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February 21, 2024

[4]:
```python
import os
os.getcwd()
os.chdir("C:\Data")
os.getcwd()
```

[4]: 'C:\\Data'

[5]:
```python
pip install skimpy
```

```
Requirement already satisfied: skimpy in c:\users\dylan\anaconda3\lib\site-
packages (0.0.5)
Requirement already satisfied: click==7.1.2 in
c:\users\dylan\anaconda3\lib\site-packages (from skimpy) (7.1.2)
Requirement already satisfied: pandas<2.0.0,>=1.3.2 in
c:\users\dylan\anaconda3\lib\site-packages (from skimpy) (1.3.4)
Requirement already satisfied: typeguard<3.0.0,>=2.12.1 in
c:\users\dylan\anaconda3\lib\site-packages (from skimpy) (2.13.3)
Requirement already satisfied: Pygments<3.0.0,>=2.10.0 in
c:\users\dylan\anaconda3\lib\site-packages (from skimpy) (2.10.0)
Requirement already satisfied: rich<11.0.0,>=10.9.0 in
c:\users\dylan\anaconda3\lib\site-packages (from skimpy) (10.16.2)
Requirement already satisfied: pytz>=2017.3 in
c:\users\dylan\anaconda3\lib\site-packages (from pandas<2.0.0,>=1.3.2->skimpy)
(2021.3)
Requirement already satisfied: numpy>=1.17.3 in
c:\users\dylan\anaconda3\lib\site-packages (from pandas<2.0.0,>=1.3.2->skimpy)
(1.20.3)
Requirement already satisfied: python-dateutil>=2.7.3 in
c:\users\dylan\anaconda3\lib\site-packages (from pandas<2.0.0,>=1.3.2->skimpy)
(2.8.2)
Requirement already satisfied: six>=1.5 in c:\users\dylan\anaconda3\lib\site-
packages (from python-dateutil>=2.7.3->pandas<2.0.0,>=1.3.2->skimpy) (1.16.0)
Requirement already satisfied: colorama<0.5.0,>=0.4.0 in
c:\users\dylan\anaconda3\lib\site-packages (from rich<11.0.0,>=10.9.0->skimpy)
(0.4.4)
Requirement already satisfied: commonmark<0.10.0,>=0.9.0 in
c:\users\dylan\anaconda3\lib\site-packages (from rich<11.0.0,>=10.9.0->skimpy)
(0.9.1)
```

Note: you may need to restart the kernel to use updated packages.

[6]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
import statsmodels.formula.api as smf
from patsy import dmatrix
from pyearth import Earth
from sklearn.metrics import (mean_squared_error, r2_score, roc_curve, auc,␣
↪precision_recall_curve, make_scorer,
                             recall_score, accuracy_score, precision_score,␣
↪confusion_matrix)
from sklearn.model_selection import (cross_val_score, train_test_split, KFold,␣
↪StratifiedKFold,
                                     GridSearchCV, ParameterGrid)
from sklearn.tree import DecisionTreeRegressor,DecisionTreeClassifier
from sklearn.ensemble import (BaggingRegressor, BaggingClassifier,␣
↪RandomForestRegressor, RandomForestClassifier,
                              GradientBoostingRegressor,␣
↪GradientBoostingClassifier, AdaBoostRegressor, AdaBoostClassifier,
                              VotingRegressor, VotingClassifier,␣
↪StackingRegressor, StackingClassifier)
from sklearn.linear_model import LinearRegression, LogisticRegression, LassoCV,␣
↪RidgeCV, ElasticNetCV
from sklearn.neighbors import KNeighborsRegressor
import itertools as it
import xgboost as xgb
import time as time
import random
from skimpy import clean_columns

#Libraries for visualizing trees
from sklearn.tree import export_graphviz
from six import StringIO
from IPython.display import Image
import pydotplus
```

1 Importing and Cleaning Data

[7]:
```
data = pd.read_csv('heart_2020_cleaned.csv')
data
```

[7]:
```
       HeartDisease    BMI Smoking AlcoholDrinking Stroke  PhysicalHealth  \
0                No  16.60     Yes              No     No             3.0
```

```
1                No  20.34      No               No     Yes            0.0
2                No  26.58     Yes               No      No           20.0
3                No  24.21      No               No      No            0.0
4                No  23.71      No               No      No           28.0
…               …    …     …             …    …            …
319790          Yes  27.41     Yes               No      No            7.0
319791           No  29.84     Yes               No      No            0.0
319792           No  24.24      No               No      No            0.0
319793           No  32.81      No               No      No            0.0
319794           No  46.56      No               No      No            0.0

        MentalHealth DiffWalking     Sex  AgeCategory      Race Diabetic  \
0               30.0          No  Female        55-59     White      Yes
1                0.0          No  Female  80 or older     White       No
2               30.0          No    Male        65-69     White      Yes
3                0.0          No  Female        75-79     White       No
4                0.0         Yes  Female        40-44     White       No
…                …         …     …        …        …      …
319790           0.0         Yes    Male        60-64  Hispanic      Yes
319791           0.0          No    Male        35-39  Hispanic       No
319792           0.0          No  Female        45-49  Hispanic       No
319793           0.0          No  Female        25-29  Hispanic       No
319794           0.0          No  Female  80 or older  Hispanic       No

       PhysicalActivity  GenHealth  SleepTime Asthma KidneyDisease SkinCancer
0                   Yes  Very good        5.0    Yes            No        Yes
1                   Yes  Very good        7.0     No            No         No
2                   Yes       Fair        8.0    Yes            No         No
3                    No       Good        6.0     No            No        Yes
4                   Yes  Very good        8.0     No            No         No
…                   …        …        …    …           …        …
319790               No       Fair        6.0    Yes            No         No
319791              Yes  Very good        5.0    Yes            No         No
319792              Yes       Good        6.0     No            No         No
319793               No       Good       12.0     No            No         No
319794              Yes       Good        8.0     No            No         No

[319795 rows x 18 columns]
```

[8]:
```python
print(data.isnull().values.any())
data.dtypes
```

```
False
```

[8]:
```
HeartDisease         object
BMI                 float64
Smoking              object
```

```
AlcoholDrinking      object
Stroke               object
PhysicalHealth      float64
MentalHealth        float64
DiffWalking          object
Sex                  object
AgeCategory          object
Race                 object
Diabetic             object
PhysicalActivity     object
GenHealth            object
SleepTime           float64
Asthma               object
KidneyDisease        object
SkinCancer           object
dtype: object
```

[9]:
```python
#convert age to numerical
import re
ages = list(data['AgeCategory'].unique())
ages = [re.findall(r'\d+', i) for i in ages]
ages = [[int(j) for j in i] for i in ages]
mean_ages = [np.array(i).mean() for i in ages]
ranges = data['AgeCategory'].unique()
d = {}
for i in range(len(mean_ages)):
    d[ranges[i]] = mean_ages[i]
print(d)
data['Age'] = data['AgeCategory'].apply(lambda x: d[x])
```

```
{'55-59': 57.0, '80 or older': 80.0, '65-69': 67.0, '75-79': 77.0, '40-44':
42.0, '70-74': 72.0, '60-64': 62.0, '50-54': 52.0, '45-49': 47.0, '18-24': 21.0,
'35-39': 37.0, '30-34': 32.0, '25-29': 27.0}
```

[10]:
```python
data.head()
```

[10]:
```
  HeartDisease    BMI Smoking AlcoholDrinking Stroke  PhysicalHealth  \
0           No  16.60     Yes              No     No             3.0
1           No  20.34      No              No    Yes             0.0
2           No  26.58     Yes              No     No            20.0
3           No  24.21      No              No     No             0.0
4           No  23.71      No              No     No            28.0

   MentalHealth DiffWalking     Sex  AgeCategory   Race Diabetic  \
0          30.0          No  Female        55-59  White      Yes
1           0.0          No  Female  80 or older  White       No
2          30.0          No    Male        65-69  White      Yes
```

```
3           0.0           No  Female        75-79  White       No
4           0.0          Yes  Female        40-44  White       No

  PhysicalActivity  GenHealth  SleepTime Asthma KidneyDisease SkinCancer   Age
0              Yes  Very good        5.0    Yes            No        Yes  57.0
1              Yes  Very good        7.0     No            No         No  80.0
2              Yes       Fair        8.0    Yes            No         No  67.0
3               No       Good        6.0     No            No        Yes  77.0
4              Yes  Very good        8.0     No            No         No  42.0
```

[11]:
```
pd.get_dummies(data).corr()['HeartDisease_Yes'].sort_values()
```

[11]:
```
HeartDisease_No                       -1.000000
DiffWalking_No                        -0.201258
Stroke_No                             -0.196835
Diabetic_No                           -0.170977
KidneyDisease_No                      -0.145197
GenHealth_Excellent                   -0.116042
Smoking_No                            -0.107764
GenHealth_Very good                   -0.101886
PhysicalActivity_Yes                  -0.100030
SkinCancer_No                         -0.093317
AgeCategory_18-24                     -0.075385
Sex_Female                            -0.070040
AgeCategory_35-39                     -0.066685
AgeCategory_25-29                     -0.065759
AgeCategory_30-34                     -0.065611
AgeCategory_40-44                     -0.059196
AgeCategory_45-49                     -0.049733
Asthma_No                             -0.041444
Race_Hispanic                         -0.036163
AgeCategory_50-54                     -0.032648
AlcoholDrinking_Yes                   -0.032080
Race_Asian                            -0.030262
Diabetic_Yes (during pregnancy)       -0.013930
AgeCategory_55-59                     -0.013276
Race_Black                            -0.010156
Race_Other                            -0.003039
SleepTime                              0.008327
Race_American Indian/Alaskan Native    0.008547
AgeCategory_60-64                      0.016152
Diabetic_No, borderline diabetes       0.016182
MentalHealth                           0.028591
AlcoholDrinking_No                     0.032080
GenHealth_Good                         0.039033
Race_White                             0.040121
Asthma_Yes                             0.041444
```

```
AgeCategory_65-69                        0.042626
BMI                                      0.051803
Sex_Male                                 0.070040
AgeCategory_70-74                        0.082578
SkinCancer_Yes                           0.093317
AgeCategory_75-79                        0.098690
PhysicalActivity_No                      0.100030
Smoking_Yes                              0.107764
AgeCategory_80 or older                  0.143041
KidneyDisease_Yes                        0.145197
GenHealth_Fair                           0.147954
PhysicalHealth                           0.170721
GenHealth_Poor                           0.174662
Diabetic_Yes                             0.183072
Stroke_Yes                               0.196835
DiffWalking_Yes                          0.201258
Age                                      0.231583
HeartDisease_Yes                         1.000000
Name: HeartDisease_Yes, dtype: float64
```

[12]:
```python
data_dum = data.drop(columns = ['SleepTime', 'AgeCategory'])
data_dum = pd.get_dummies(data_dum)
data_dum.columns
```

[12]:
```
Index(['BMI', 'PhysicalHealth', 'MentalHealth', 'Age', 'HeartDisease_No',
       'HeartDisease_Yes', 'Smoking_No', 'Smoking_Yes', 'AlcoholDrinking_No',
       'AlcoholDrinking_Yes', 'Stroke_No', 'Stroke_Yes', 'DiffWalking_No',
       'DiffWalking_Yes', 'Sex_Female', 'Sex_Male',
       'Race_American Indian/Alaskan Native', 'Race_Asian', 'Race_Black',
       'Race_Hispanic', 'Race_Other', 'Race_White', 'Diabetic_No',
       'Diabetic_No, borderline diabetes', 'Diabetic_Yes',
       'Diabetic_Yes (during pregnancy)', 'PhysicalActivity_No',
       'PhysicalActivity_Yes', 'GenHealth_Excellent', 'GenHealth_Fair',
       'GenHealth_Good', 'GenHealth_Poor', 'GenHealth_Very good', 'Asthma_No',
       'Asthma_Yes', 'KidneyDisease_No', 'KidneyDisease_Yes', 'SkinCancer_No',
       'SkinCancer_Yes'],
      dtype='object')
```

[13]:
```python
no_var = []

for col in list(pd.get_dummies(data_dum).columns):
    if col.endswith('_No'):
        no_var.append(col)

no_var
```

[13]:
```
['HeartDisease_No',
 'Smoking_No',
 'AlcoholDrinking_No',
 'Stroke_No',
 'DiffWalking_No',
 'Diabetic_No',
 'PhysicalActivity_No',
 'Asthma_No',
 'KidneyDisease_No',
 'SkinCancer_No']
```

[14]:
```
#reducing levels of categorical predictors
data_dum = data_dum.drop(columns = no_var)
data_dum = data_dum.drop(columns = ['Sex_Female', 'Race_American Indian/Alaskan␣
 ↪Native',
                                    'Race_Asian', 'Race_Black',␣
 ↪'Race_Hispanic', 'Race_Other',
                                    'Diabetic_No, borderline diabetes',␣
 ↪'Diabetic_Yes (during pregnancy)'])
data_dum.head()
```

[14]:
```
     BMI  PhysicalHealth  MentalHealth   Age  HeartDisease_Yes  Smoking_Yes  \
0  16.60             3.0          30.0  57.0                 0            1
1  20.34             0.0           0.0  80.0                 0            0
2  26.58            20.0          30.0  67.0                 0            1
3  24.21             0.0           0.0  77.0                 0            0
4  23.71            28.0           0.0  42.0                 0            0

   AlcoholDrinking_Yes  Stroke_Yes  DiffWalking_Yes  Sex_Male  …  \
0                    0           0                0         0  …
1                    0           1                0         0  …
2                    0           0                0         1  …
3                    0           0                0         0  …
4                    0           0                1         0  …

   Diabetic_Yes  PhysicalActivity_Yes  GenHealth_Excellent  GenHealth_Fair  \
0             1                     1                    0               0
1             0                     1                    0               0
2             1                     1                    0               1
3             0                     0                    0               0
4             0                     1                    0               0

   GenHealth_Good  GenHealth_Poor  GenHealth_Very good  Asthma_Yes  \
0               0               0                    1           1
1               0               0                    1           0
2               0               0                    0           1
3               1               0                    0           0
```

```
4              0              0                   1          0

   KidneyDisease_Yes  SkinCancer_Yes
0                  0               1
1                  0               0
2                  0               0
3                  0               1
4                  0               0

[5 rows x 21 columns]
```

[15]:
```python
#didn't end up using skimpy since that made everything lowercase
data_dum.columns = data_dum.columns.str.replace(' ', '_')
data_dum.columns
```

[15]:
```
Index(['BMI', 'PhysicalHealth', 'MentalHealth', 'Age', 'HeartDisease_Yes',
       'Smoking_Yes', 'AlcoholDrinking_Yes', 'Stroke_Yes', 'DiffWalking_Yes',
       'Sex_Male', 'Race_White', 'Diabetic_Yes', 'PhysicalActivity_Yes',
       'GenHealth_Excellent', 'GenHealth_Fair', 'GenHealth_Good',
       'GenHealth_Poor', 'GenHealth_Very_good', 'Asthma_Yes',
       'KidneyDisease_Yes', 'SkinCancer_Yes'],
      dtype='object')
```

[16]:
```python
#Balancing positive and negative responses
yes = data_dum[data_dum['HeartDisease_Yes'] == 1]
print(yes.shape)
yes.head()
```

```
(27373, 21)
```

[16]:
```
      BMI  PhysicalHealth  MentalHealth   Age  HeartDisease_Yes  Smoking_Yes  \
5   28.87             6.0           0.0  77.0                 1            1
10  34.30            30.0           0.0  62.0                 1            1
35  32.98            10.0           0.0  77.0                 1            1
42  25.06             0.0           0.0  80.0                 1            0
43  30.23             6.0           2.0  77.0                 1            1

    AlcoholDrinking_Yes  Stroke_Yes  DiffWalking_Yes  Sex_Male  …  \
5                     0           0                1         0  …
10                    0           0                1         1  …
35                    0           1                1         1  …
42                    0           0                1         0  …
43                    0           0                1         0  …

    Diabetic_Yes  PhysicalActivity_Yes  GenHealth_Excellent  GenHealth_Fair  \
5              0                     0                    0               1
10             1                     0                    0               0
```

```
35             1                      1                     0                0
42             1                      0                     0                0
43             1                      1                     0                1

    GenHealth_Good  GenHealth_Poor  GenHealth_Very_good  Asthma_Yes  \
5                0               0                    0           0
10               0               1                    0           1
35               0               1                    0           0
42               1               0                    0           0
43               0               0                    0           0

    KidneyDisease_Yes  SkinCancer_Yes
5                   0               0
10                  0               0
35                  0               1
42                  0               1
43                  1               0

[5 rows x 21 columns]
```

[17]:

```
no = data_dum[data_dum['HeartDisease_Yes'] == 0]
print(no.shape)
no = no.sample(n = 27373)
print(no.shape)
no.head()
```

```
(292422, 21)
(27373, 21)
```

[17]:

```
          BMI  PhysicalHealth  MentalHealth   Age  HeartDisease_Yes  \
241662  36.61             0.0          30.0  47.0                 0
119618  27.89             0.0           0.0  42.0                 0
5352    27.44             0.0           3.0  67.0                 0
29156   19.97             3.0           0.0  32.0                 0
243296  45.19             0.0          15.0  32.0                 0

        Smoking_Yes  AlcoholDrinking_Yes  Stroke_Yes  DiffWalking_Yes  \
241662            1                    0           0                0
119618            1                    0           0                0
5352              1                    0           0                0
29156             0                    0           0                1
243296            1                    0           0                1

        Sex_Male  …  Diabetic_Yes  PhysicalActivity_Yes  \
241662         0  …             0                     1
119618         1  …             0                     1
5352           0  …             0                     1
```

```
29156          0  ...           0                     0
243296         0  ...           0                     1

        GenHealth_Excellent  GenHealth_Fair  GenHealth_Good  GenHealth_Poor  \
241662                    0               0               1               0
119618                    0               0               1               0
5352                      0               0               1               0
29156                     0               1               0               0
243296                    0               0               1               0

        GenHealth_Very_good  Asthma_Yes  KidneyDisease_Yes  SkinCancer_Yes
241662                    0           0                  0               0
119618                    0           0                  0               0
5352                      0           0                  0               0
29156                     0           1                  0               0
243296                    0           1                  0               0

[5 rows x 21 columns]
```

[18]:
```python
data_balanced = pd.concat([no, yes], ignore_index = True)
print(data_balanced.shape)
data_balanced.head()
```

```
(54746, 21)
```

[18]:
```
     BMI  PhysicalHealth  MentalHealth   Age  HeartDisease_Yes  Smoking_Yes  \
0  36.61             0.0          30.0  47.0                 0            1
1  27.89             0.0           0.0  42.0                 0            1
2  27.44             0.0           3.0  67.0                 0            1
3  19.97             3.0           0.0  32.0                 0            0
4  45.19             0.0          15.0  32.0                 0            1

   AlcoholDrinking_Yes  Stroke_Yes  DiffWalking_Yes  Sex_Male  ...  \
0                    0           0                0         0  ...
1                    0           0                0         1  ...
2                    0           0                0         0  ...
3                    0           0                1         0  ...
4                    0           0                1         0  ...

