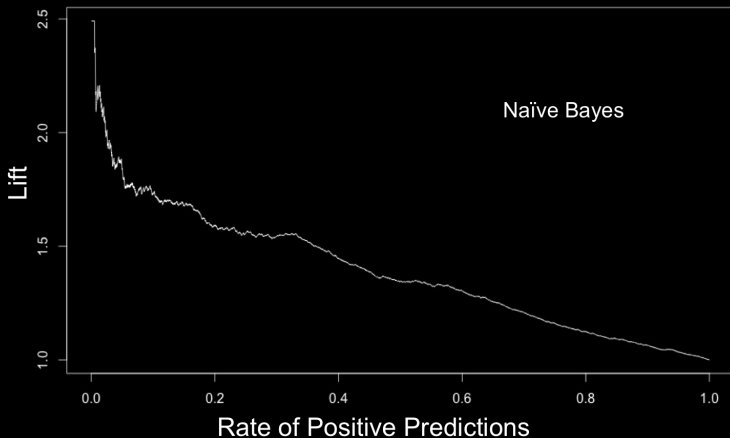
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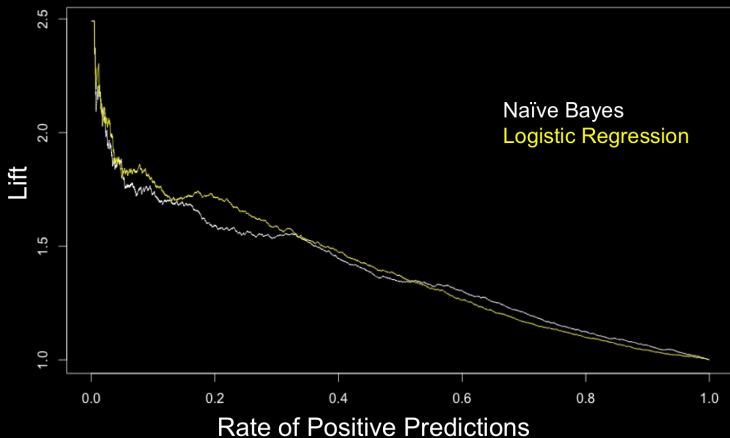
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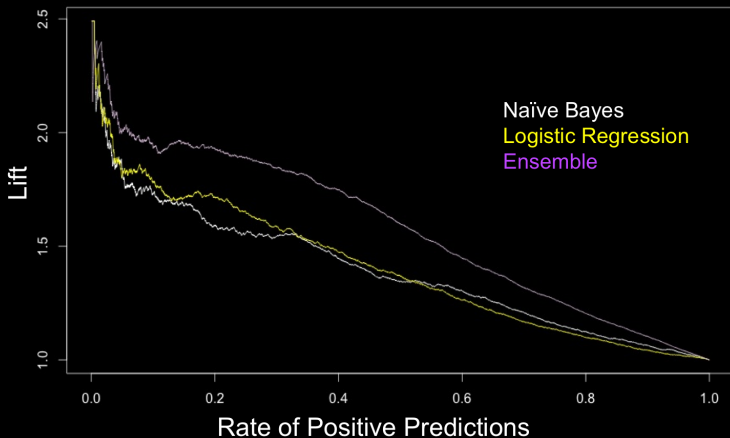
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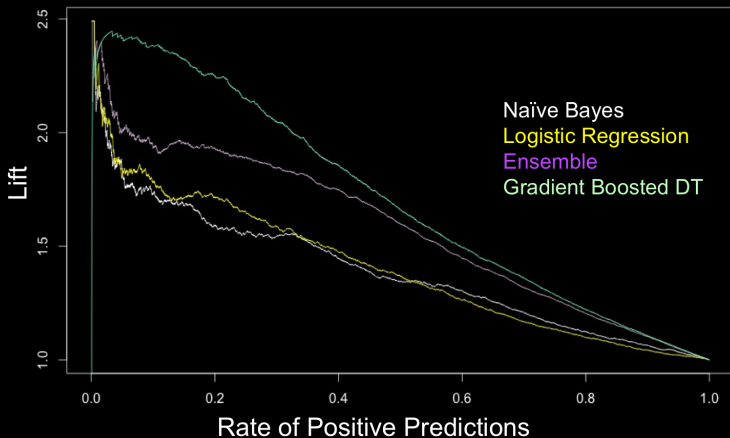
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# Conclusions

- Significant differences
  - Across locations
  - Among insurance types
- Predictions on Medical Outcomes
  - Hard problem without considering all medical details

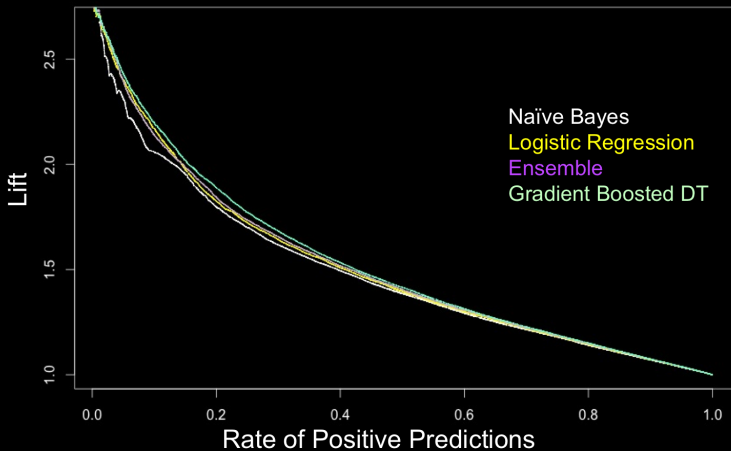


Questions?

