

# Heart Disease Detection

Metis Classification  
Project

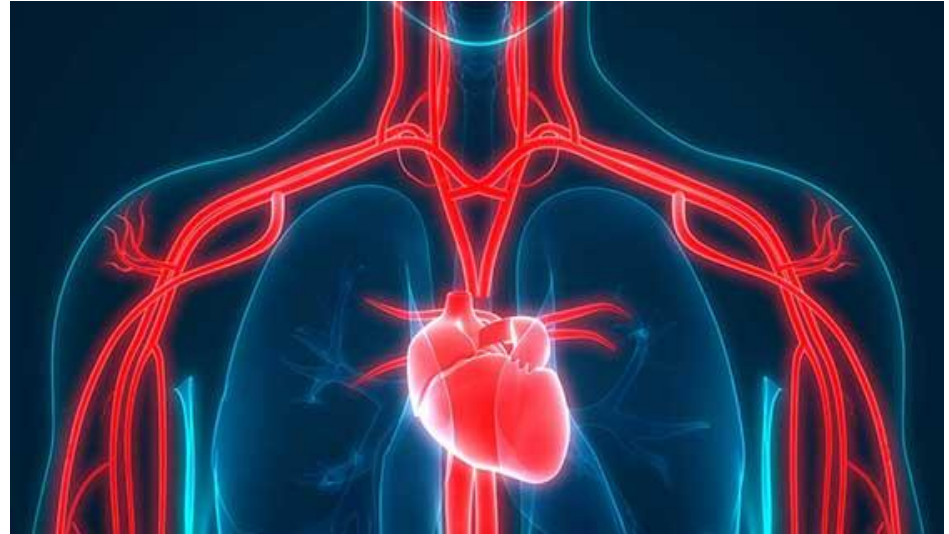
# Background

## GOALS

- Implement classification model to predict likelihood of heart disease or a heart attack based on other health and lifestyle characteristics
- Identify who to target for early detection and intervention
- Understand feature importance to inform screening

## DATA

- Obtained from [Kaggle](#)
- Comes originally from the [CDC](#)
- 21 different attributes for 253,680 individuals



# Learning the heart way

- Heart disease is the leading cause of death in the United States
- ~659,000 people in the United States die from heart disease each year
- Every 40 seconds an American will have a heart attack

<https://www.cdc.gov/heartdisease/facts.htm>

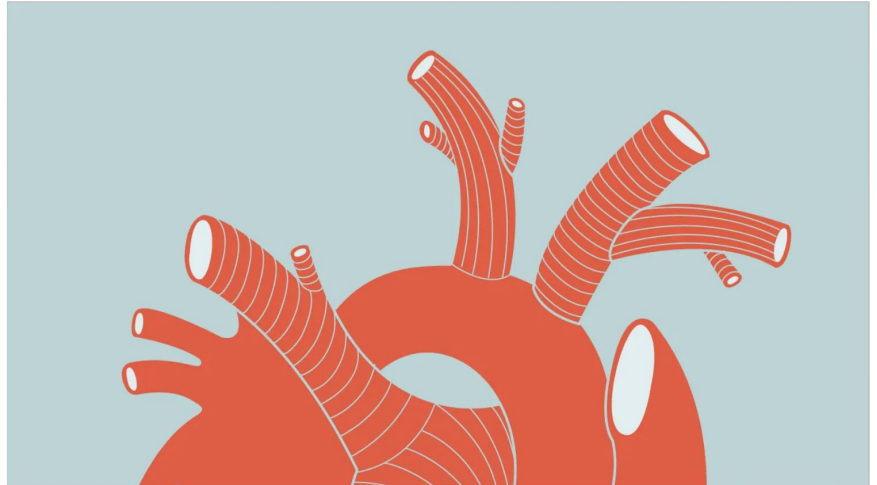
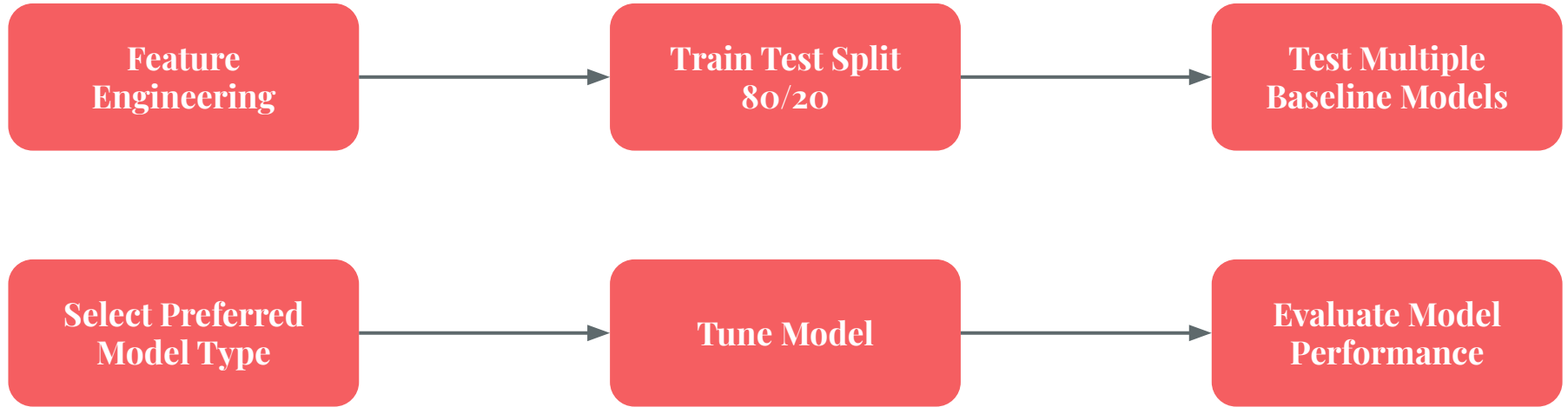