   Diabetic_Yes  PhysicalActivity_Yes  GenHealth_Excellent  GenHealth_Fair  \
0             0                     1                    0               0
1             0                     1                    0               0
2             0                     1                    0               0
3             0                     0                    0               1
4             0                     1                    0               0

   GenHealth_Good  GenHealth_Poor  GenHealth_Very_good  Asthma_Yes  \
```

```
0                1                0                     0            0
1                1                0                     0            0
2                1                0                     0            0
3                0                0                     0            1
4                1                0                     0            1

   KidneyDisease_Yes  SkinCancer_Yes
0                  0               0
1                  0               0
2                  0               0
3                  0               0
4                  0               0

[5 rows x 21 columns]
```

[19]:
```
X = data_balanced.drop(columns = 'HeartDisease_Yes')
X.head()
```

[19]:
```
     BMI  PhysicalHealth  MentalHealth   Age  Smoking_Yes  \
0  36.61             0.0          30.0  47.0            1
1  27.89             0.0           0.0  42.0            1
2  27.44             0.0           3.0  67.0            1
3  19.97             3.0           0.0  32.0            0
4  45.19             0.0          15.0  32.0            1

   AlcoholDrinking_Yes  Stroke_Yes  DiffWalking_Yes  Sex_Male  Race_White  \
0                    0           0                0         0           1
1                    0           0                0         1           0
2                    0           0                0         0           0
3                    0           0                1         0           1
4                    0           0                1         0           0

   Diabetic_Yes  PhysicalActivity_Yes  GenHealth_Excellent  GenHealth_Fair  \
0             0                     1                    0               0
1             0                     1                    0               0
2             0                     1                    0               0
3             0                     0                    0               1
4             0                     1                    0               0

   GenHealth_Good  GenHealth_Poor  GenHealth_Very_good  Asthma_Yes  \
0               1               0                    0           0
1               1               0                    0           0
2               1               0                    0           0
3               0               0                    0           1
4               1               0                    0           1

   KidneyDisease_Yes  SkinCancer_Yes
```

```
0                   0               0
1                   0               0
2                   0               0
3                   0               0
4                   0               0
```

[20]:
```
y = data_balanced.HeartDisease_Yes
y.head()
```

[20]:
```
0    0
1    0
2    0
3    0
4    0
Name: HeartDisease_Yes, dtype: uint8
```

[21]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 4000,␣
 ↪test_size = 1000, random_state = 1, stratify = y)
X_train2, X_test2, y_train2, y_test2 = train_test_split(X, y, train_size =␣
 ↪4000, test_size = 1000, random_state = 2, stratify = y)
```

[22]:
```
#Checking to make sure responses are still balanced
print(y_train.value_counts())
print(y_test.value_counts())
print(y_train2.value_counts())
print(y_test2.value_counts())
```

```
0    2000
1    2000
Name: HeartDisease_Yes, dtype: int64
0    500
1    500
Name: HeartDisease_Yes, dtype: int64
0    2000
1    2000
Name: HeartDisease_Yes, dtype: int64
0    500
1    500
Name: HeartDisease_Yes, dtype: int64
```

[23]:
```
#Checking if X_train and X_train2 overlap
np.unique([X_train.index.values == X_train2.index.values], return_counts = True)
```

[23]:
```
(array([False]), array([4000], dtype=int64))
```

[24]:
```
X_train.head()
```

[24]:

```
         BMI  PhysicalHealth  MentalHealth   Age  Smoking_Yes  \
16548  30.34             0.0           0.0  67.0            0
1305   25.83             0.0           0.0  72.0            1
8061   23.71             0.0           0.0  77.0            0
20173  32.93            20.0           3.0  62.0            1
44566  24.11             0.0           0.0  77.0            1

       AlcoholDrinking_Yes  Stroke_Yes  DiffWalking_Yes  Sex_Male  Race_White  \
16548                    0           0                0         0           1
1305                     0           0                0         1           1
8061                     0           0                0         1           1
20173                    0           0                1         0           1
44566                    0           0                0         1           1

       Diabetic_Yes  PhysicalActivity_Yes  GenHealth_Excellent  \
16548             0                     1                    1
1305              0                     1                    1
8061              0                     1                    0
20173             1                     0                    0
44566             1                     1                    0

       GenHealth_Fair  GenHealth_Good  GenHealth_Poor  GenHealth_Very_good  \
16548               0               0               0                    0
1305                0               0               0                    0
8061                0               1               0                    0
20173               1               0               0                    0
44566               1               0               0                    0

       Asthma_Yes  KidneyDisease_Yes  SkinCancer_Yes
16548           0                  0               0
1305            0                  0               0
8061            0                  0               1
20173           0                  0               0
44566           0                  0               0
```

2 Functions

[25]:

```
#Function to compute confusion matrix and prediction accuracy on test/train␣
↪data using tree models
def confusion_matrix_data(data,actual_values,model,cutoff=0.5):
#Predict the values using the Logit model
    pred_values = model.predict_proba(data)[:,1]
# Specify the bins
    bins=np.array([0,cutoff,1])
#Confusion matrix
    cm = np.histogram2d(actual_values, pred_values, bins=bins)[0]
```

```
    cm_df = pd.DataFrame(cm)
    cm_df.columns = ['Predicted 0','Predicted 1']
    cm_df = cm_df.rename(index={0: 'Actual 0',1:'Actual 1'})
# Calculate the accuracy
    accuracy = 100*(cm[0,0]+cm[1,1])/cm.sum()
    fnr = 100*(cm[1,0])/(cm[1,0]+cm[1,1])
    precision = 100*(cm[1,1])/(cm[0,1]+cm[1,1])
    fpr = 100*(cm[0,1])/(cm[0,0]+cm[0,1])
    tpr = 100*(cm[1,1])/(cm[1,0]+cm[1,1])
    print("Accuracy = ", accuracy)
    print("Precision = ", precision)
    print("FNR = ", fnr)
#    print("FPR = ", fpr)
    print("TPR or Recall = ", tpr)
    print("Confusion matrix = \n", cm_df)
    return (" ")
```

[26]:
```
def plot_precision_recall_vs_threshold(precisions, recalls, thresholds):
    plt.figure(figsize = (8, 8))
    plt.title('Precision and Recall Scores as a function of the decision␣
 ↪threshold')
    plt.plot(thresholds, precisions[:-1], 'b--', label = 'Precision')
    plt.plot(thresholds, recalls[:-1], 'g-', label = 'Recall')
    plt.ylabel('Score')
    plt.xlabel('Decision Threshold')
    plt.legend(loc = 'best')
```

[27]:
```
def ols_formula(df, dependent_var):
    df_columns = list(df.columns.values)
    df_columns.remove(dependent_var)
    return dependent_var + ' ~ ' + ' + '.join(df_columns)
```

[28]:
```
def confusion_matrix_train(model, cutoff = 0.5):
    # Confusion matrix
    cm_df = pd.DataFrame(model.pred_table(threshold = cutoff))
    #Formatting the confusion matrix
    cm_df.columns = ['Predicted 0', 'Predicted 1']
    cm_df = cm_df.rename(index={0: 'Actual 0',1: 'Actual 1'})
    cm = np.array(cm_df)
    # Calculate the accuracy
    accuracy = 100*(cm[0,0]+cm[1,1])/cm.sum()
    fnr = 100*(cm[1,0])/(cm[1,0]+cm[1,1])
    precision = 100*(cm[1,1])/(cm[0,1]+cm[1,1])
    fpr = 100*(cm[0,1])/(cm[0,0]+cm[0,1])
    tpr = 100*(cm[1,1])/(cm[1,0]+cm[1,1])
    print("Accuracy = ", accuracy)
    print("Precision = ", precision)
```

```
    print("FNR = ", fnr)
    #print("FPR = ", fpr)
    print("TPR or Recall = ", tpr)
    print("Confusion matrix = \n", cm_df)
    return (" ")
    return cm_df, accuracy
```

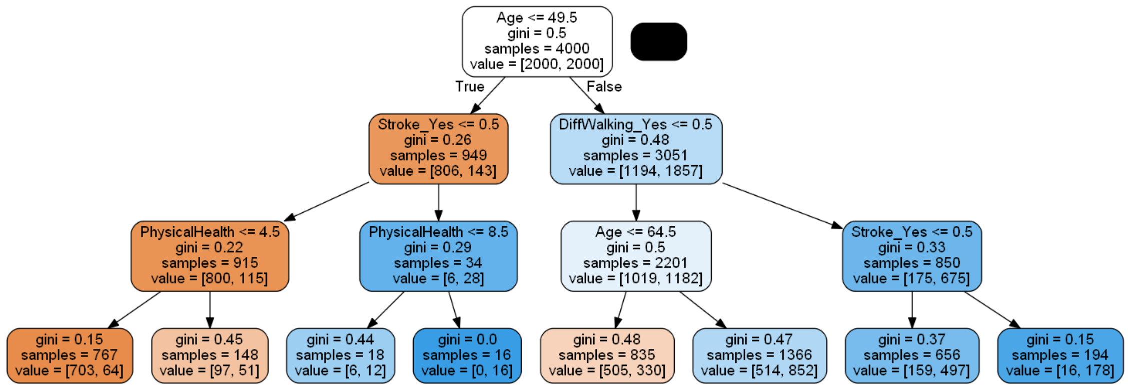
[29]:
```
#Function to compute confusion matrix and prediction accuracy on test data
def confusion_matrix_test(data,actual_values,model,cutoff=0.5): #Predict the␣
↪values using the Logit model
    pred_values = model.predict(data) # Specify the bins
    bins=np.array([0,cutoff,1]) #Confusion matrix
    cm = np.histogram2d(actual_values, pred_values, bins=bins)[0]
    cm_df = pd.DataFrame(model.pred_table(threshold = cutoff))
    cm_df.columns = ['Predicted 0','Predicted 1']
    cm_df = cm_df.rename(index={0: 'Actual 0',1:'Actual 1'})
    # Calculate the accuracy
    accuracy = 100*(cm[0,0]+cm[1,1])/cm.sum() # Return the confusion matrix and␣
↪the accuracy
    fnr = 100*(cm[1,0])/(cm[1,0]+cm[1,1])
    precision = 100*(cm[1,1])/(cm[0,1]+cm[1,1])
    fpr = 100*(cm[0,1])/(cm[0,0]+cm[0,1])
    tpr = 100*(cm[1,1])/(cm[1,0]+cm[1,1])
    print("Accuracy = ", accuracy)
    print("Precision = ", precision)
    print("FNR = ", fnr)
    #print("FPR = ", fpr)
    print("TPR or Recall = ", tpr)
    print("Confusion matrix = \n", cm_df)
    return (" ")
```

3 Classification Tree

[34]:
```
#Defining the object to build a regression tree
model = DecisionTreeClassifier(random_state=1, max_depth=3)

#Fitting the regression tree to the data
model.fit(X_train, y_train)

#Visualizing the regression tree
dot_data = StringIO()
export_graphviz(model, out_file=dot_data,
filled=True, rounded=True,
feature_names = X_train.columns,precision=2)
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
#graph.write_png('car_price_tree.png')
```

```
Image(graph.create_png())
```

[34]:



[35]:
```
pred=model.predict_proba(X_test)[:,0]
confusion_matrix_data(X_train,y_train,model,cutoff=0.4)
```

```
Accuracy =  71.5
Precision =  69.11111111111111
FNR =  22.25
TPR or Recall =  77.75
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0       1305.0        695.0
Actual 1        445.0       1555.0
```

[35]: ' '

[39]:
```
#Defining parameters and the range of values over which to optimize
param_grid = {
'max_depth': range(1,10),
'max_leaf_nodes': range(10,30),
}

skf = StratifiedKFold(n_splits=5)
#The folds are made by preserving the percentage of samples for each class.
#Minimizing FNR is equivalent to maximizing recall
grid_search = GridSearchCV(DecisionTreeClassifier(random_state=1), param_grid,
                           scoring=['precision','recall','accuracy'],
                           refit="recall", cv=skf, n_jobs=-1, verbose = True)
grid_search.fit(X_train, y_train)
# make the predictions
y_pred = grid_search.predict(X_test)
print('Best params for recall')
print(grid_search.best_params_)
```

```
Fitting 5 folds for each of 180 candidates, totalling 900 fits
Best params for recall
{'max_depth': 2, 'max_leaf_nodes': 10}
```

[46]:

```
#All results of the grid search can be seen with cv_results_
cv_scores = pd.DataFrame(grid_search.cv_results_)

model = DecisionTreeClassifier(random_state=1, max_depth = 5, max_leaf_nodes=25)
model.fit(X_train,y_train)
print(confusion_matrix_data(X_train,y_train,model))
print(confusion_matrix_data(X_test,y_test,model))
print(confusion_matrix_data(X_train,y_train,model,cutoff=0.2))
print(confusion_matrix_data(X_test,y_test,model,cutoff=0.2))
```

```
Accuracy =  74.2
Precision =  72.83018867924528
FNR =  22.8
TPR or Recall =  77.2
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0       1424.0        576.0
Actual 1        456.0       1544.0

Accuracy =  72.5
Precision =  70.49180327868852
FNR =  22.6
TPR or Recall =  77.4
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0        338.0        162.0
Actual 1        113.0        387.0

Accuracy =  65.925
Precision =  59.77293648358392
FNR =  2.6
TPR or Recall =  97.4
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0        689.0       1311.0
Actual 1         52.0       1948.0

Accuracy =  66.5
Precision =  60.19777503090235
FNR =  2.6
TPR or Recall =  97.4
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0        178.0        322.0
```

```
Actual 1         13.0        487.0
```

[56]:
```python
clf = DecisionTreeClassifier(random_state=1)
param_grid = {
'max_depth': range(1,10),
'max_leaf_nodes': range(10,30),
'max_features': range(3,8)
}

refit_score = "roc_auc"

skf = StratifiedKFold(n_splits=5)
grid_search = GridSearchCV(clf,␣
 ↪param_grid,scoring=['precision','recall','accuracy','roc_auc'],
                           refit=refit_score,cv=skf, n_jobs=-1, verbose = True)
grid_search.fit(X_train, y_train)

# make the predictions
y_pred = grid_search.predict(X_test)

print('Best params for', refit_score)
print(grid_search.best_params_)
```

```
Fitting 5 folds for each of 900 candidates, totalling 4500 fits
Best params for roc_auc
{'max_depth': 7, 'max_features': 5, 'max_leaf_nodes': 28}
```

[57]:
```python
model = DecisionTreeClassifier(random_state=1, max_depth = 7, max_leaf_nodes =␣
 ↪28, max_features = 5)
model.fit(X_train,y_train)
print(confusion_matrix_data(X_train,y_train,model))
print(confusion_matrix_data(X_test,y_test,model))
print(confusion_matrix_data(X_train,y_train,model,cutoff=0.2))
print(confusion_matrix_data(X_test,y_test,model,cutoff=0.2))
```

```
Accuracy =  75.425
Precision =  72.8744939271255
FNR =  19.0
TPR or Recall =  81.0
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0       1397.0        603.0
Actual 1        380.0       1620.0

Accuracy =  74.1
Precision =  71.63375224416517
FNR =  20.2
```

```
TPR or Recall =  79.8
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0        342.0        158.0
Actual 1        101.0        399.0

Accuracy =  66.725
Precision =  60.44985941893158
FNR =  3.25
TPR or Recall =  96.75
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0        734.0       1266.0
Actual 1         65.0       1935.0

Accuracy =  67.3
Precision =  61.10397946084724
FNR =  4.8
TPR or Recall =  95.2
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0        197.0        303.0
Actual 1         24.0        476.0
```

[36]:
```
model = DecisionTreeClassifier(random_state = 1)#model without any restrictions
path= model.cost_complexity_pruning_path(X_train,y_train)# Compute the pruning␣
 ↪path during Minimal Cost-Complexity Pruning.
alphas=path['ccp_alphas']
len(alphas)
```

[36]: 408

[58]:
```
#Grid search to optimize parameter values
param_grid = {
'ccp_alpha':alphas,
}

skf = StratifiedKFold(n_splits=5)
grid_search = GridSearchCV(DecisionTreeClassifier(random_state = 1), param_grid,
                                                 ␣
 ↪scoring=['precision','recall','accuracy'],
                                                  refit="recall", cv=skf,␣
 ↪n_jobs=-1, verbose = True)
grid_search.fit(X_train, y_train)

# make the predictions
```

```
y_pred = grid_search.predict(X_test)

print('Best params for recall')
print(grid_search.best_params_)
```

```
Fitting 5 folds for each of 408 candidates, totalling 2040 fits
Best params for recall
{'ccp_alpha': 0.020264403994903202}
```

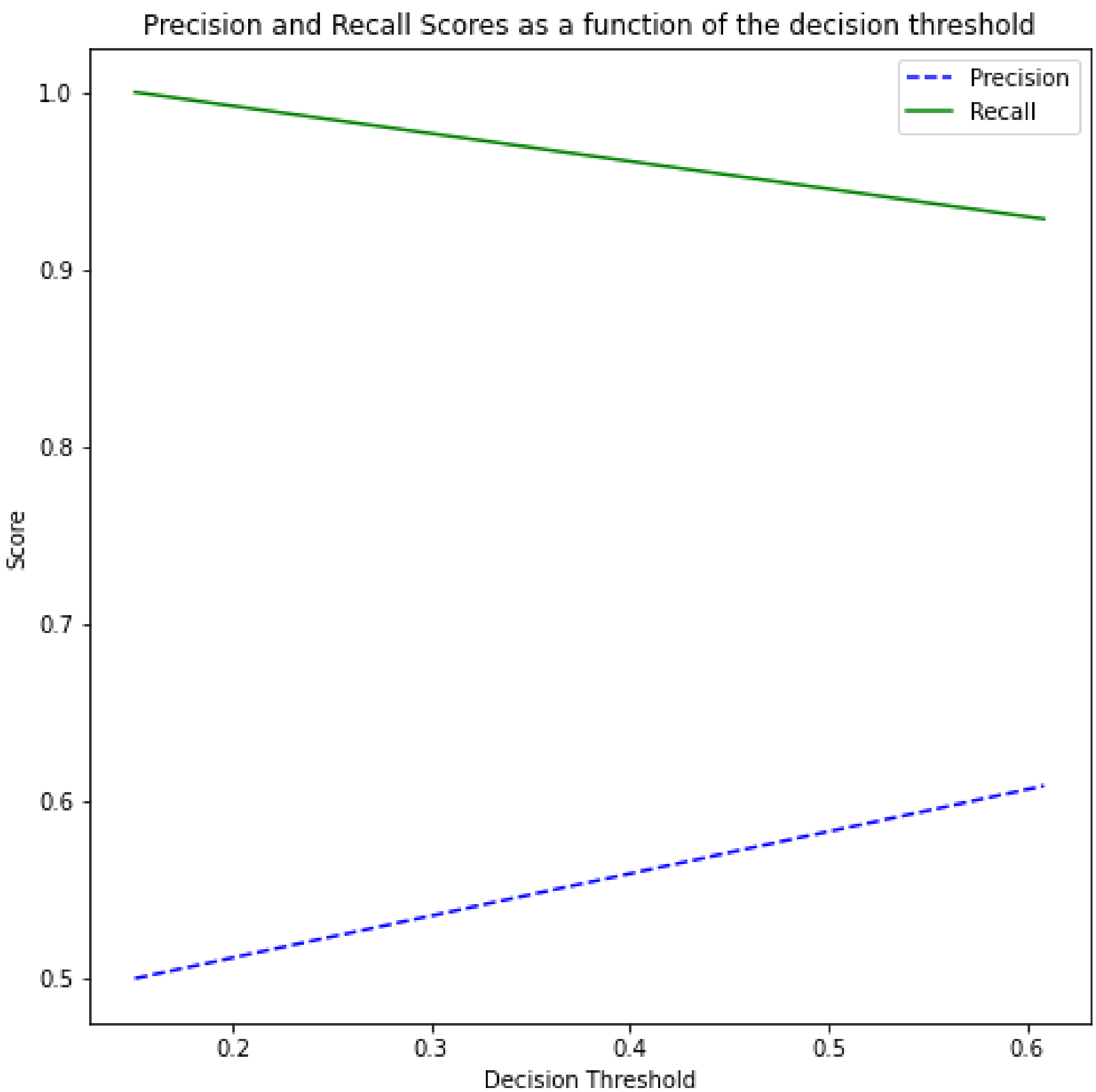
[59]:

```
tree = DecisionTreeClassifier(ccp_alpha=0.020264403994903202,random_state=1)
tree.fit(X_train, y_train)
print(confusion_matrix_data(X_train,y_train,tree))
print(confusion_matrix_data(X_test,y_pred,tree))
print(confusion_matrix_data(X_train,y_train,model,cutoff=0.2))
print(confusion_matrix_data(X_test,y_pred,model,cutoff=0.2))
```

```
Accuracy =  66.575
Precision =  60.86529006882989
FNR =  7.15
TPR or Recall =  92.85
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0        806.0       1194.0
Actual 1        143.0       1857.0

Accuracy =  100.0
Precision =  100.0
FNR =  0.0
TPR or Recall =  100.0
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0        229.0          0.0
Actual 1          0.0        771.0

Accuracy =  66.725
Precision =  60.44985941893158
FNR =  3.25
TPR or Recall =  96.75
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0        734.0       1266.0
Actual 1         65.0       1935.0

Accuracy =  93.6
Precision =  95.37869062901156
FNR =  3.6316472114137484
TPR or Recall =  96.36835278858625
Confusion matrix =
```

```
          Predicted 0  Predicted 1
Actual 0        193.0         36.0
Actual 1         28.0        743.0
```