Thanks!

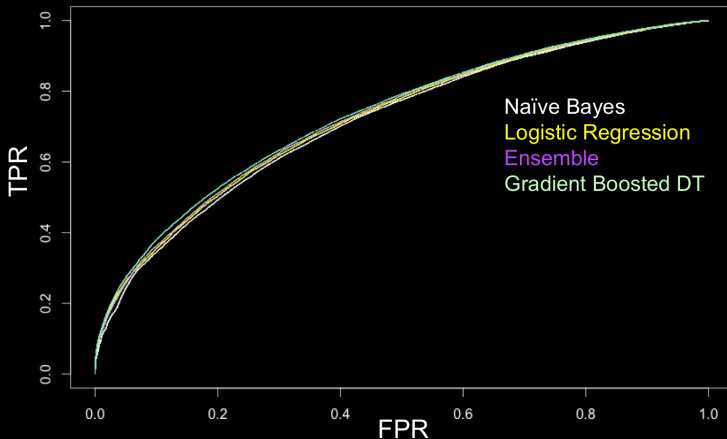
# Backup

## Heart Failure - LOS



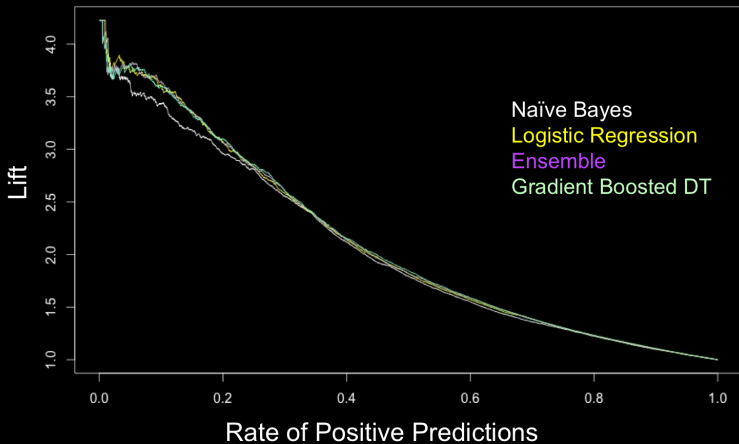
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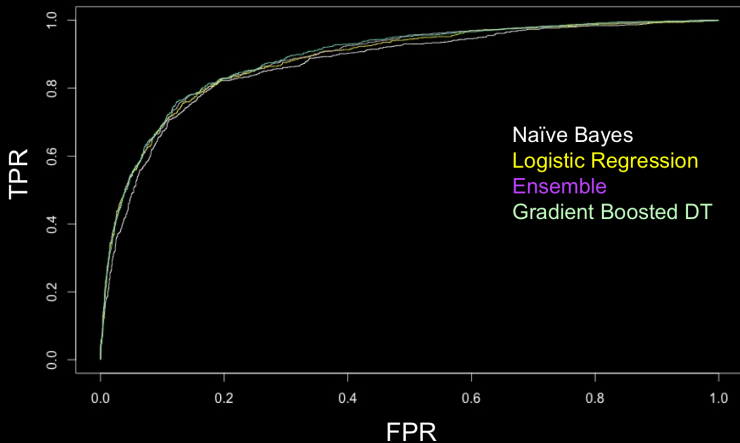
# Backup

## Cardiac Arrhythmia - LOS



# Backup

## Cardiac Arrhythmia - LOS



# Backup

Diabetes

Model	Accuracy	AUROC
Baseline	0.679	-
Naive Bayes	0.770	0.792
Logistic Regression	0.779	0.809
GBDT	0.787	0.818

# Backup

Diabetes

Model	Accuracy	AUROC
Baseline	0.716	-
Naïve Bayes	0.809	0.819
Logistic Regression	0.812	0.836
GBDT	0.828	0.863

# Backup

Cardiac Arrhythmia LOS

Model	Accuracy	AUROC
Baseline	0.763	-
Naïve Bayes	0.846	0.871
Logistic Regression	0.853	0.884
GBDT	0.857	0.890
Ensemble - Ave Prob	0.853	0.888



# Backup

Model	Accuracy	AUROC
Baseline	0.771	-
Naïve Bayes	0.807	0.795
Logistic Regression	0.814	0.807
GBDT	0.820	0.816

Hypertension

# Backup

Model	Accuracy	AUROC
Baseline	0.731	-
Naïve Bayes	0.805	0.821
Logistic Regression	0.810	0.835
GBDT	0.832	0.865

Hypertension

# Backup

Model	Accuracy	AUROC
Baseline	0.707	-
Naïve Bayes	0.765	0.749
Logistic Regression	0.775	0.773
GBDT	0.782	0.791

Prostate Cancer

# Backup

Model	Accuracy	AUROC
Baseline	0.659	-
Naïve Bayes	0.751	0.803
Logistic Regression	0.759	0.822
GBDT	0.792	0.855

Prostate Cancer

# Backup

Model	Accuracy	AUROC
Baseline	0.707	-
Naïve Bayes	0.690	0.608
Logistic Regression	0.713	0.630
GBDT	0.721	0.696

Schizophrenia

# Backup

Model	Accuracy	AUROC
Baseline	0.712	-
Naïve Bayes	0.712	0.644
Logistic Regression	0.729	0.668
GBDT	0.758	0.776

Schizophrenia