Illustration by Ruth Basagoitia and Maya Chastain

# Modeling Approach



# Features

- Heart disease or attack
- Cholesterol
- Cholesterol check
- BMI
- Smoker
- Stroke
- Diabetes
- Physical activity
- Fruits
- Vegetables
- Skipped doctor visit b/c cost
- Alcohol consumption
- Health care
- Difficulty walking
- Sex
- Age
- Education
- Income
- General health
- Mental health
- BP

# Baseline Model Comparison

Model	Neg Log Loss	Precision	Recall
Logistic Regression	-0.573144	0.439604	0.135823
Random Forest	-0.585770	0.430109	0.130722
XGB	-0.580914	0.450486	0.137719
KNN	-0.566398	0.449111	0.136477

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### Baseline Model

	precision	recall	f1-score	support
0.0	0.99	0.41	0.58	45957
1.0	0.15	0.97	0.25	4779
accuracy			0.46	50736
macro avg	0.57	0.69	0.42	50736
weighted avg	0.91	0.46	0.55	50736

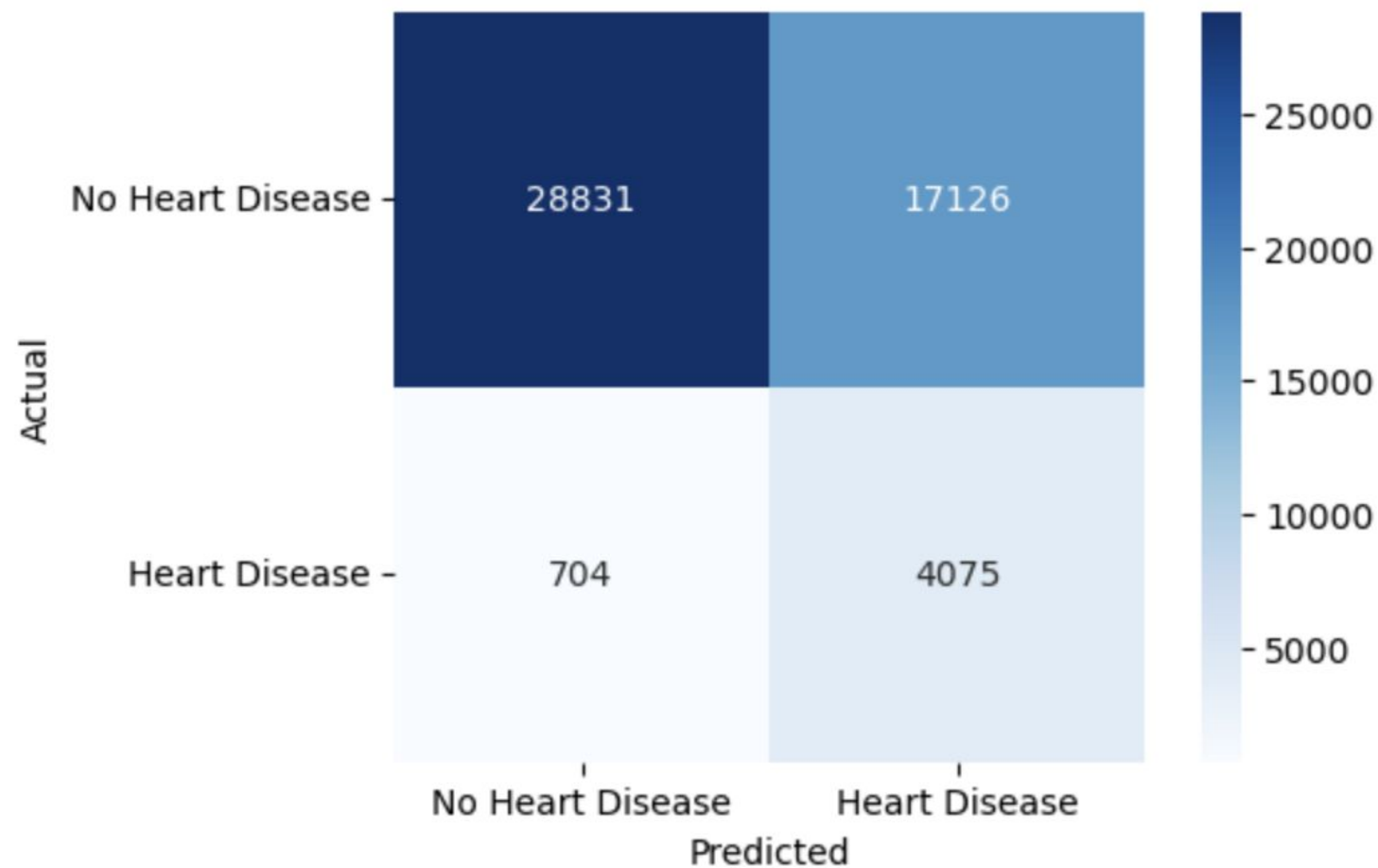
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### Tuned Model