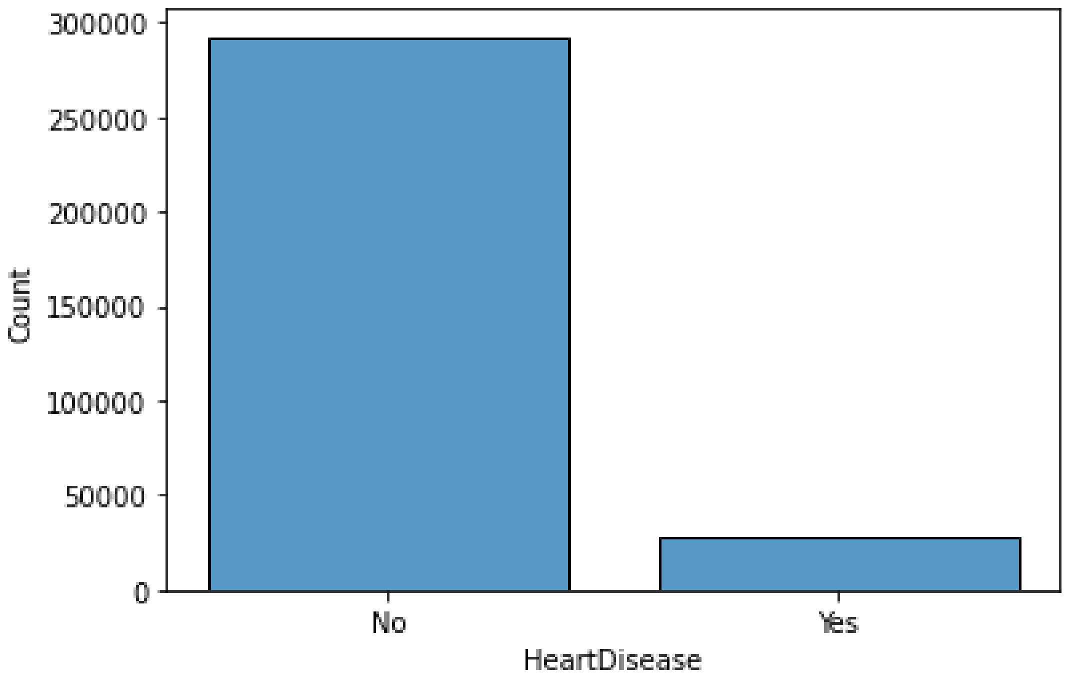
[60]:
```
ypred = tree.predict_proba(X_train)[:, 1]
p, r, thresholds = precision_recall_curve(y_train, ypred)

plot_precision_recall_vs_threshold(p, r, thresholds)
```



4 Exploratory Data Analysis

[243]:
```
sns.histplot(data = data, x = 'HeartDisease', shrink = 0.8)
```

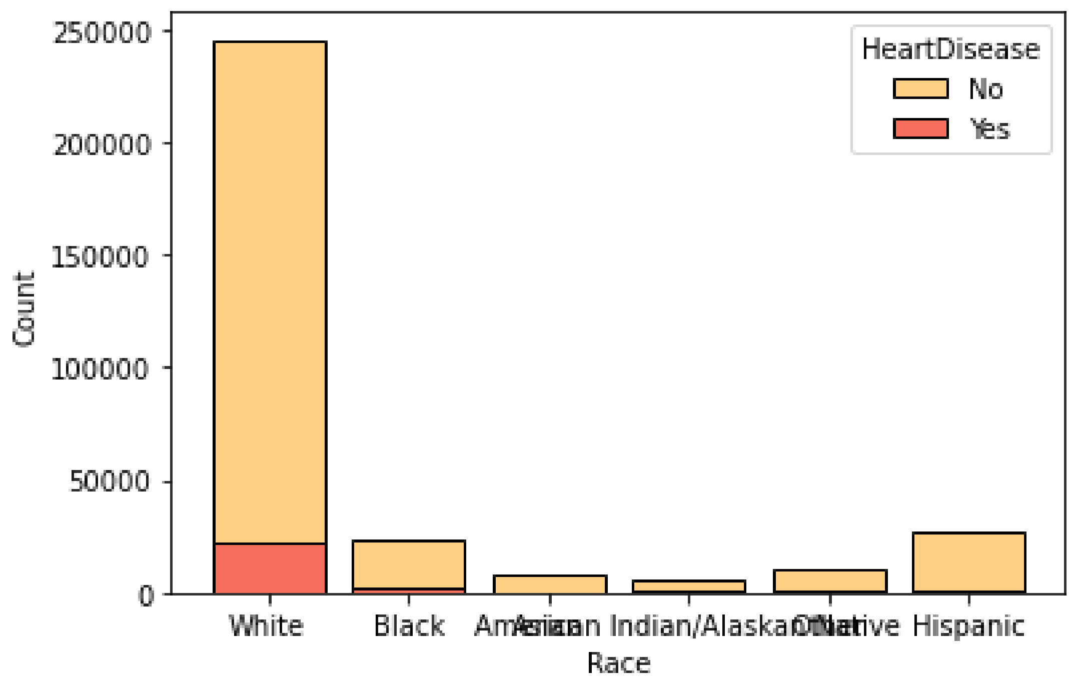
[243]: <AxesSubplot:xlabel='HeartDisease', ylabel='Count'>



- There are many more negative samples, so precision-recall is appropriate

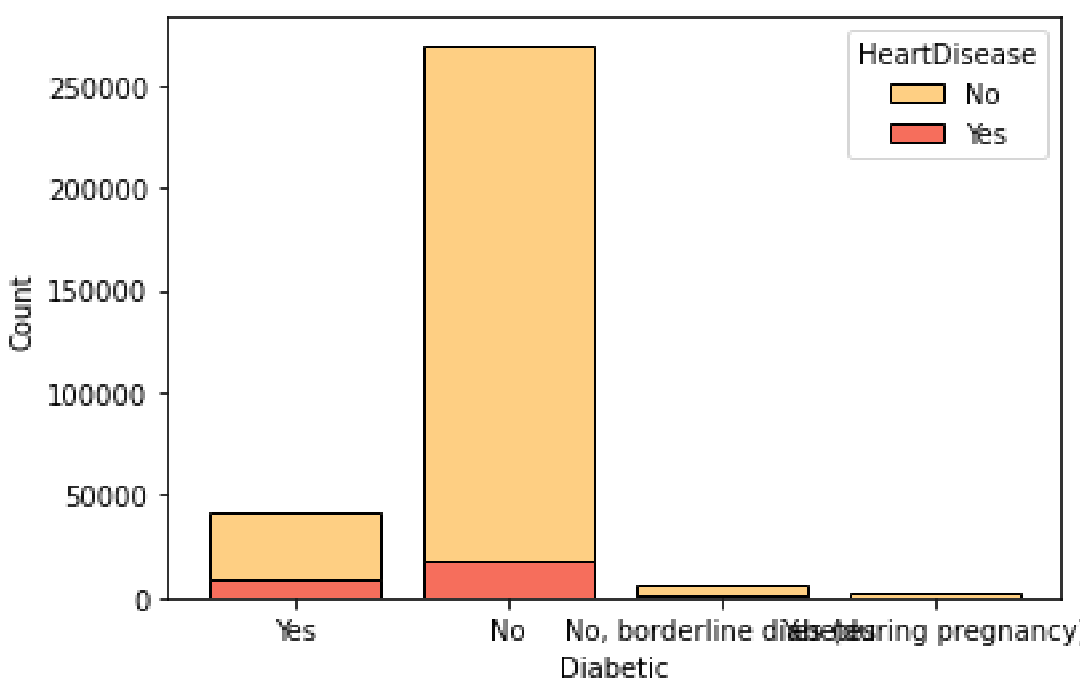
[89]:
```
sns.histplot(x = "Race", hue = "HeartDisease", data = data,
             stat = "count", shrink = 0.8, multiple = 'stack', palette="YlOrRd")
```

[89]: <AxesSubplot:xlabel='Race', ylabel='Count'>



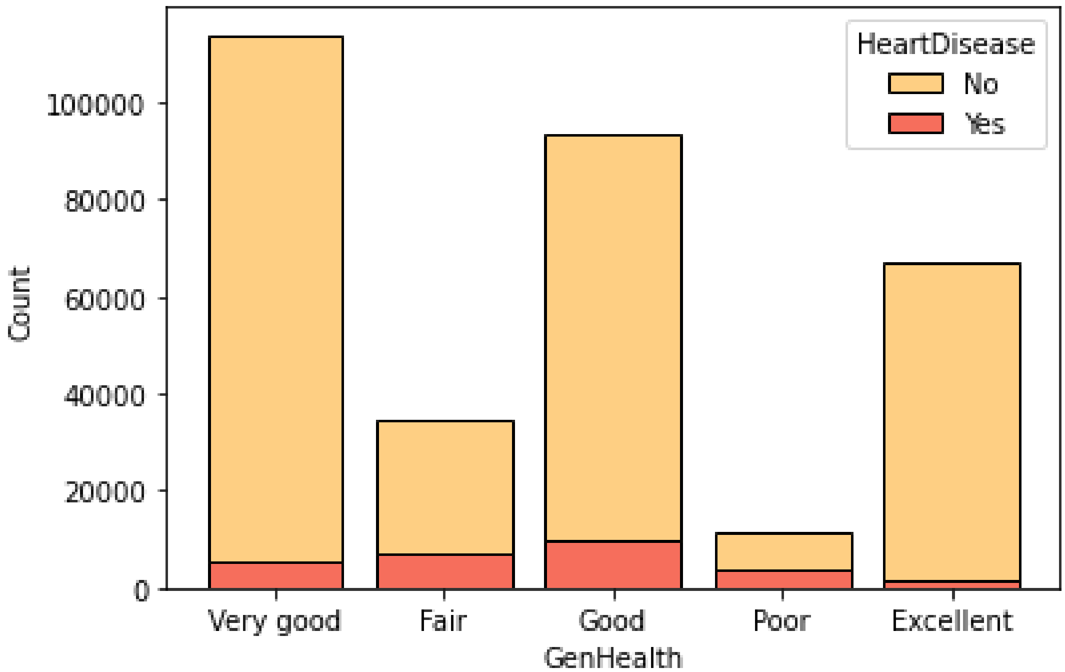
[90]:
```
sns.histplot(x = "Diabetic", hue = "HeartDisease", data = data,
             stat = "count", shrink = 0.8, multiple = 'stack', palette="YlOrRd")
```

[90]: `<AxesSubplot:xlabel='Diabetic', ylabel='Count'>`



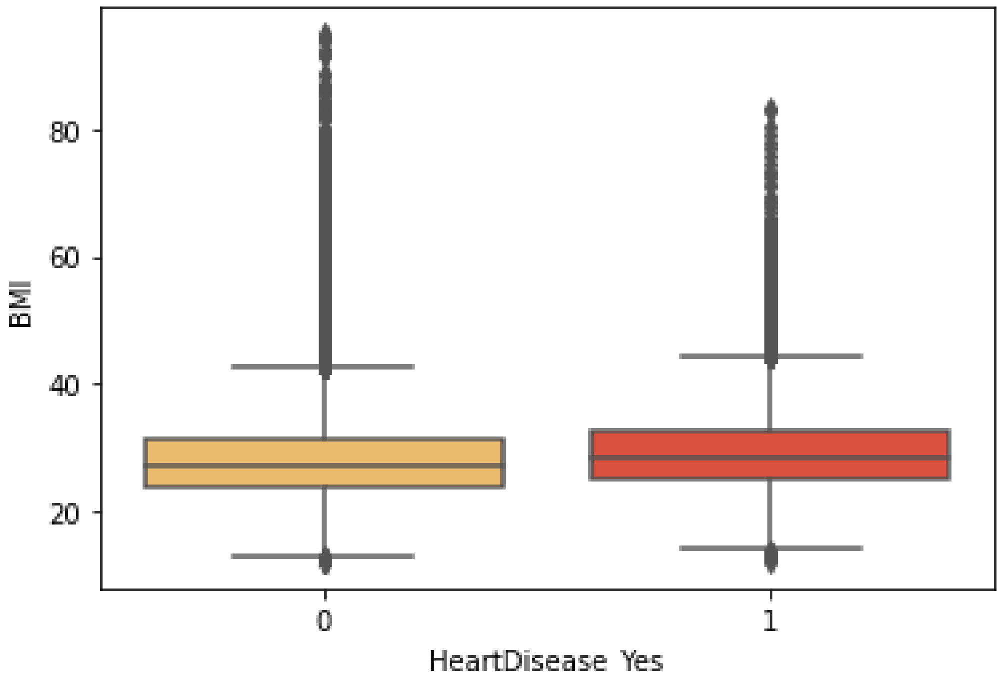
[93]:
```
sns.histplot(x = "GenHealth", hue = "HeartDisease", data = data,
             stat = "count", shrink = 0.8, multiple = 'stack', palette="YlOrRd")
```

[93]: <AxesSubplot:xlabel='GenHealth', ylabel='Count'>



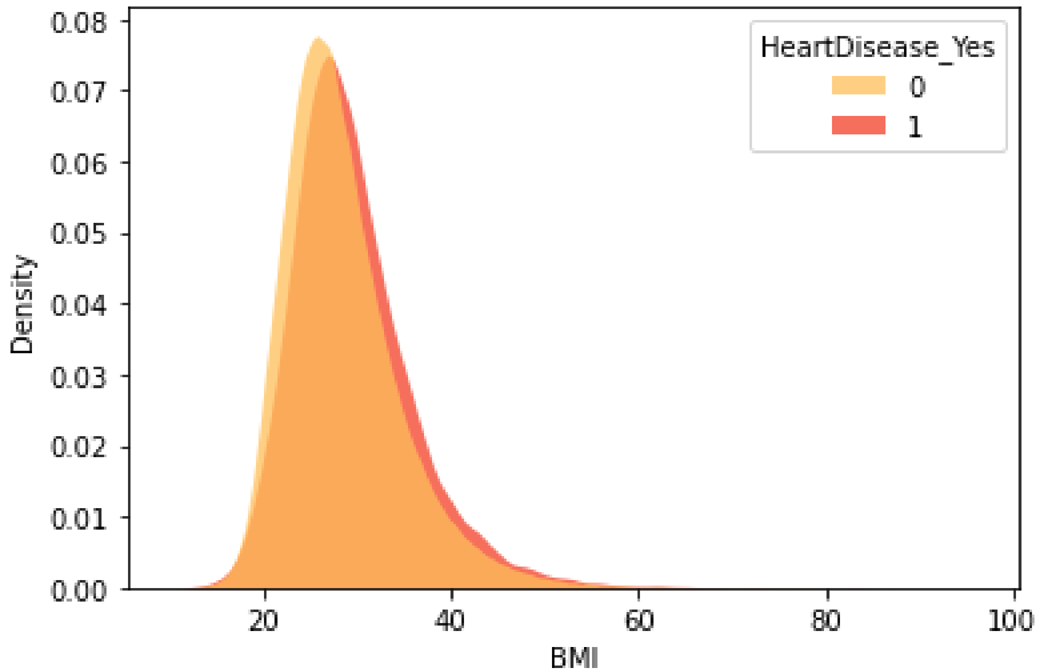
[153]:
```
sns.boxplot(x="HeartDisease_Yes", y="BMI", data=data_dum, palette='YlOrRd')
```

[153]: <AxesSubplot:xlabel='HeartDisease_Yes', ylabel='BMI'>



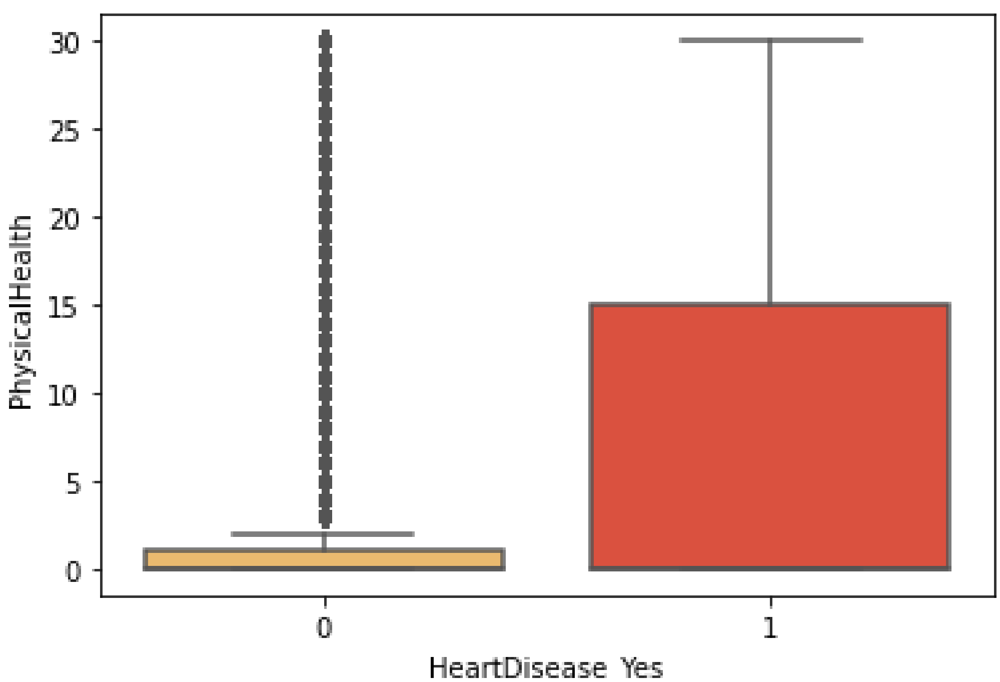
[154]:
```
sns.kdeplot(
   data=data_dum, x="BMI", hue="HeartDisease_Yes",
   fill=True, common_norm=False, palette="YlOrRd",
    linewidth=0, alpha=.75
)
```

[154]: <AxesSubplot:xlabel='BMI', ylabel='Density'>



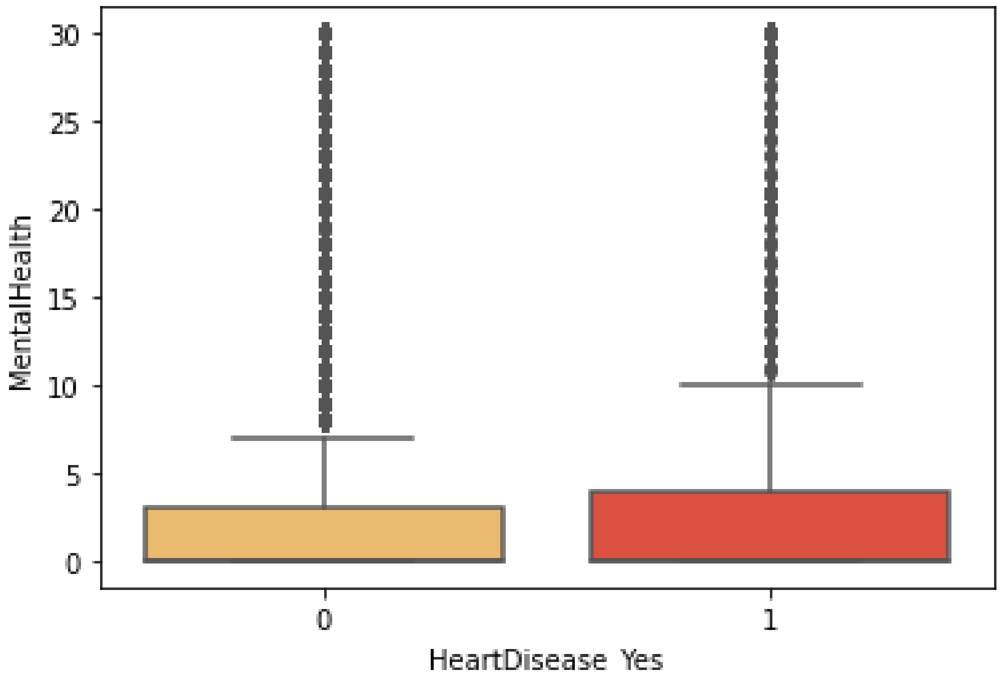
[98]:
```
sns.boxplot(x="HeartDisease_Yes", y="PhysicalHealth", data=data_dum,␣
↪palette='YlOrRd')
```