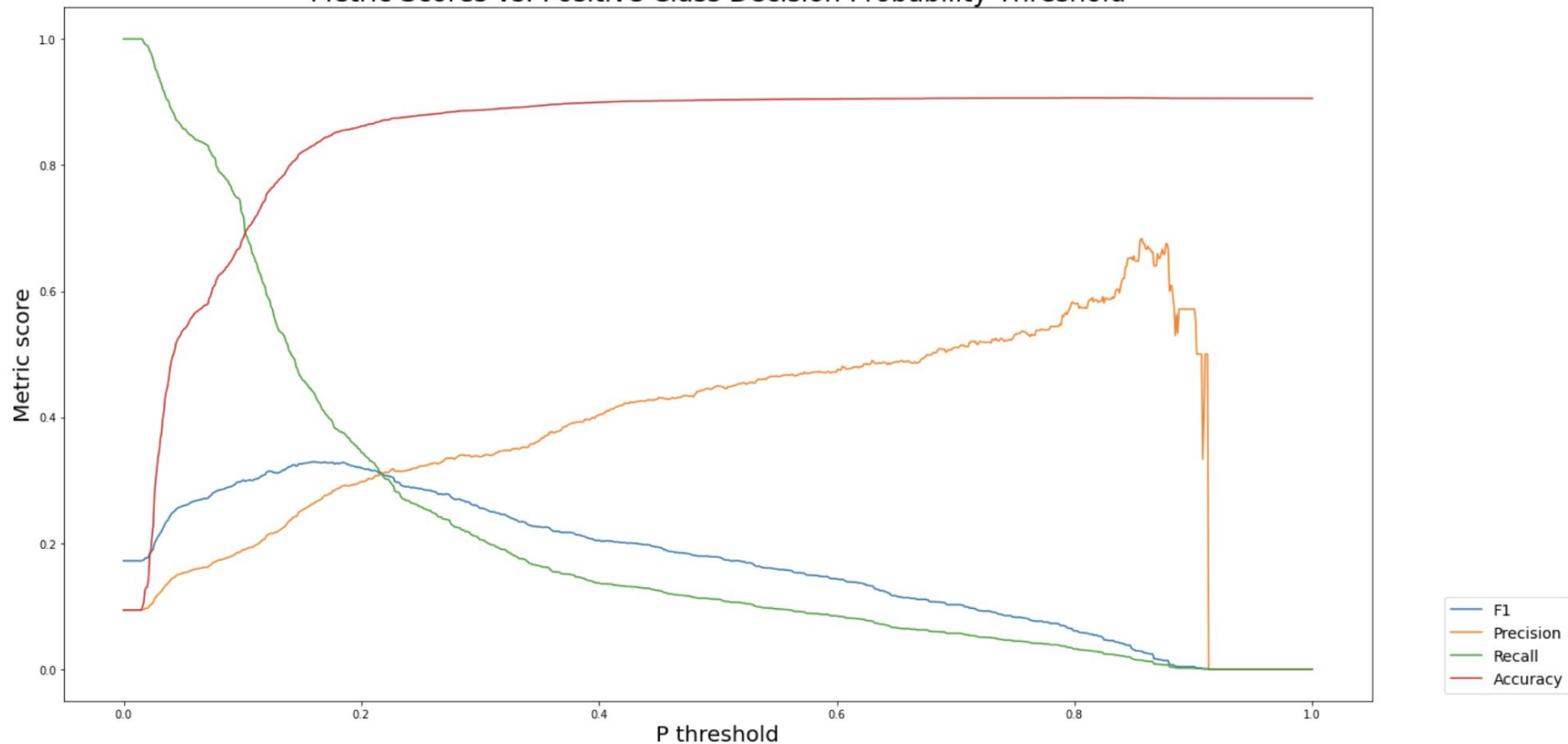
	precision	recall	f1-score	support
0.0	0.98	0.63	0.76	45957
1.0	0.19	0.85	0.31	4779
accuracy			0.65	50736
macro avg	0.58	0.74	0.54	50736
weighted avg	0.90	0.65	0.72	50736