[98]:
```
<AxesSubplot:xlabel='HeartDisease_Yes', ylabel='PhysicalHealth'>
```



[99]:
```
sns.boxplot(x="HeartDisease_Yes", y="MentalHealth", data=data_dum,␣
↪palette='YlOrRd')
```

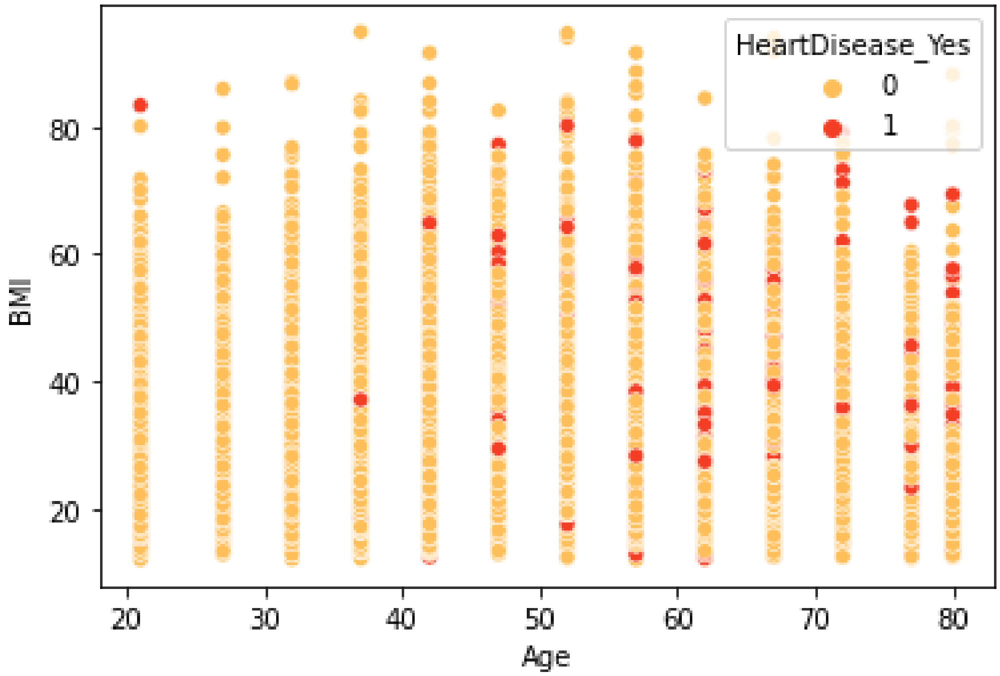
[99]: <AxesSubplot:xlabel='HeartDisease_Yes', ylabel='MentalHealth'>



[156]:
```
sns.scatterplot(data=data_dum, x="Age", y="BMI", hue="HeartDisease_Yes",␣
↪palette='YlOrRd')
```

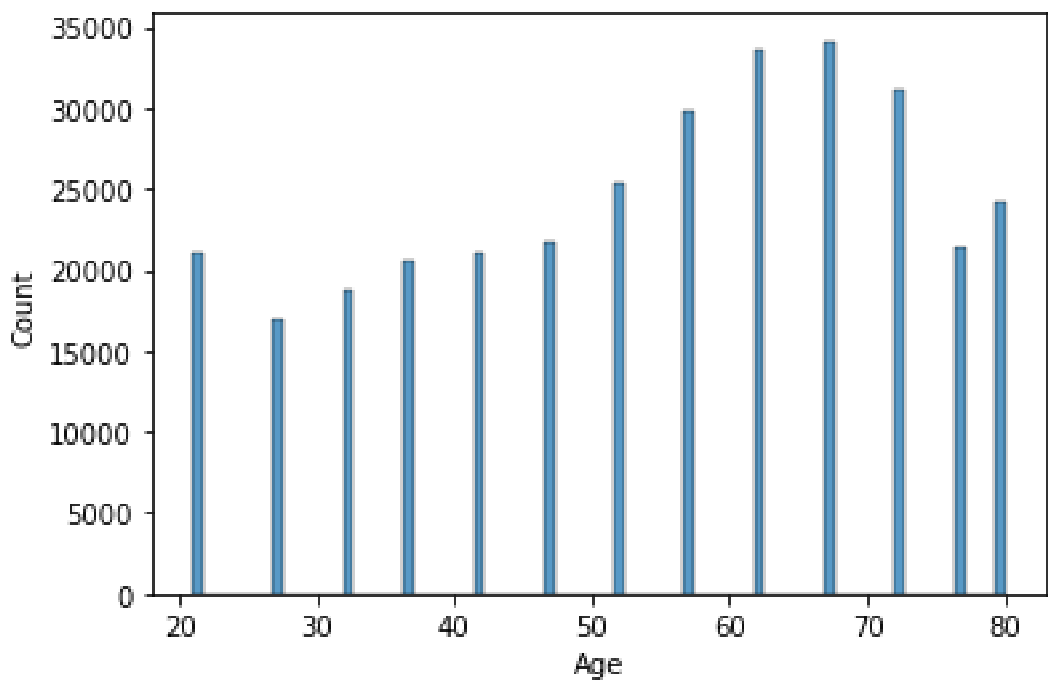
[156]: <AxesSubplot:xlabel='Age', ylabel='BMI'>

```
C:\ProgramData\Anaconda3\lib\site-packages\IPython\core\pylabtools.py:132:
UserWarning: Creating legend with loc="best" can be slow with large amounts of
data.
  fig.canvas.print_figure(bytes_io, **kw)
```



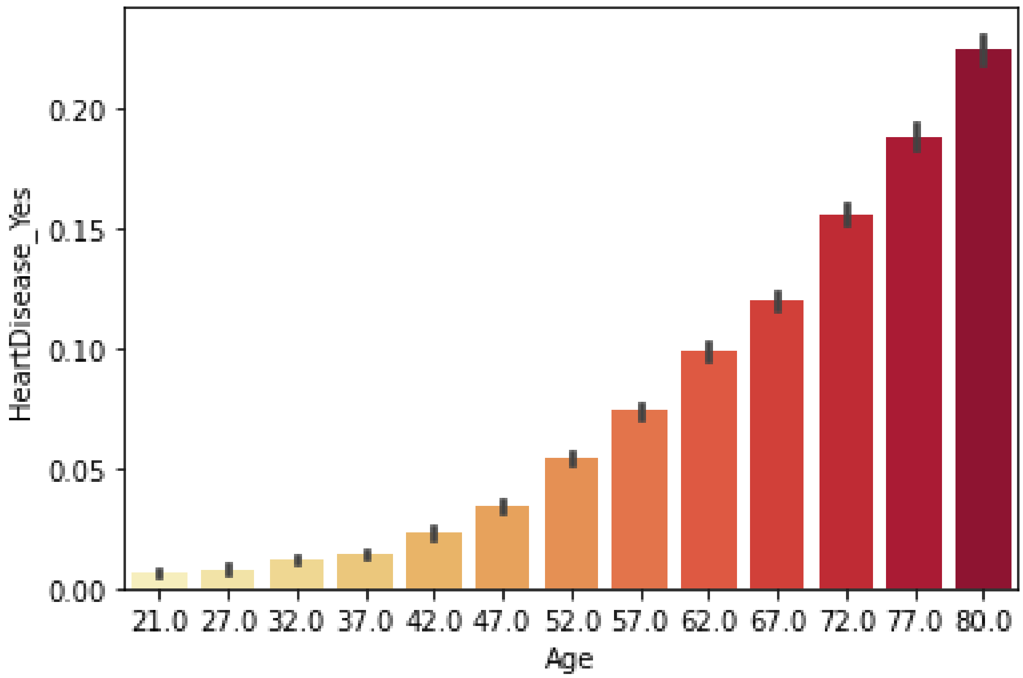
[240]:
```
sns.histplot(data=data, x = "Age", stat = 'count', palette = "YlOrRd")
```

[240]: <AxesSubplot:xlabel='Age', ylabel='Count'>



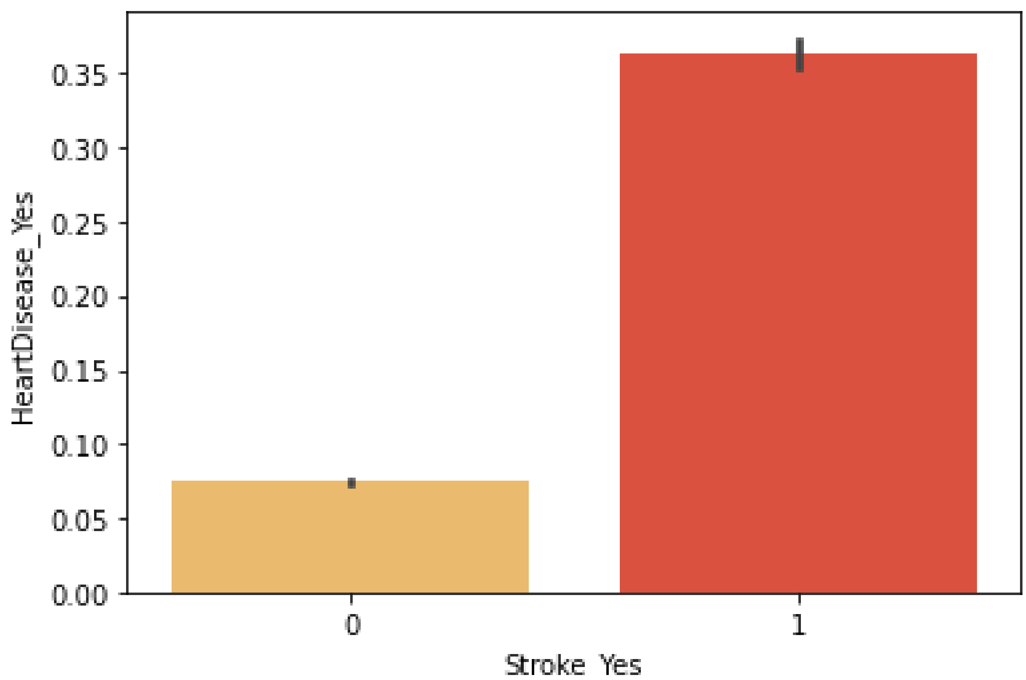
[158]:
```
sns.barplot(data=data_dum, x="Age", y = 'HeartDisease_Yes', palette = "YlOrRd")
```

[158]: <AxesSubplot:xlabel='Age', ylabel='HeartDisease_Yes'>



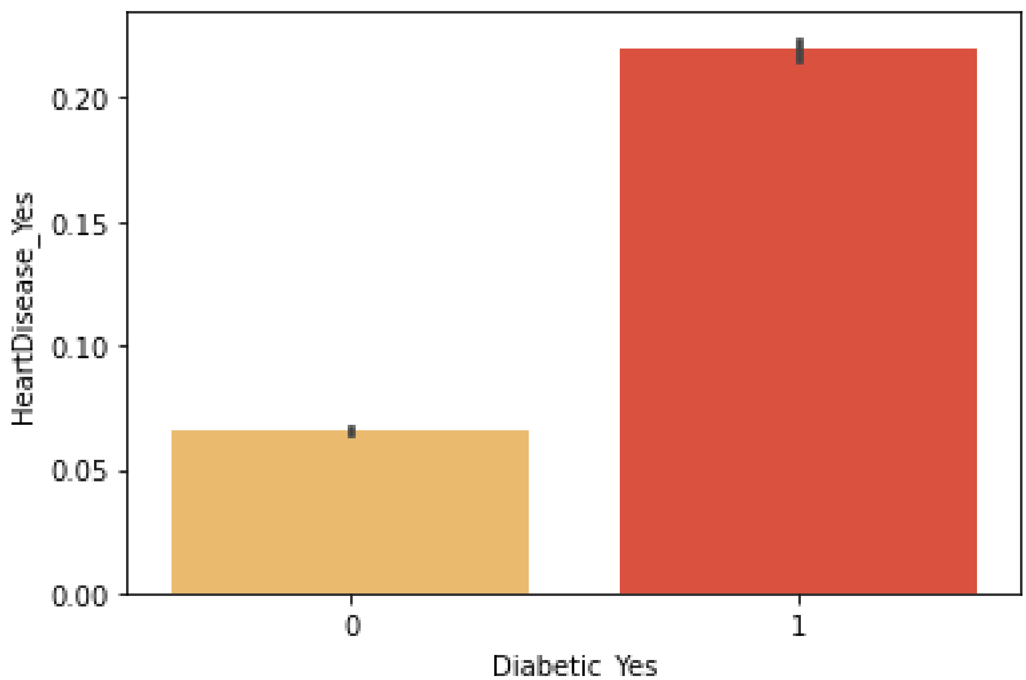
[159]:
```
sns.barplot(data=data_dum, x="Stroke_Yes", y = 'HeartDisease_Yes', palette =␣
↪"YlOrRd")
```

[159]: <AxesSubplot:xlabel='Stroke_Yes', ylabel='HeartDisease_Yes'>



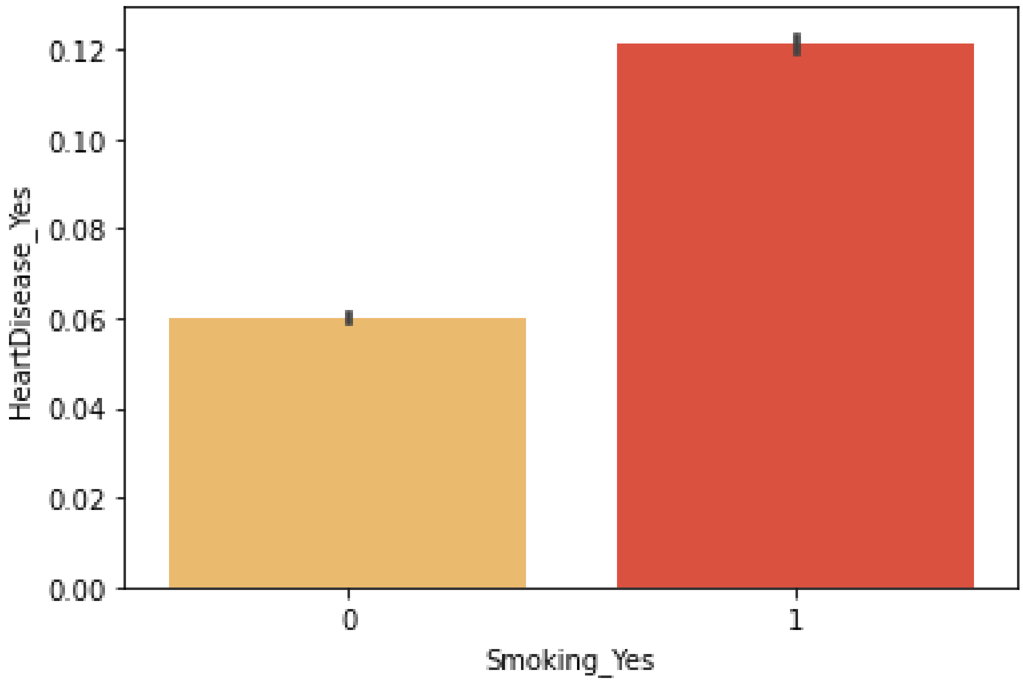
[160]:
```
sns.barplot(data=data_dum, x="Diabetic_Yes", y = 'HeartDisease_Yes', palette =
    "YlOrRd")
```

[160]: <AxesSubplot:xlabel='Diabetic_Yes', ylabel='HeartDisease_Yes'>



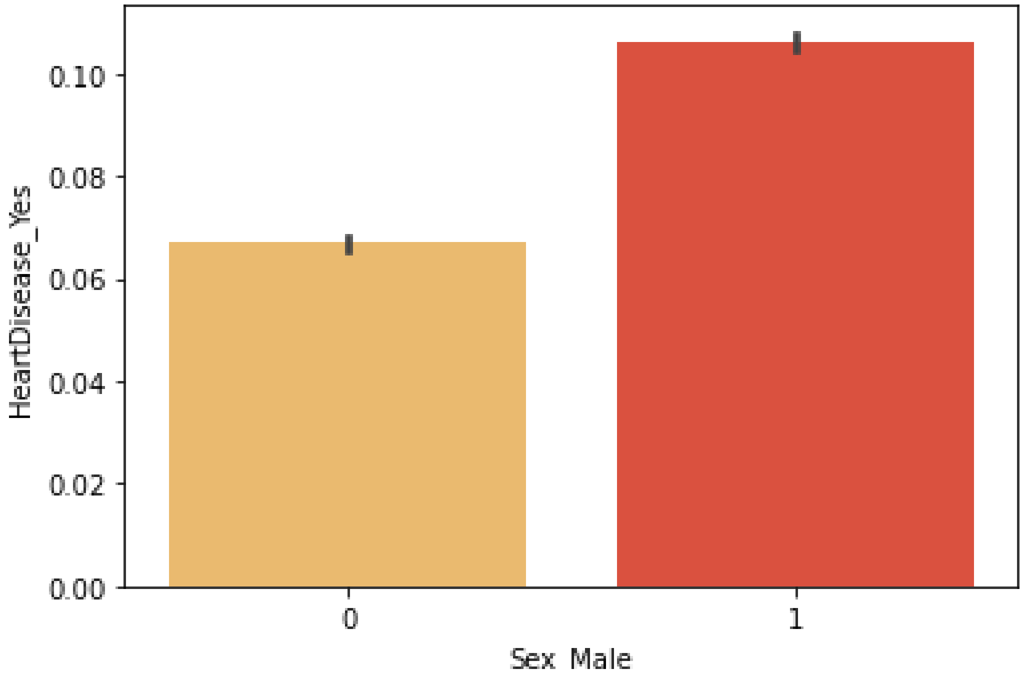
[100]:
```
sns.barplot(data=data_dum, x="Smoking_Yes", y = 'HeartDisease_Yes', palette =␣
↪"YlOrRd")
```

[100]: <AxesSubplot:xlabel='Smoking_Yes', ylabel='HeartDisease_Yes'>



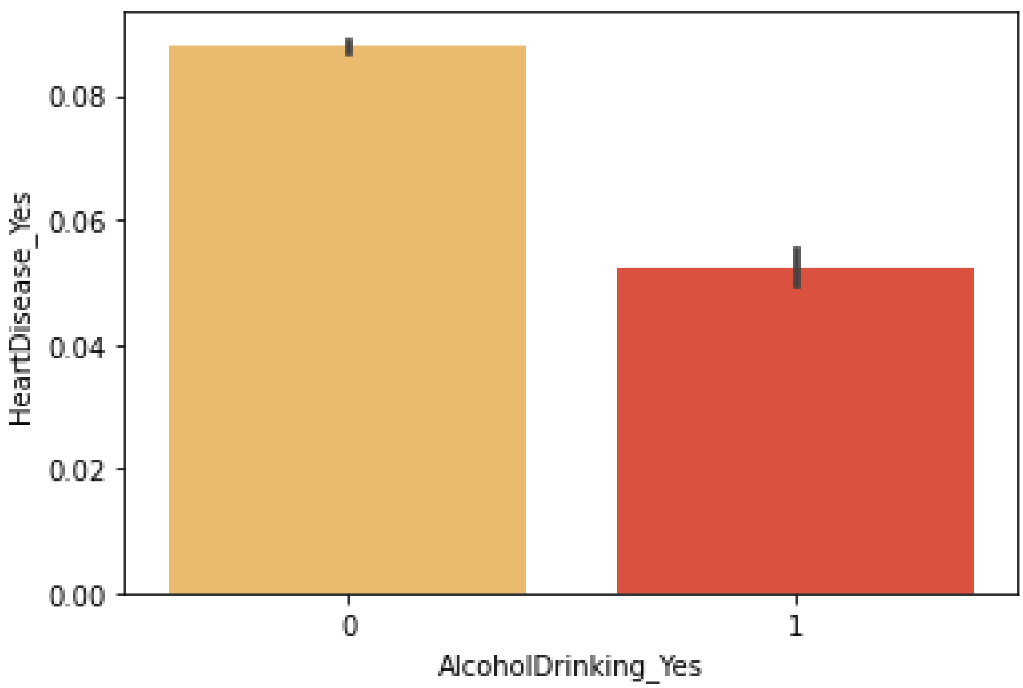
[149]:
```
sns.barplot(data=data_dum, x = 'Sex_Male', y = 'HeartDisease_Yes', palette =␣
↪"YlOrRd")
```