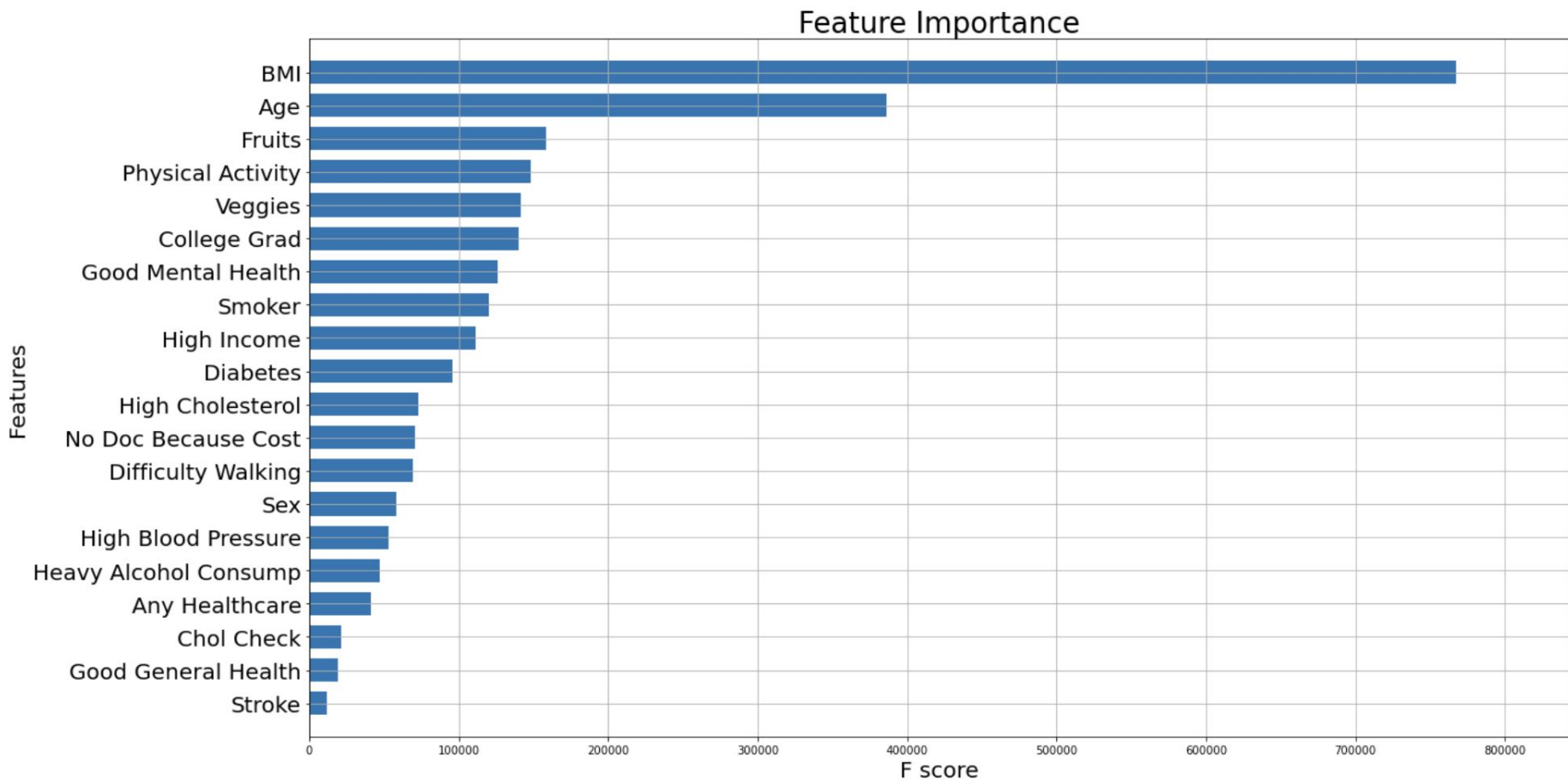
Confusion Martix



Metric Scores vs. Positive Class Decision Probability Threshold



Best F1 score 0.330 at decision threshold  $\geq 0.161$



# Conclusion

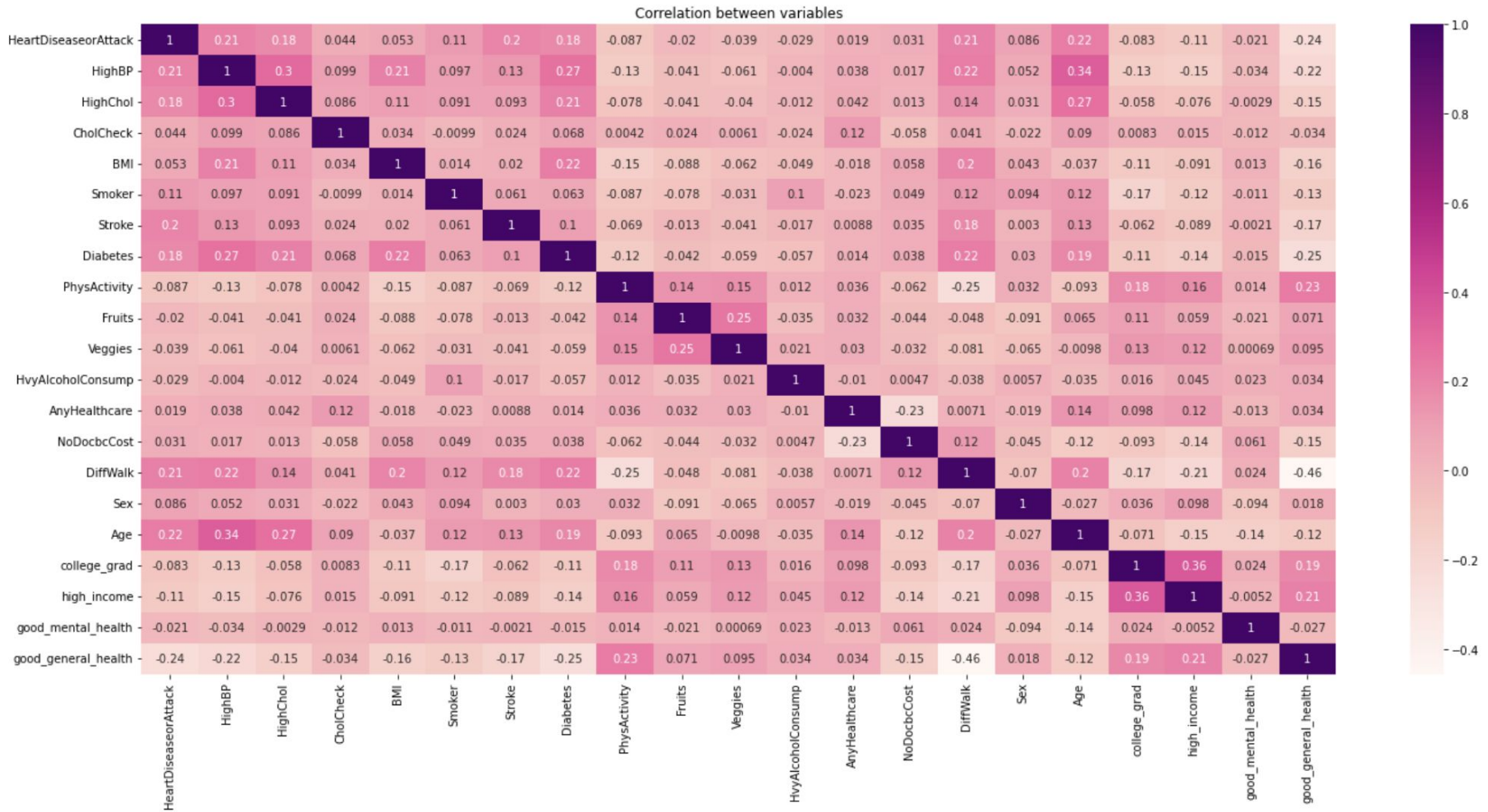
## KEY TAKEAWAYS

- BMI and age are key features
- Minimizing false negatives comes with the cost of increasing false positives

## NEXT STEPS

- Age for screening?
- Cost of a false positive vs a false negative?
- Could ensembling improve prediction performance?

# Appendix



```
1  #create dummy variable to indicate whether someone has a college degree
2  df['college_grad'] = (df['Education'] == 6).astype(int)