[149]: <AxesSubplot:xlabel='Sex_Male', ylabel='HeartDisease_Yes'>



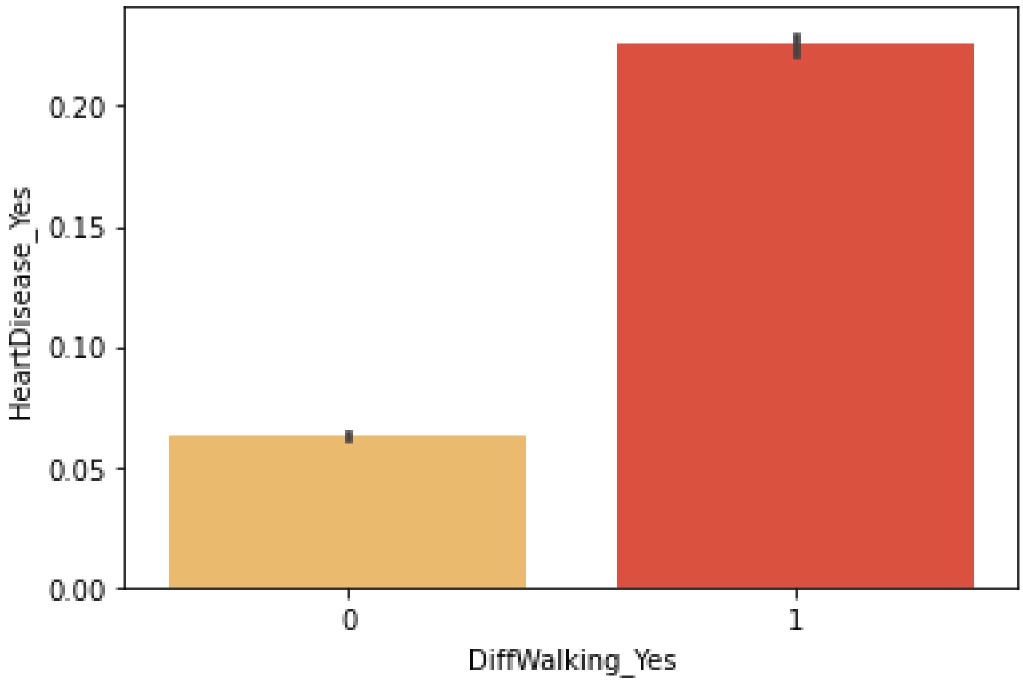
[150]:
```
sns.barplot(data=data_dum, x = 'AlcoholDrinking_Yes', y = 'HeartDisease_Yes',␣
 ↪palette = "YlOrRd")
```

[150]: <AxesSubplot:xlabel='AlcoholDrinking_Yes', ylabel='HeartDisease_Yes'>



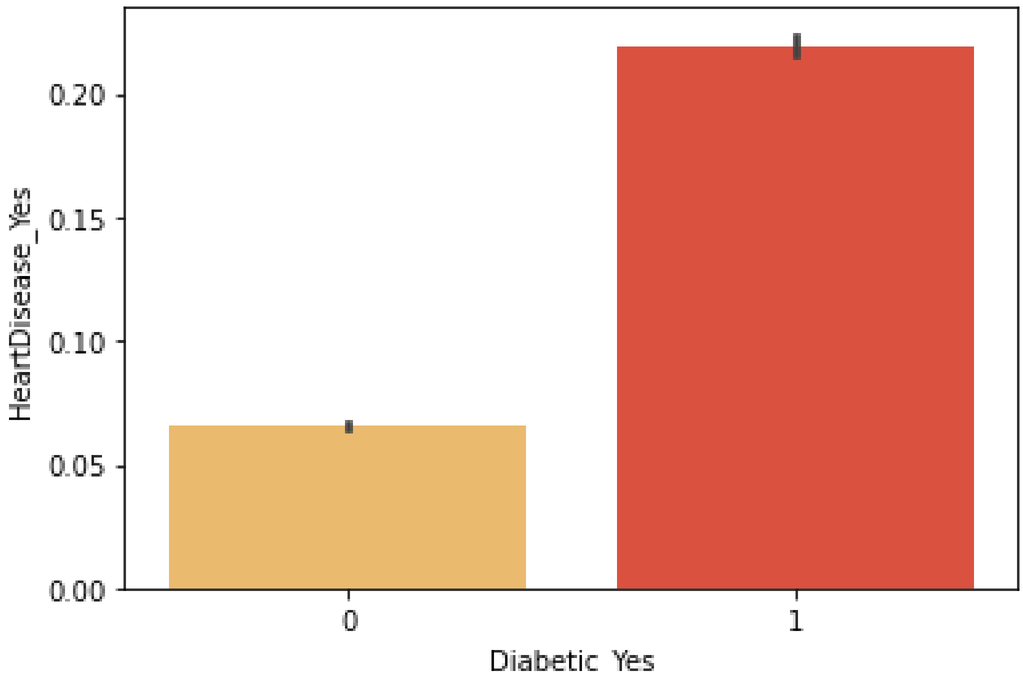
```
[151]: sns.barplot(data=data_dum, x = 'DiffWalking_Yes', y = 'HeartDisease_Yes',
       palette = "YlOrRd")
```

```
[151]: <AxesSubplot:xlabel='DiffWalking_Yes', ylabel='HeartDisease_Yes'>
```



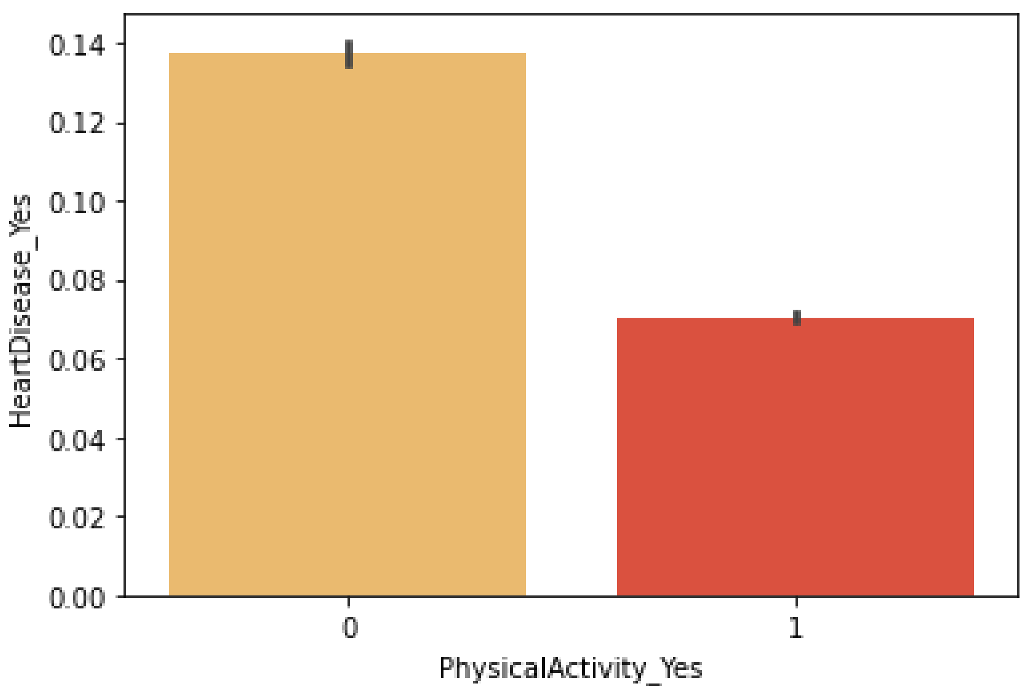

```
[152]: sns.barplot(data=data_dum, x = 'Diabetic_Yes', y = 'HeartDisease_Yes', palette
       = "YlOrRd")
```

```
[152]: <AxesSubplot:xlabel='Diabetic_Yes', ylabel='HeartDisease_Yes'>
```



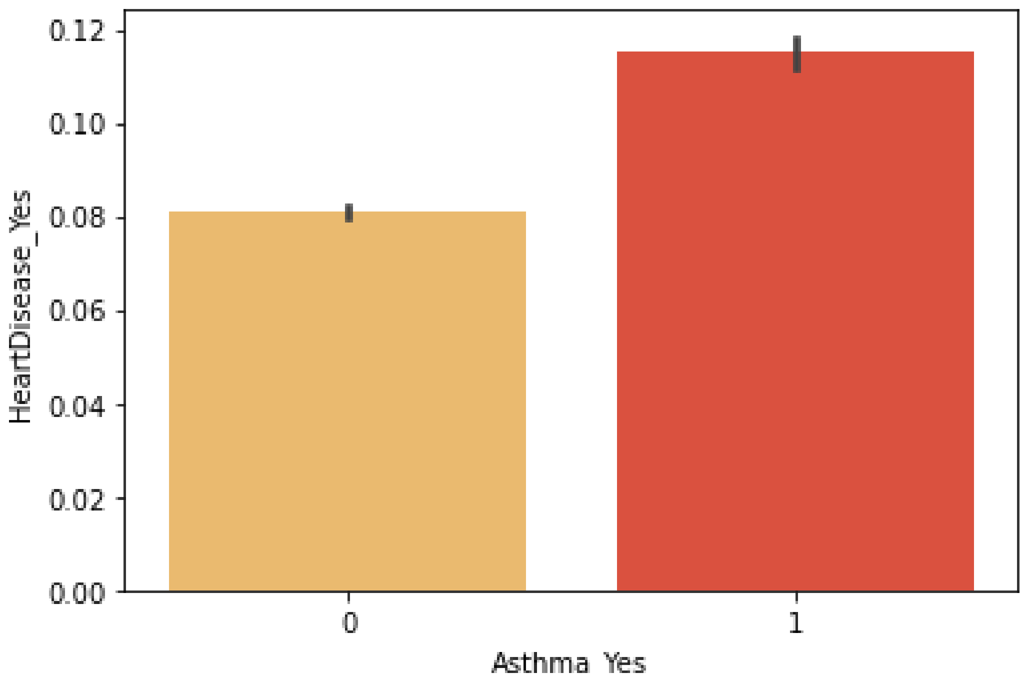
[153]:
```
sns.barplot(data=data_dum, x = 'PhysicalActivity_Yes', y = 'HeartDisease_Yes',␣
↪palette = "YlOrRd")
```

[153]: <AxesSubplot:xlabel='PhysicalActivity_Yes', ylabel='HeartDisease_Yes'>



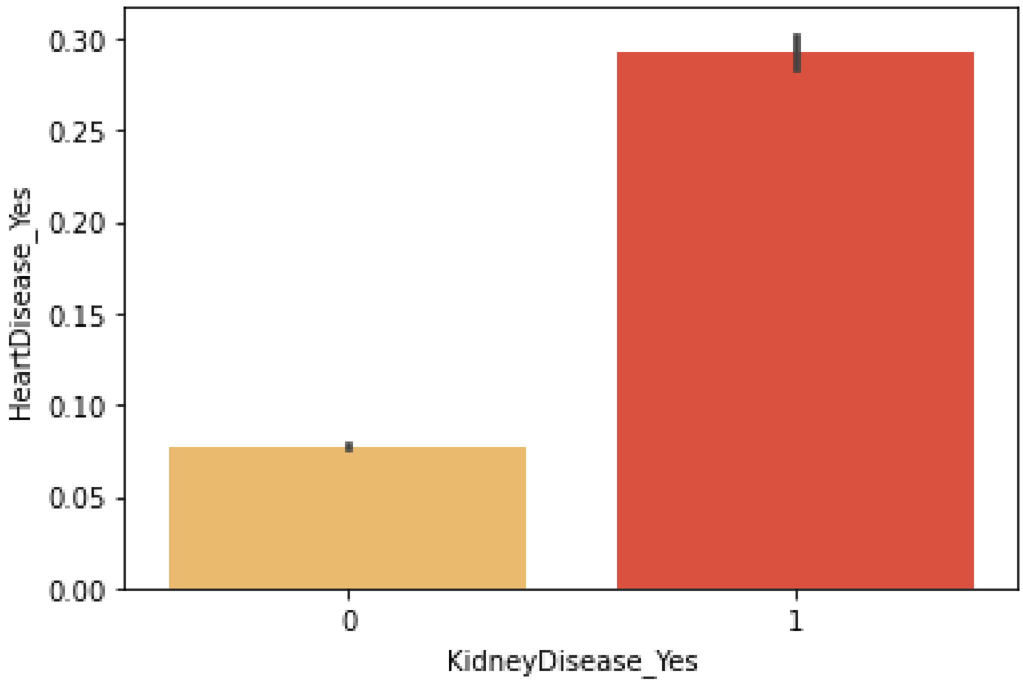
[154]:
```
sns.barplot(data=data_dum, x = 'Asthma_Yes', y = 'HeartDisease_Yes', palette =␣
↪"YlOrRd")
```

[154]: <AxesSubplot:xlabel='Asthma_Yes', ylabel='HeartDisease_Yes'>



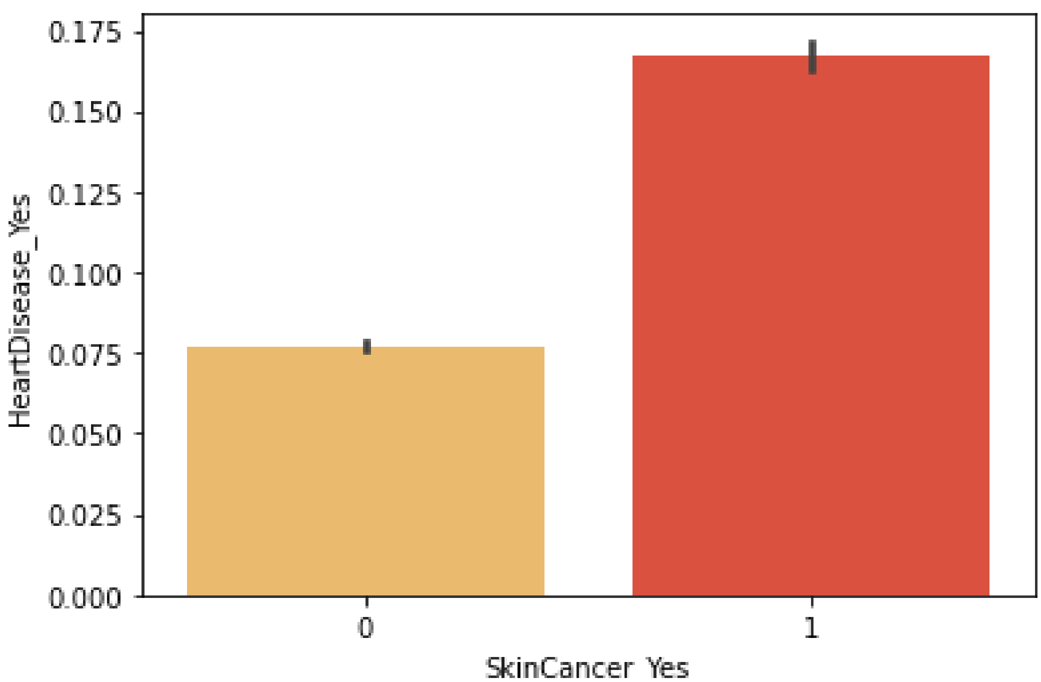
[156]:
```
sns.barplot(data=data_dum, x = 'KidneyDisease_Yes', y = 'HeartDisease_Yes',␣
↪palette = "YlOrRd")
```

[156]: <AxesSubplot:xlabel='KidneyDisease_Yes', ylabel='HeartDisease_Yes'>



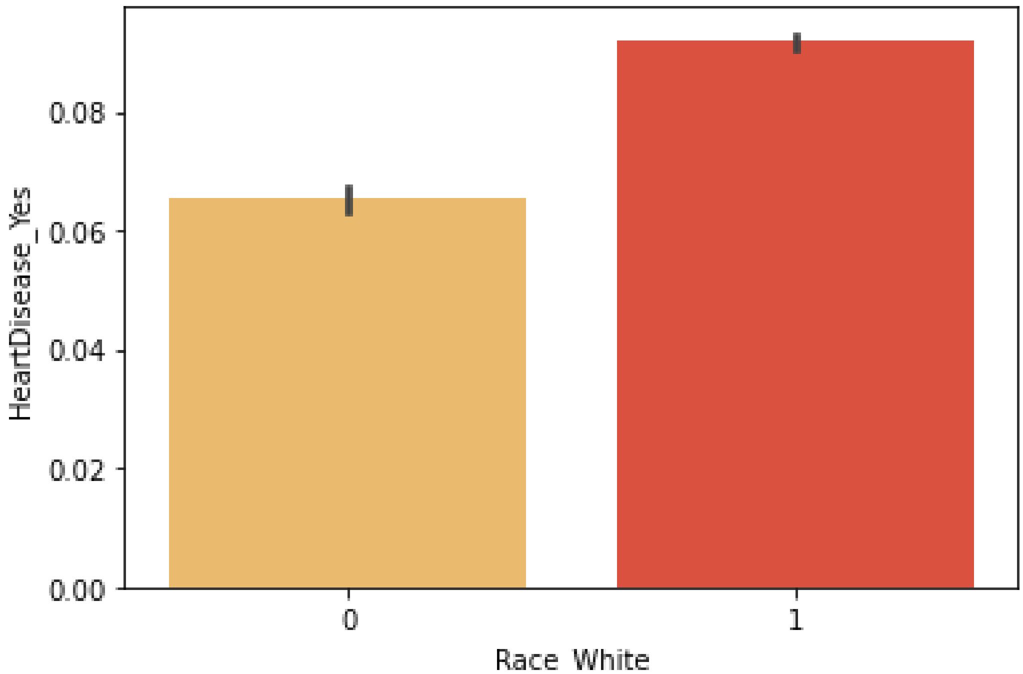
[157]:
```
sns.barplot(data=data_dum, x = 'SkinCancer_Yes', y = 'HeartDisease_Yes',␣
↪palette = "YlOrRd")
```