3
4  #create variable to indicate whether someone makes more than $50,000 annually
5  df['high_income'] = (df['Income'].isin([8,9]).astype(int))
6
7  #create variable to indicate whether people reported having poor mental health in more than 15 of the past 30 days
8  few_days = []
9  few_days.extend(range(1,15))
10 few_days.append(88)
11 df['good_mental_health'] = (df['MentHlth'].isin(few_days).astype(int)) #88 is "None"
12
13 #create variable to indicate whether people report health as good/very good/excellent (1) vs fair/poor (0)
14 df['good_general_health'] = (df['GenHlth'].isin([1,2,3]).astype(int))
15
```

y_test	rf and xgb agree	
0.0	True	30214
	False	15743
1.0	False	3319
	True	1460



	<b>variables</b>	<b>vif</b>
<b>0</b>	HighBP	2.302320
<b>1</b>	HighChol	2.033872
<b>2</b>	CholCheck	21.481795
<b>3</b>	BMI	16.239262
<b>4</b>	Smoker	1.933629
<b>5</b>	Stroke	1.104151
<b>6</b>	Diabetes	1.416915
<b>7</b>	PhysActivity	4.581396
<b>8</b>	Fruits	3.022398
<b>9</b>	Veggies	5.701816
<b>10</b>	HvyAlcoholConsump	1.082131
<b>11</b>	AnyHealthcare	19.026871
<b>12</b>	NoDocbcCost	1.168536
<b>13</b>	DiffWalk	1.687309
<b>14</b>	Sex	1.872135
<b>15</b>	Age	9.822311
<b>16</b>	college_grad	2.112582
<b>17</b>	high_income	1.953899
<b>18</b>	good_mental_health	1.309966
<b>19</b>	good_general_health	7.375602