[157]: <AxesSubplot:xlabel='SkinCancer_Yes', ylabel='HeartDisease_Yes'>



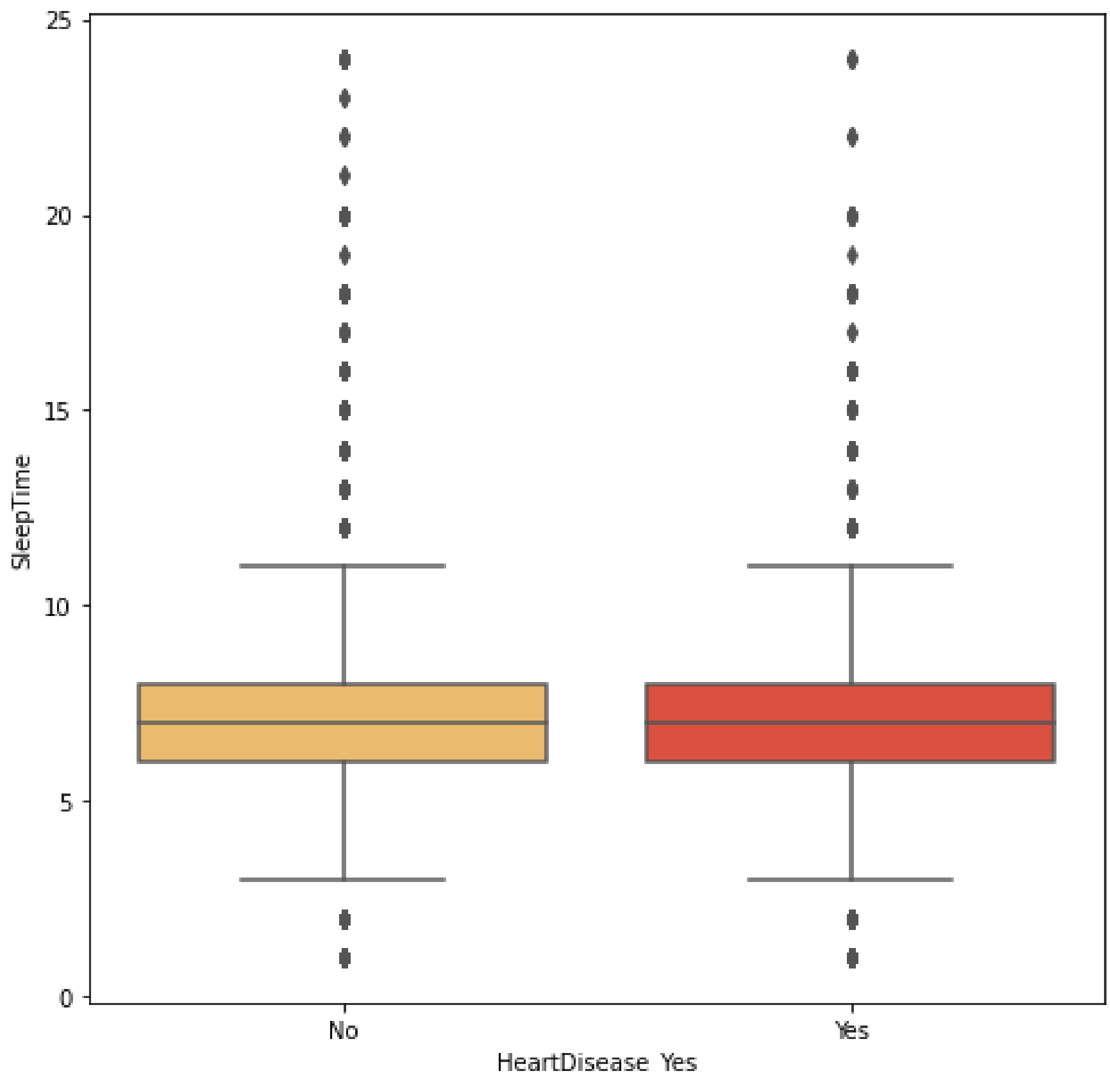
[182]:
```
sns.barplot(data=data_dum, x = 'Race_White', y = 'HeartDisease_Yes', palette =␣
↪"YlOrRd")
```

[182]: <AxesSubplot:xlabel='Race_White', ylabel='HeartDisease_Yes'>



[161]:
```
fig, axes = plt.subplots(1, 1, figsize = (8,8))

p2 = sns.boxplot(data = data_dum, x = 'HeartDisease_Yes', y = 'SleepTime',␣
↪palette = 'YlOrRd')

p2.set_title("")
plt.xticks([0,1],['No','Yes'])
```

[161]:
```
([<matplotlib.axis.XTick at 0x1ca0855fee0>,
  <matplotlib.axis.XTick at 0x1ca0855feb0>],
 [Text(0, 0, 'No'), Text(1, 0, 'Yes')])
```



5 Simple Logistic Regression

[162]:
```
train = pd.concat([X_train, y_train], axis=1, join="inner")
train.head()
```

[162]:
```
          BMI  PhysicalHealth  MentalHealth  SleepTime  Smoking_Yes  \
291133  24.53               2             0          6            1
309330  33.00               0             0          7            1
307280  27.60               0             5          9            0
7469    28.70               0            14          8            1
33630   28.98               0             0          7            1

        AlcoholDrinking_Yes  Stroke_Yes  DiffWalking_Yes  Sex_Female  \
```

```
291133                       0           0                 0           1
309330                       0           0                 0           0
307280                       0           0                 0           0
7469                         0           0                 0           0
33630                        0           0                 0           0

        Sex_Male  …  PhysicalActivity_Yes  GenHealth_Excellent  \
291133         0  …                     1                    0
309330         1  …                     1                    1
307280         1  …                     1                    1
7469           1  …                     1                    1
33630          1  …                     1                    0

        GenHealth_Fair  GenHealth_Good  GenHealth_Poor  GenHealth_Very_good  \
291133               1               0               0                    0
309330               0               0               0                    0
307280               0               0               0                    0
7469                 0               0               0                    0
33630                0               1               0                    0

        Asthma_Yes  KidneyDisease_Yes  SkinCancer_Yes  HeartDisease_Yes
291133           0                  0               0                 0
309330           0                  0               0                 0
307280           0                  0               0                 0
7469             0                  0               0                 0
33630            0                  0               0                 1

[5 rows x 42 columns]
```

[163]:
```python
test = pd.concat([X_test, y_test], axis=1, join="inner")
test.head()
```

[163]:
```
          BMI  PhysicalHealth  MentalHealth  SleepTime  Smoking_Yes  \
301988  24.30               0            15          7            0
223127  23.78               0             0          7            1
216797  20.60               0             0          7            1
234217  28.29               0            20          4            1
30822   33.00               0             0          8            0

        AlcoholDrinking_Yes  Stroke_Yes  DiffWalking_Yes  Sex_Female  \
301988                    0           0                0           1
223127                    0           1                1           1
216797                    0           0                0           1
234217                    0           0                0           1
30822                     0           0                0           0

        Sex_Male  …  PhysicalActivity_Yes  GenHealth_Excellent  \
```

```
301988         0  ...                    1                    1
223127         0  ...                    0                    0
216797         0  ...                    1                    0
234217         0  ...                    0                    0
30822          1  ...                    1                    1

        GenHealth_Fair  GenHealth_Good  GenHealth_Poor  GenHealth_Very_good  \
301988               0               0               0                    0
223127               0               1               0                    0
216797               0               1               0                    0
234217               0               1               0                    0
30822                0               0               0                    0

        Asthma_Yes  KidneyDisease_Yes  SkinCancer_Yes  HeartDisease_Yes
301988           0                  0               0                 0
223127           0                  0               0                 1
216797           0                  0               0                 0
234217           0                  0               0                 0
30822            0                  0               0                 1

[5 rows x 42 columns]
```

[164]:
```
train.dtypes
```

[164]:
```
BMI                                  float64
PhysicalHealth                         int64
MentalHealth                           int64
SleepTime                              int64
Smoking_Yes                            uint8
AlcoholDrinking_Yes                    uint8
Stroke_Yes                             uint8
DiffWalking_Yes                        uint8
Sex_Female                             uint8
Sex_Male                               uint8
AgeCategory_18_24                      uint8
AgeCategory_25_29                      uint8
AgeCategory_30_34                      uint8
AgeCategory_35_39                      uint8
AgeCategory_40_44                      uint8
AgeCategory_45_49                      uint8
AgeCategory_50_54                      uint8
AgeCategory_55_59                      uint8
AgeCategory_60_64                      uint8
AgeCategory_65_69                      uint8
AgeCategory_70_74                      uint8
AgeCategory_75_79                      uint8
AgeCategory_80_or_older                uint8
```

```
Race_American_Indian_Alaskan_Native      uint8
Race_Asian                               uint8
Race_Black                               uint8
Race_Hispanic                            uint8
Race_Other                               uint8
Race_White                               uint8
Diabetic_No_borderline_diabetes          uint8
Diabetic_Yes                             uint8
Diabetic_Yes_during_pregnancy            uint8
PhysicalActivity_Yes                     uint8
GenHealth_Excellent                      uint8
GenHealth_Fair                           uint8
GenHealth_Good                           uint8
GenHealth_Poor                           uint8
GenHealth_Very_good                      uint8
Asthma_Yes                               uint8
KidneyDisease_Yes                        uint8
SkinCancer_Yes                           uint8
HeartDisease_Yes                         uint8
dtype: object
```

[165]:
```
test.columns
```

[165]:
```
Index(['BMI', 'PhysicalHealth', 'MentalHealth', 'SleepTime', 'Smoking_Yes',
       'AlcoholDrinking_Yes', 'Stroke_Yes', 'DiffWalking_Yes', 'Sex_Female',
       'Sex_Male', 'AgeCategory_18_24', 'AgeCategory_25_29',
       'AgeCategory_30_34', 'AgeCategory_35_39', 'AgeCategory_40_44',
       'AgeCategory_45_49', 'AgeCategory_50_54', 'AgeCategory_55_59',
       'AgeCategory_60_64', 'AgeCategory_65_69', 'AgeCategory_70_74',
       'AgeCategory_75_79', 'AgeCategory_80_or_older',
       'Race_American_Indian_Alaskan_Native', 'Race_Asian', 'Race_Black',
       'Race_Hispanic', 'Race_Other', 'Race_White',
       'Diabetic_No_borderline_diabetes', 'Diabetic_Yes',
       'Diabetic_Yes_during_pregnancy', 'PhysicalActivity_Yes',
       'GenHealth_Excellent', 'GenHealth_Fair', 'GenHealth_Good',
       'GenHealth_Poor', 'GenHealth_Very_good', 'Asthma_Yes',
       'KidneyDisease_Yes', 'SkinCancer_Yes', 'HeartDisease_Yes'],
      dtype='object')
```

[166]:
```
formula = ols_formula(train, "HeartDisease_Yes")
log_model = smf.logit(formula = formula, data = train).fit()
log_model.summary()
```

```
Warning: Maximum number of iterations has been exceeded.
         Current function value: 0.227795
         Iterations: 35
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\base\model.py:566:
```

```
ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check
mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

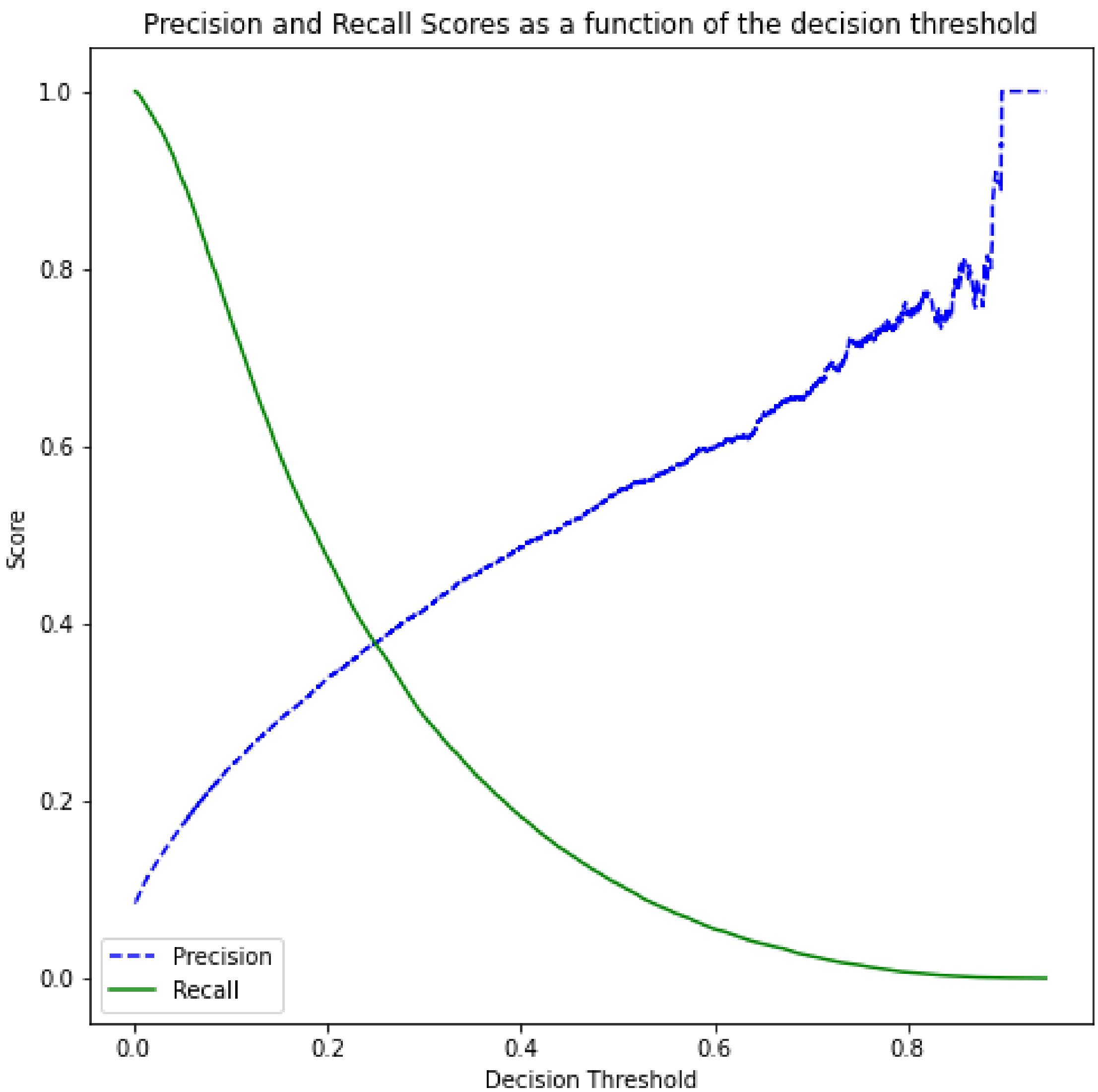
[166]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results
==============================================================================
Dep. Variable:       HeartDisease_Yes   No. Observations:               255836
Model:                          Logit   Df Residuals:                   255798
Method:                           MLE   Df Model:                           37
Date:                Mon, 16 May 2022   Pseudo R-squ.:                  0.2227
Time:                        18:16:41   Log-Likelihood:                -58278.
converged:                      False   LL-Null:                       -74974.
Covariance Type:            nonrobust   LLR p-value:                     0.000
================================================================================
=======================
                                          coef    std err          z      P>|z|
[0.025      0.975]
--------------------------------------------------------------------------------
-----------------------
Intercept                              -2.5441        nan        nan        nan
nan         nan
BMI                                     0.0092      0.001      7.203      0.000
0.007       0.012
PhysicalHealth                          0.0031      0.001      3.213      0.001
0.001       0.005
MentalHealth                            0.0047      0.001      4.753      0.000
0.003       0.007
SleepTime                              -0.0266      0.005     -5.484      0.000
-0.036      -0.017
Smoking_Yes                             0.3518      0.016     21.952      0.000
0.320       0.383
AlcoholDrinking_Yes                    -0.2325      0.037     -6.232      0.000
-0.306      -0.159
Stroke_Yes                              1.0674      0.025     42.298      0.000
1.018       1.117
DiffWalking_Yes                         0.2128      0.020     10.498      0.000
0.173       0.253
Sex_Female                             -0.2140        nan        nan        nan
nan         nan
Sex_Male                                0.4948        nan        nan        nan
nan         nan
AgeCategory_18_24                      -1.7655   6.69e+05  -2.64e-06      1.000
-1.31e+06    1.31e+06
AgeCategory_25_29                      -1.5392    6.7e+05   -2.3e-06      1.000
-1.31e+06    1.31e+06
```

```
AgeCategory_30_34                         -1.2166    6.7e+05  -1.82e-06      1.000
-1.31e+06    1.31e+06
AgeCategory_35_39                         -1.1732   6.72e+05  -1.75e-06      1.000
-1.32e+06    1.32e+06
AgeCategory_40_44                         -0.7311   6.69e+05  -1.09e-06      1.000
-1.31e+06    1.31e+06
AgeCategory_45_49                         -0.4004   6.71e+05  -5.96e-07      1.000
-1.32e+06    1.32e+06
AgeCategory_50_54                         -0.0008    6.7e+05  -1.26e-09      1.000
-1.31e+06    1.31e+06
AgeCategory_55_59                          0.2437   6.71e+05   3.63e-07      1.000
-1.31e+06    1.31e+06
AgeCategory_60_64                          0.5221   6.69e+05   7.81e-07      1.000
-1.31e+06    1.31e+06
AgeCategory_65_69                          0.7508   6.71e+05   1.12e-06      1.000
-1.32e+06    1.32e+06
AgeCategory_70_74                          1.0451   6.72e+05   1.55e-06      1.000
-1.32e+06    1.32e+06
AgeCategory_75_79                          1.2395    6.7e+05   1.85e-06      1.000
-1.31e+06    1.31e+06
AgeCategory_80_or_older                    1.4998   6.71e+05   2.24e-06      1.000
-1.32e+06    1.32e+06
Race_American_Indian_Alaskan_Native       -0.4505        nan        nan        nan
nan          nan
Race_Asian                                -0.9895        nan        nan        nan
nan          nan
Race_Black                                -0.8017        nan        nan        nan
nan          nan
Race_Hispanic                             -0.7244        nan        nan        nan
nan          nan
Race_Other                                -0.5281        nan        nan        nan
nan          nan
Race_White                                -0.5436        nan        nan        nan
nan          nan
Diabetic_No_borderline_diabetes            0.1157      0.047      2.472      0.013
0.024        0.207
Diabetic_Yes                               0.4724      0.019     25.299      0.000
0.436        0.509
Diabetic_Yes_during_pregnancy              0.0881      0.120      0.737      0.461
-0.146       0.322
PhysicalActivity_Yes                       0.0164      0.018      0.913      0.361
-0.019       0.052
GenHealth_Excellent                       -1.3443        nan        nan        nan
nan          nan
GenHealth_Fair                             0.1536        nan        nan        nan
nan          nan
GenHealth_Good                            -0.3179        nan        nan        nan
```

```
nan          nan
GenHealth_Poor                          0.5423        nan        nan        nan
nan          nan
GenHealth_Very_good                    -0.8657        nan        nan        nan
nan          nan
Asthma_Yes                              0.2862      0.021     13.358      0.000
0.244        0.328
KidneyDisease_Yes                       0.5485      0.027     20.023      0.000
0.495        0.602
SkinCancer_Yes                          0.1183      0.022      5.443      0.000
0.076        0.161
================================================================================
=======================
"""
```

Questions - Why are GenHealth, Race, Sex P-values equal to nan? perfect multicollinearity - exclude one of the dummy variables

[167]:
```
ypred = log_model.predict(train)
p, r, thresholds = precision_recall_curve(y_train, ypred)
plot_precision_recall_vs_threshold(p, r, thresholds)
```



[168]:
```
confusion_matrix_train(log_model, 0.2)
```

```
Accuracy =  87.50762207038885
Precision =  33.84420970773119
FNR =  52.49681644533382
TPR or Recall =  47.50318355466618
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0     213431.0      20417.0
Actual 1      11543.0      10445.0
```

[168]: ' '

[169]:
```
confusion_matrix_test(test,test.HeartDisease_Yes,log_model, 0.2)
```

```
Accuracy =  87.59830516424584
Precision =  33.696069645371914
FNR =  51.12349117920149
TPR or Recall =  48.87650882079851
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0     213431.0      20417.0
Actual 1      11543.0      10445.0
```

[169]: ' '

[ ]:
```

```

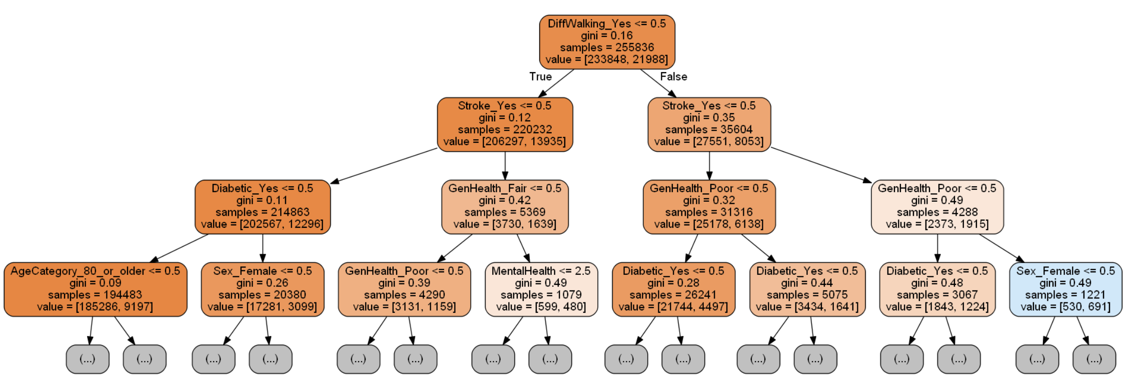
6 Classification Tree

[175]:
```
#Defining the object to build a regression tree
model = DecisionTreeClassifier(random_state=1, max_depth=5)

#Fitting the regression tree to the data
model.fit(X_train, y_train)
```

[175]: `DecisionTreeClassifier(max_depth=5, random_state=1)`

[176]:
```
#Visualizing the regression tree
dot_data = StringIO()
export_graphviz(model, out_file=dot_data,
                filled=True, rounded=True, max_depth = 3,
                feature_names = X_train.columns,precision=2)
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
#graph.write_png('car_price_tree.png')
Image(graph.create_png())
```

[176]:



[177]:
```
confusion_matrix_data(X_train,y_train,model,cutoff=0.4)
```

```
Accuracy =  91.41129473569005
Precision =  50.149730485126774
FNR =  88.57558668364562
TPR or Recall =  11.424413316354375
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0     231351.0       2497.0
Actual 1      19476.0       2512.0
```

[177]: ' '

[178]:
```
X_train.columns
```

[178]:
```
Index(['BMI', 'PhysicalHealth', 'MentalHealth', 'SleepTime', 'Smoking_Yes',
       'AlcoholDrinking_Yes', 'Stroke_Yes', 'DiffWalking_Yes', 'Sex_Female',
       'Sex_Male', 'AgeCategory_18_24', 'AgeCategory_25_29',
       'AgeCategory_30_34', 'AgeCategory_35_39', 'AgeCategory_40_44',
       'AgeCategory_45_49', 'AgeCategory_50_54', 'AgeCategory_55_59',
       'AgeCategory_60_64', 'AgeCategory_65_69', 'AgeCategory_70_74',
       'AgeCategory_75_79', 'AgeCategory_80_or_older',
       'Race_American_Indian_Alaskan_Native', 'Race_Asian', 'Race_Black',
       'Race_Hispanic', 'Race_Other', 'Race_White',
       'Diabetic_No_borderline_diabetes', 'Diabetic_Yes',
       'Diabetic_Yes_during_pregnancy', 'PhysicalActivity_Yes',
       'GenHealth_Excellent', 'GenHealth_Fair', 'GenHealth_Good',
       'GenHealth_Poor', 'GenHealth_Very_good', 'Asthma_Yes',
       'KidneyDisease_Yes', 'SkinCancer_Yes'],
      dtype='object')
```

[179]:
```
#Defining parameters and the range of values over which to optimize
param_grid = {
    'max_depth': range(1,10),
    'max_leaf_nodes': range(10,30),
}

skf = StratifiedKFold(n_splits=5)
#The folds are made by preserving the percentage of samples for each class.
#Minimizing FNR is equivalent to maximizing recall
grid_search = GridSearchCV(DecisionTreeClassifier(random_state=1), param_grid,
                           scoring=['precision','recall','accuracy'],
                           refit="recall", cv=skf, n_jobs=-1, verbose = True)
grid_search.fit(X_train.iloc[:10000, :], y_train.iloc[:10000])
# make the predictions
y_pred = grid_search.predict(X_test)
print('Best params for recall')
```

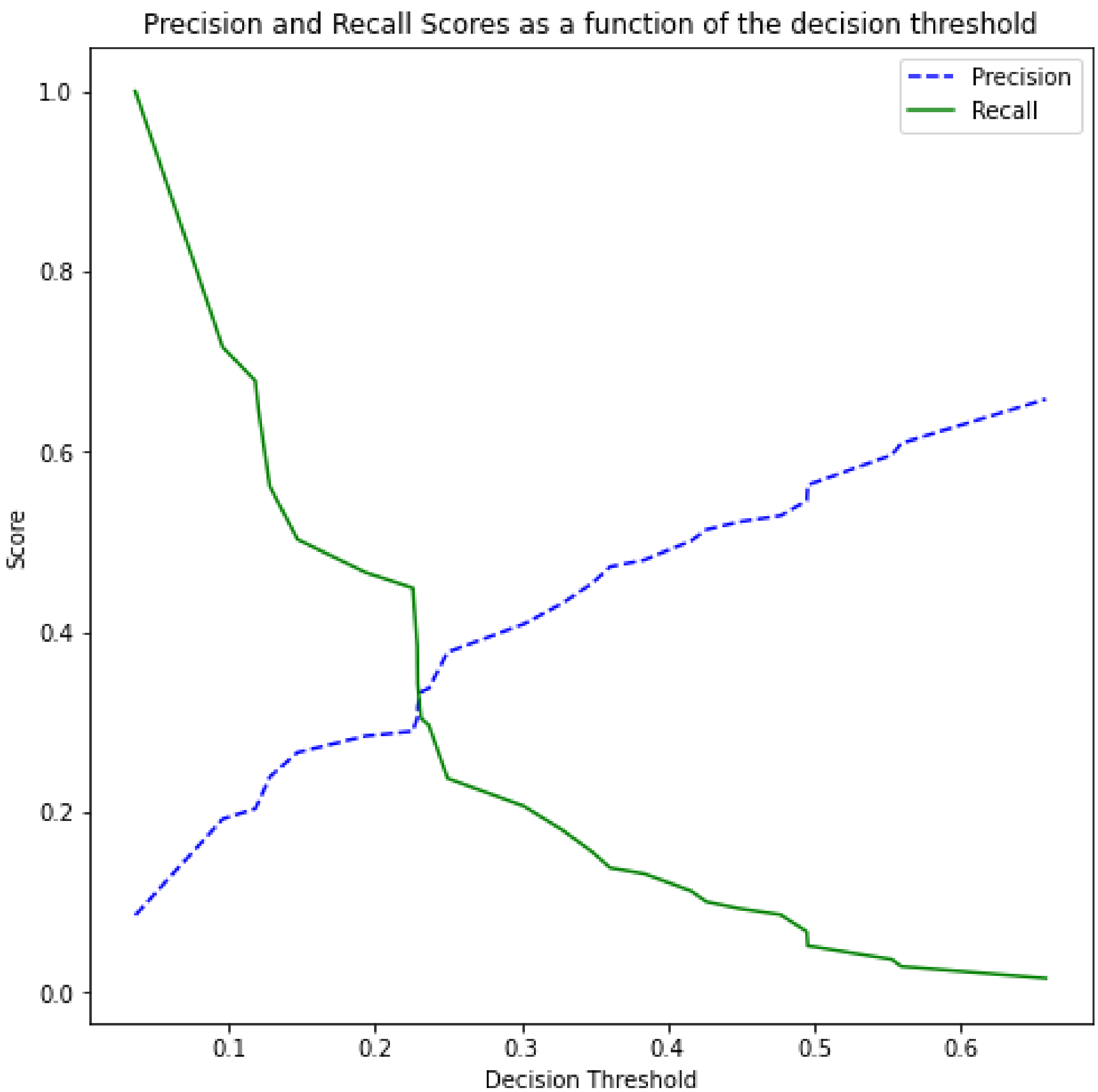
```
print(grid_search.best_params_)
```

```
Fitting 5 folds for each of 180 candidates, totalling 900 fits
Best params for recall
{'max_depth': 5, 'max_leaf_nodes': 27}
```

[180]:
```
#All results of the grid search can be seen with cv_results_
cv_scores = pd.DataFrame(grid_search.cv_results_)

model = DecisionTreeClassifier(random_state=1, max_depth = 5, max_leaf_nodes=27)
model.fit(X_train,y_train)
print(confusion_matrix_data(X_train,y_train,model))
print(confusion_matrix_data(X_test,y_test,model))
```

```
Accuracy =  91.50823183601995
Precision =  59.66201322556943
FNR =  96.3070765872294
TPR or Recall =  3.692923412770602
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0     233299.0        549.0
Actual 1      21176.0        812.0

Accuracy =  91.60868681499085
Precision =  52.71084337349398
FNR =  96.7502321262767
TPR or Recall =  3.2497678737233056
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0      58417.0        157.0
Actual 1       5210.0        175.0
```

[181]:
```
ypred = model.predict_proba(X_train)[:, 1]
p, r, thresholds = precision_recall_curve(y_train, ypred)
plot_precision_recall_vs_threshold(p, r, thresholds)
```



[182]:
```
print(confusion_matrix_data(X_train,y_train,model,cutoff=0.2))
print(confusion_matrix_data(X_test,y_test,model,cutoff=0.2))
```

```
Accuracy =  85.8202129489204
Precision =  29.005906379477537
FNR =  55.10733127160269
TPR or Recall =  44.89266872839731
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0     209688.0      24160.0
Actual 1      12117.0       9871.0

Accuracy =  86.04574805734924
```

```
Precision =  28.90345649582837
FNR =  54.967502321262764
TPR or Recall =  45.032497678737236
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0      52609.0       5965.0
Actual 1       2960.0       2425.0
```

Cost Complexity Pruning

[183]:
```
model = DecisionTreeClassifier(random_state = 1)#model without any restrictions
path= model.cost_complexity_pruning_path(X_train.iloc[:10000, :],y_train.iloc[:
 ↪10000])# Compute the pruning path during Minimal Cost-Complexity Pruning.
```

[184]:
```
alphas=path['ccp_alphas']
len(alphas)
```

[184]: 382

[185]:
```
#Grid search to optimize parameter values

skf = StratifiedKFold(n_splits=5)
grid_search = GridSearchCV(DecisionTreeClassifier(random_state = 1), param_grid␣
 ↪= {'ccp_alpha':alphas},
                                                    ␣
 ↪scoring=['precision','recall','accuracy'],
                                                     refit="recall", cv=skf,␣
 ↪n_jobs=-1, verbose = True)
grid_search.fit(X_train.iloc[:10000, :], y_train.iloc[:10000])

# make the predictions
y_pred = grid_search.predict(X_test)

print('Best params for recall')
print(grid_search.best_params_)
```

```
Fitting 5 folds for each of 382 candidates, totalling 1910 fits
Best params for recall
{'ccp_alpha': 0.0}
```

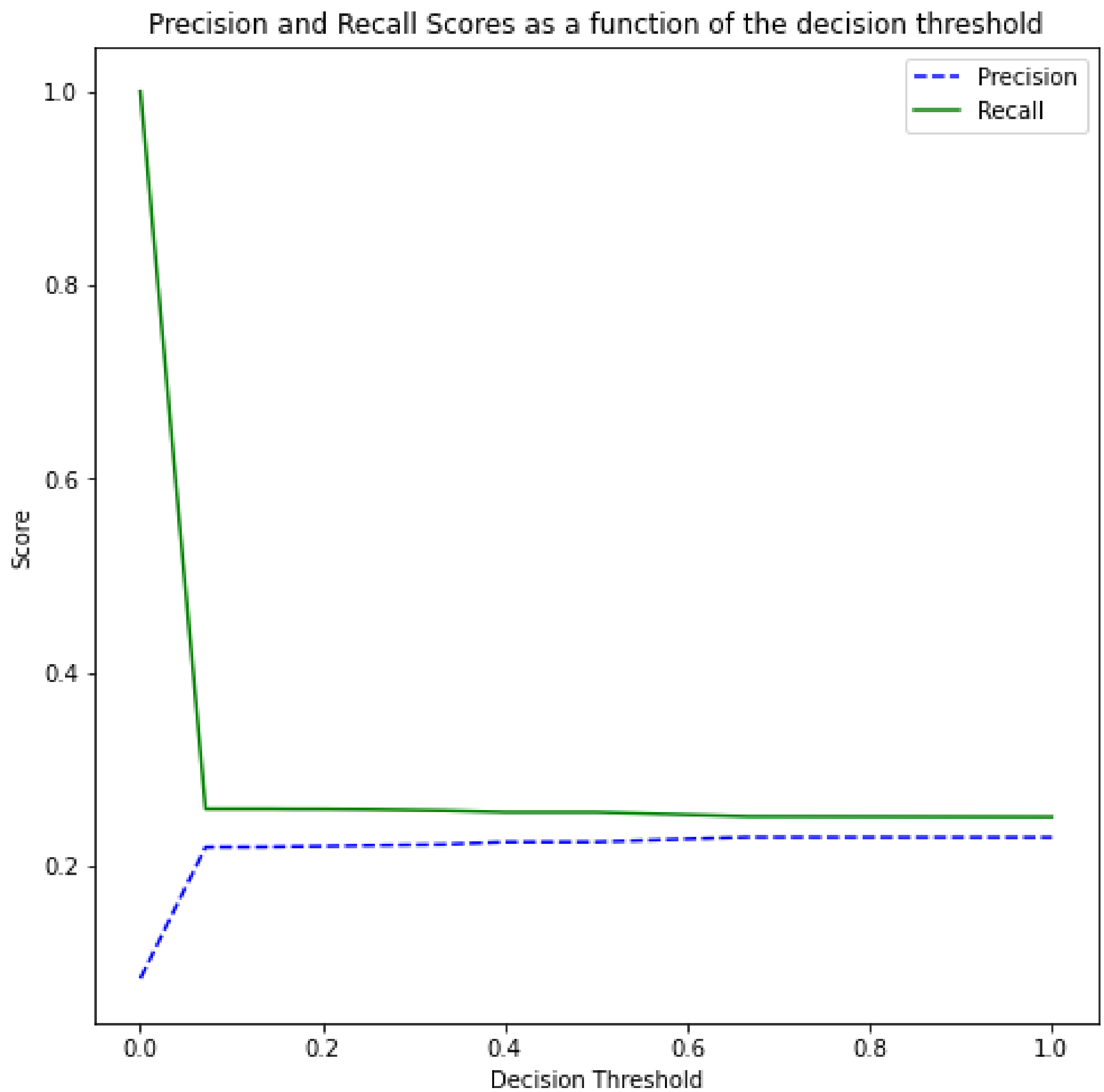
[186]:
```
tree = DecisionTreeClassifier(ccp_alpha=0.0,random_state=1)
tree.fit(X_train, y_train)
print(confusion_matrix_data(X_train,y_train,tree,cutoff = 0.2))
print(confusion_matrix_data(X_test,y_test,tree, cutoff = 0.2))
```

```
Accuracy =  99.52899513750997
Precision =  94.88187275946962
```

```
FNR =  0.09095870474804439
TPR or Recall =  99.90904129525195
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0     232663.0       1185.0
Actual 1         20.0      21968.0

Accuracy =  86.06607357838615
Precision =  22.074425969912905
FNR =  74.11327762302693
TPR or Recall =  25.886722376973072
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0      53653.0       4921.0
Actual 1       3991.0       1394.0
```

[187]:

```
ypred = tree.predict_proba(X_test)[:, 1]
p, r, thresholds = precision_recall_curve(y_test, ypred)
plot_precision_recall_vs_threshold(p, r, thresholds)
```



[ ]:

7 Random forests

Categorical Age

[314]:
```
recall = [0]*5
```

[315]:
```
i = 0
start_time = time.time()

for pr in range(10, 15):
```

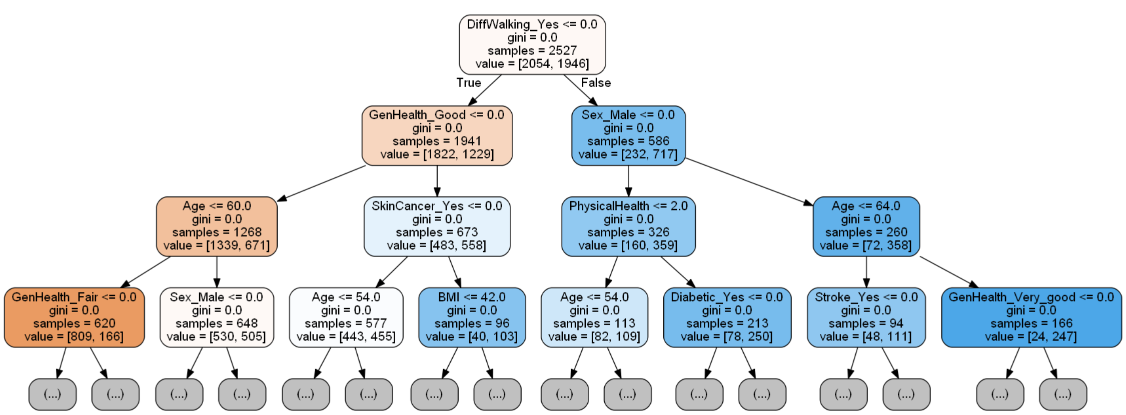
```
    model = RandomForestClassifier(random_state = 1, oob_score = True, verbose = False,
                                   n_estimators = 500, max_features = pr,
                                   n_jobs = -1).fit(X_train, y_train)
    oob_pred = model.oob_decision_function_[:, 1]
    bins = np.array([0, 0.5, 1])
    cm = np.histogram2d(y_train, oob_pred, bins = bins)[0]
    recall[i] = 100*(cm[1, 1]) / (cm[1, 0] + cm[1, 1])
    i += 1

end_time = time.time()

#took 0.2 min for range of 5 and 4000 obs
print('Time taken = ', (end_time-start_time)/60, 'min')
print('max recall = ', np.max(recall) + 10)
print('Best value of max_features = ', np.argmax(recall) + 10)
```

```
Time taken =  0.18982399702072145 min
max recall =  87.65
Best value of max_features =  12
```

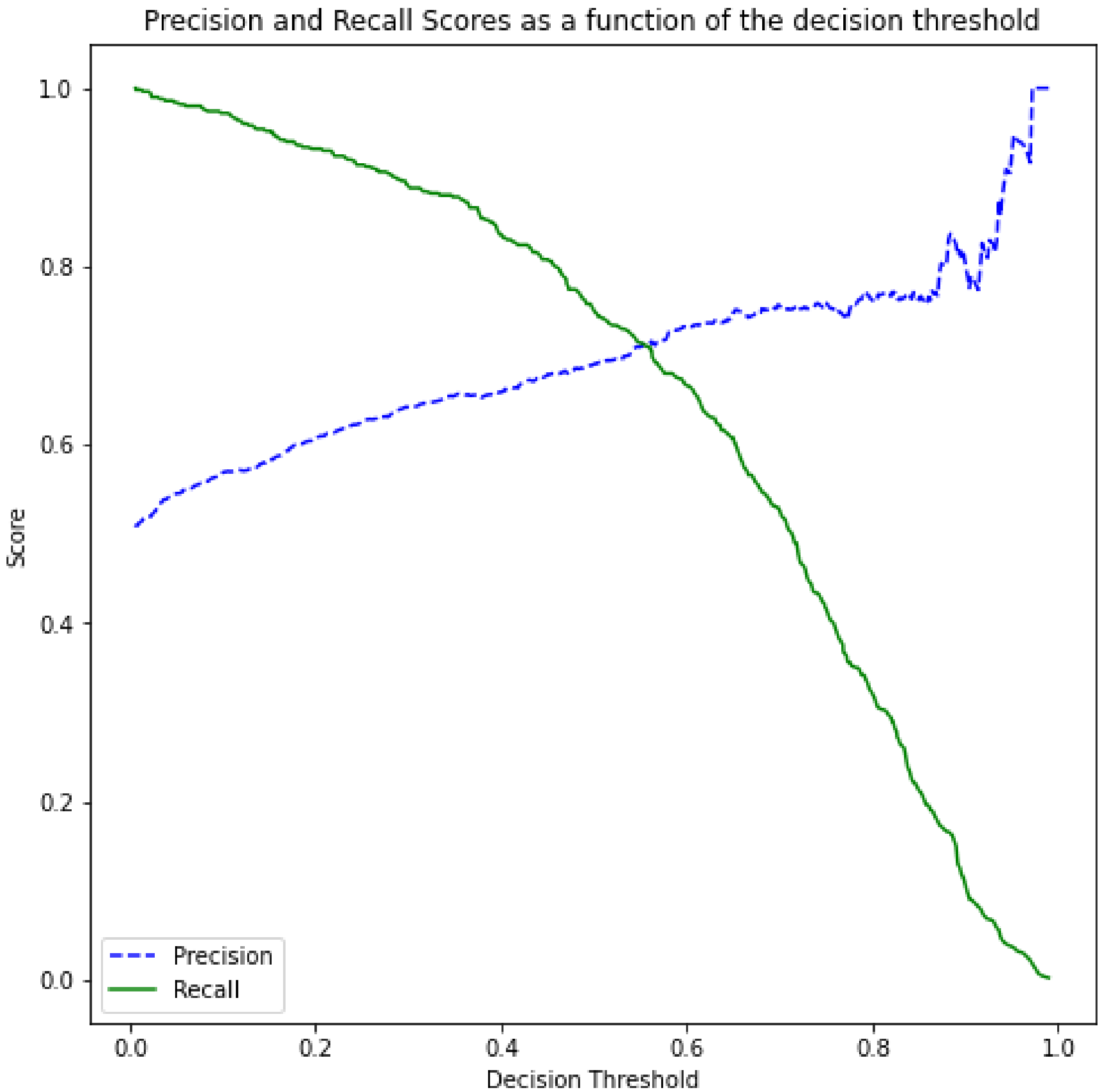
[318]:
```
model_rf = RandomForestClassifier(random_state = 1, n_jobs = -1, max_features = 12,
                                  n_estimators = 500).fit(X_train, y_train)
```

[320]:
```
dot_data = StringIO()
export_graphviz(model_rf.estimators_[0], out_file = dot_data,
                filled = True, rounded = True, max_depth = 3,
                feature_names = X_train.columns, precision=0)
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
#graph.write_png('car_price_tree.png')
Image(graph.create_png())
```

[320]:



[321]:
```
ypred = model_rf.predict_proba(X_test)[:, 1]
p, r, thresholds = precision_recall_curve(y_test, ypred)
plot_precision_recall_vs_threshold(p, r, thresholds)
```



[327]:
```
confusion_matrix_data(X_train, y_train, model_rf, 0.4)
```

```
Accuracy =  99.875
Precision =  99.75062344139651
FNR =  0.0
TPR or Recall =  100.0
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0       1995.0          5.0
```

```
Actual 1           0.0       2000.0
```

[327]: ' '

[334]:
```
confusion_matrix_data(X_test, y_test, model_rf, 0.4)
```

```
Accuracy =  70.2
Precision =  65.93059936908517
FNR =  16.4
TPR or Recall =  83.6
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0         284.0        216.0
Actual 1          82.0        418.0
```

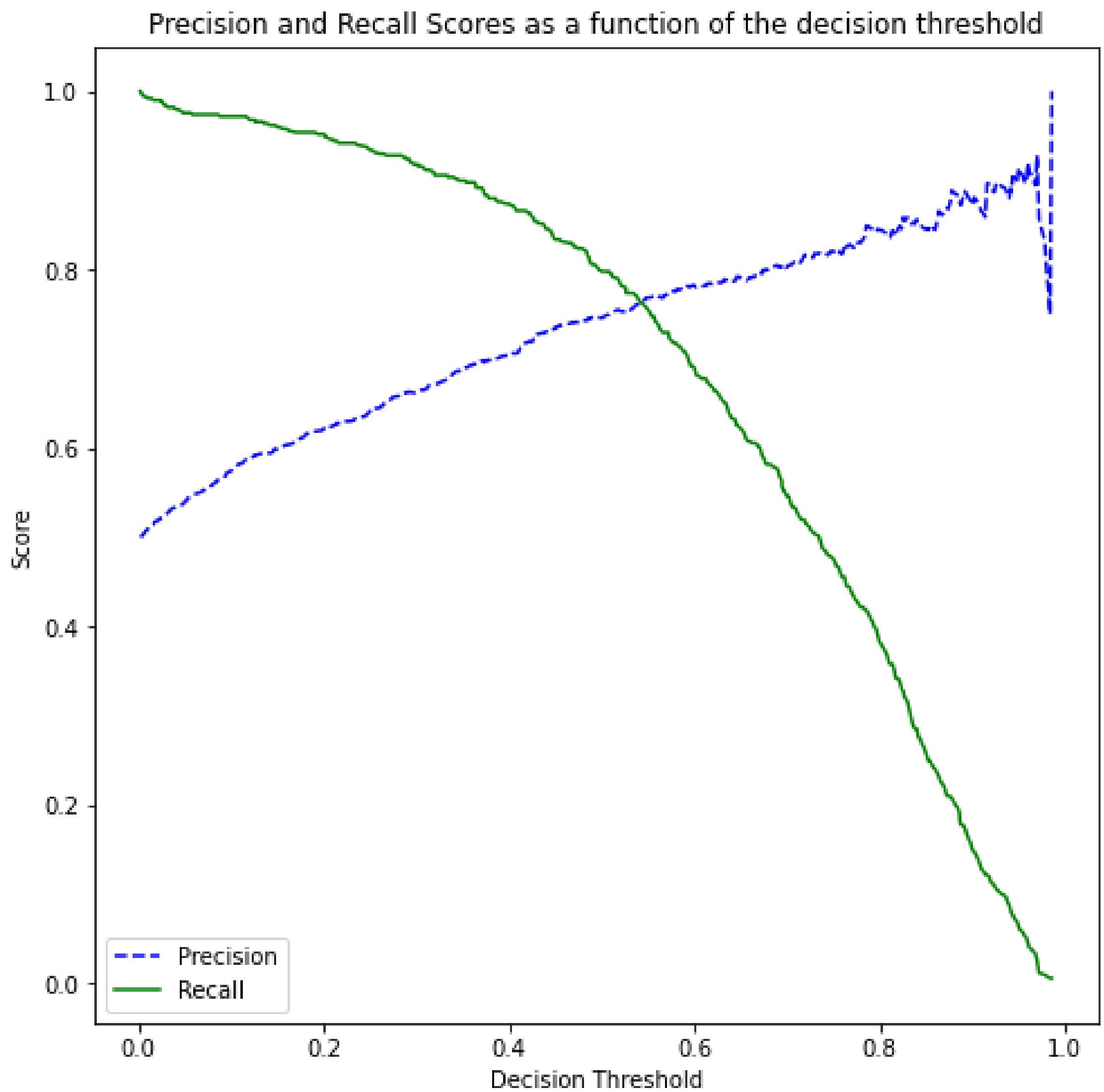
[334]: ' '

- Using cutoff = 0.4, accuracy decreases 0.5%, precision decreases 3%, but recall improves by 8%

Using X_train2

[335]:
```
model_rf2 = RandomForestClassifier(random_state = 1, n_jobs = -1, max_features␣
 ↪= 12,
                                  n_estimators = 500).fit(X_train2, y_train2)
```

[341]:
```
ypred = model_rf2.predict_proba(X_test)[:, 1]
p, r, thresholds = precision_recall_curve(y_test, ypred)
plot_precision_recall_vs_threshold(p, r, thresholds)
```



[350]:
```
confusion_matrix_data(X_train2, y_train2, model_rf2, 0.5)
```

```
Accuracy =  99.775
Precision =  99.79989994997499
FNR =  0.25
TPR or Recall =  99.75
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0       1996.0          4.0
Actual 1          5.0       1995.0
```

[350]: ''

[349]:
```
confusion_matrix_data(X_test, y_test, model_rf2, 0.5)
```

```
Accuracy =  76.3
Precision =  74.57943925233644
FNR =  20.2
TPR or Recall =  79.8
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0        364.0        136.0
Actual 1        101.0        399.0
```

[349]: ' '

8 AdaBoost

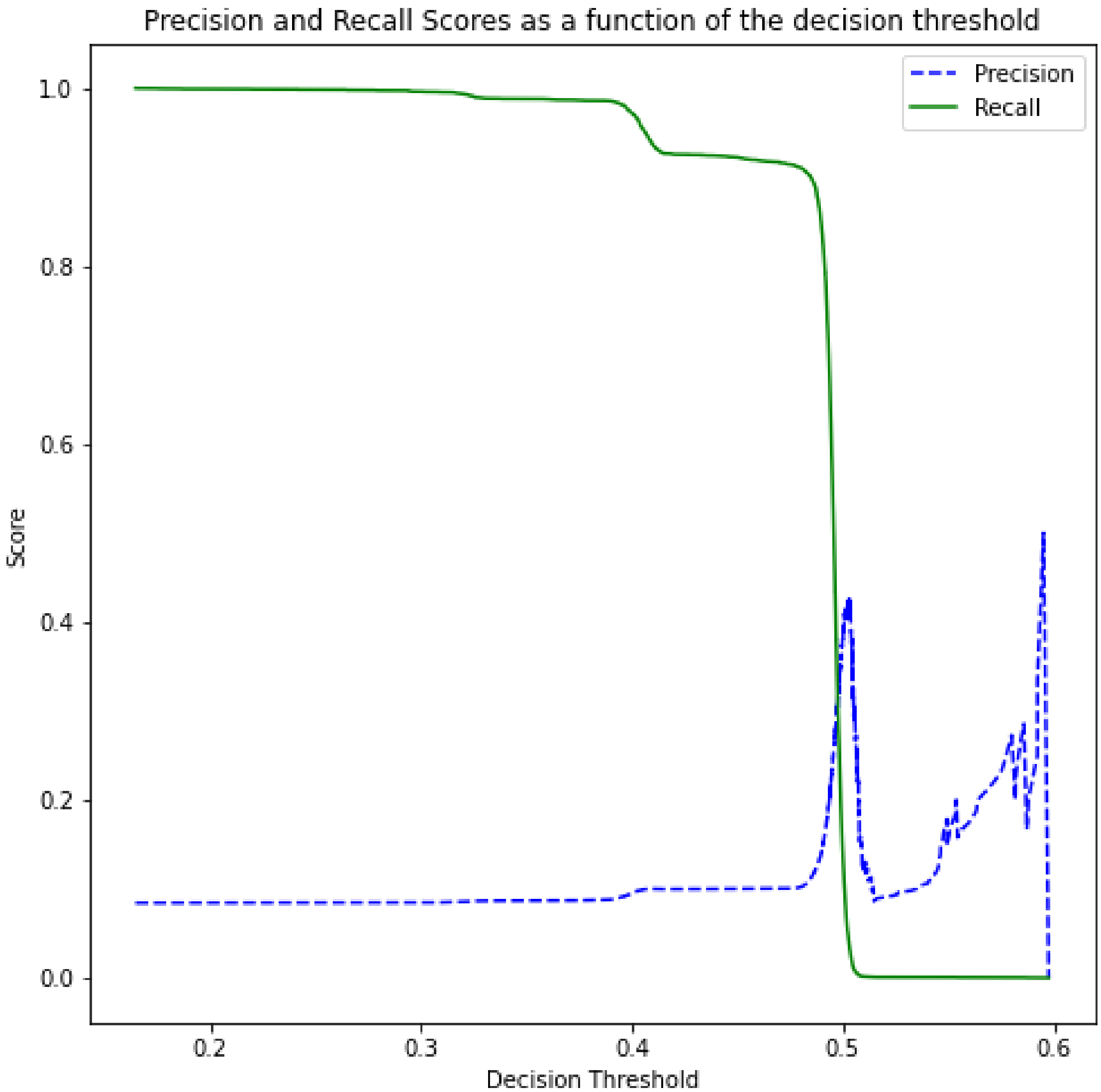
[44]:
```
#tuning params
start_time = time.time()

model_ab = AdaBoostClassifier(random_state = 1)
grid = dict()
grid['n_estimators'] = [10, 50, 100, 200, 500]
grid['learning_rate'] = [0.0001, 0.001, 0.01, 0.1, 1.0]
grid['base_estimator'] = [DecisionTreeClassifier(max_depth = 1),␣
 ↪DecisionTreeClassifier(max_depth = 2),
                          DecisionTreeClassifier(max_depth = 3),␣
 ↪DecisionTreeClassifier(max_depth = 4)]

cv = StratifiedKFold(n_splits = 5, shuffle = True, random_state = 1)
grid_search = GridSearchCV(estimator = model_ab, param_grid = grid, n_jobs = -1,
                           cv = cv, scoring = ['precision', 'recall',␣
 ↪'accuracy'], refit = 'recall')
grid_result = grid_search.fit(X_train.iloc[:1000], y_train.iloc[:1000])

print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
print("Time taken = ",(time.time()-start_time)/60," minutes")
```

```
Best: 0.223529 using {'base_estimator': DecisionTreeClassifier(max_depth=2),
'learning_rate': 1.0, 'n_estimators': 100}
Time taken =  1.7052798986434936  minutes
```

- took 1.7 minutes with 1000 obs

[46]:
```
#creating model with optimal params
model_ab = AdaBoostClassifier(random_state = 1, base_estimator =␣
 ↪DecisionTreeClassifier(max_depth = 2),
                             learning_rate = 1.0, n_estimators = 100).
 ↪fit(X_train.iloc[:10000], y_train.iloc[:10000])
```

[47]:
```
ypred = model_ab.predict_proba(X_test)[:, 1]
p, r, thresholds = precision_recall_curve(y_test, ypred)
plot_precision_recall_vs_threshold(p, r, thresholds)
```



[49]:
```
confusion_matrix_data(X_train, y_train, model_ab, 0.5)
```

```
Accuracy =  90.75579668224957
Precision =  38.88740304894357
FNR =  86.77460432963434
TPR or Recall =  13.225395670365653
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0     229278.0       4570.0
```

```
Actual 1      19080.0       2908.0
```

[49]: ' '

[51]:
```
confusion_matrix_data(X_test, y_test, model_ab, 0.5)
```

```
Accuracy =  90.88947607060773
Precision =  38.29449152542373
FNR =  86.57381615598885
TPR or Recall =  13.426183844011142
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0      57409.0       1165.0
Actual 1       4662.0        723.0
```

[51]: ' '

[ ]:
```

```

9 Gradient Boosting

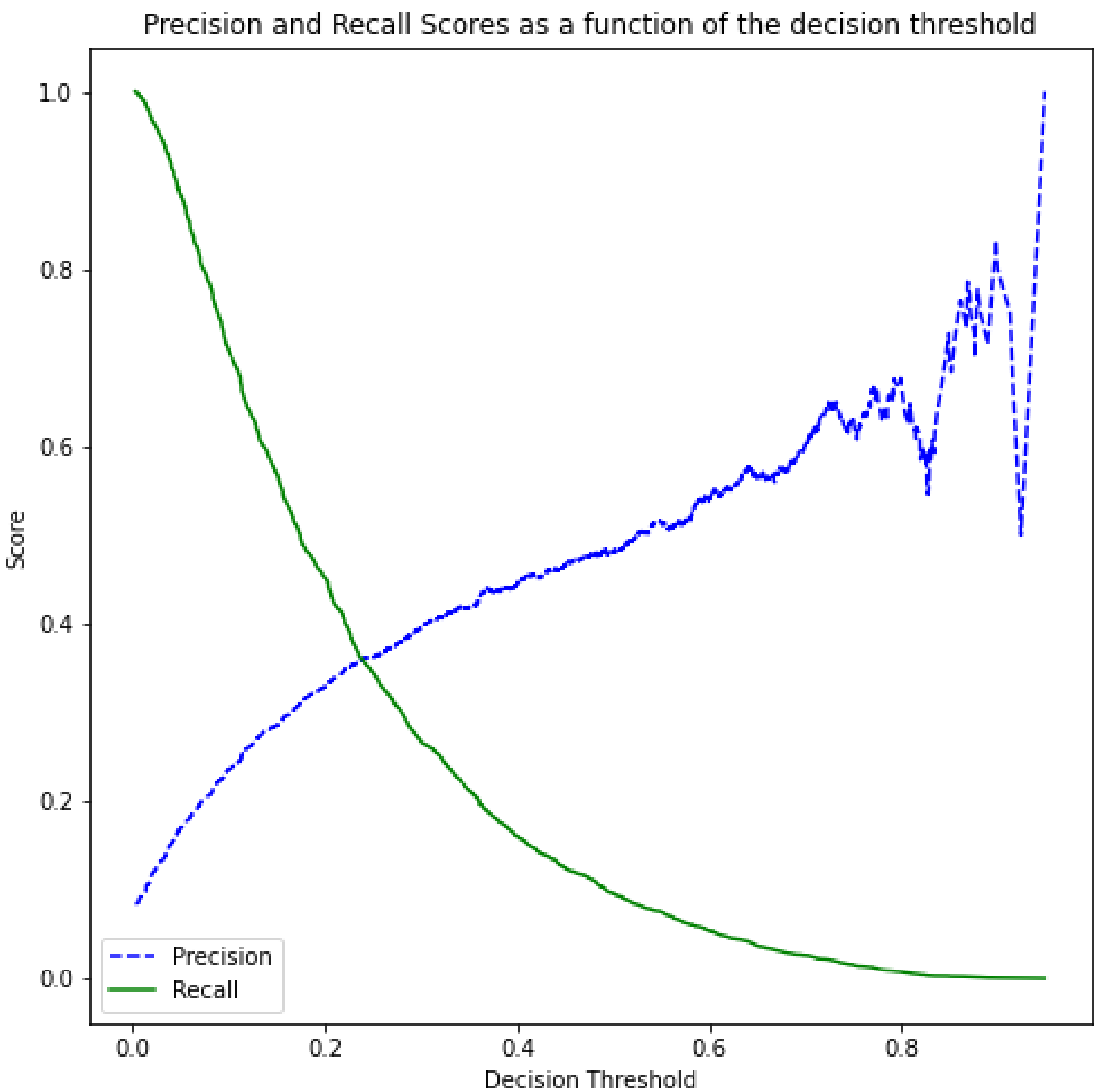
[52]:
```
#tuning params
start_time = time.time()

model_gb = GradientBoostingClassifier(random_state = 1, max_features = 'sqrt')
grid = dict()
grid['n_estimators'] = [10, 50, 100, 200, 500]
grid['learning_rate'] = [0.0001, 0.001, 0.01, 0.1, 1.0]
grid['max_depth'] = [1, 2, 3, 4, 5]
grid['subsample'] = [0.5, 1.0]

cv = StratifiedKFold(n_splits = 5, shuffle = True, random_state = 1)
grid_search = GridSearchCV(estimator = model_gb, param_grid = grid, n_jobs = -1,
                           cv = cv, scoring = ['precision', 'recall',
 ↪'accuracy'],
                           refit = 'recall')
grid_result = grid_search.fit(X_train.iloc[:1000], y_train.iloc[:1000])

print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
print("Time taken = ",(time.time()-start_time)/60," minutes")
```

```
Best: 0.458824 using {'learning_rate': 1.0, 'max_depth': 1, 'n_estimators': 100,
'subsample': 0.5}
Time taken =  1.3608951171239216  minutes
```

- took 1.36 min using 1000 obs

[53]:
```
model_gb = GradientBoostingClassifier(random_state = 1, max_depth = 1,␣
↪learning_rate = 1.0,
                                      n_estimators = 100, subsample = 0.5).
↪fit(X_train.iloc[:10000], y_train.iloc[:10000])
```

[54]:
```
ypred = model_gb.predict_proba(X_test)[:, 1]
p, r, thresholds = precision_recall_curve(y_test, ypred)
plot_precision_recall_vs_threshold(p, r, thresholds)
```



[58]:
```
confusion_matrix_data(X_train, y_train, model_gb, 0.2)
```

```
Accuracy =  87.33211901374318
Precision =  32.378504514863536
```

```
FNR =  56.458068037111154
TPR or Recall =  43.541931962888846
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0     213853.0      19995.0
Actual 1      12414.0       9574.0
```

[58]: ' '

[59]:
```
confusion_matrix_data(X_test, y_test, model_gb, 0.2)
```

```
Accuracy =  87.62957519661033
Precision =  32.92336802270577
FNR =  54.76323119777159
TPR or Recall =  45.23676880222841
Confusion matrix =
           Predicted 0  Predicted 1
Actual 0      53611.0       4963.0
Actual 1       2949.0       2436.0
```

[59]: ' '