National Health and Nutrition Examination Survey

August 21, 2020

The National Health and Nutrition Examination Survey (NHANES) is a program of studies designed to assess the health and nutritional status of adults and children in the United States. The survey is unique in that it combines interviews and physical examinations.

For two-year cycles (e.g., 2015-2016), cross-sectional national samples of individuals living in the United States are invited to participate in both aspects of the data collection. The data produced are widely considered by the research community as among the most important scientific indicators of the health and well-being of the U.S. population.

For this specialization, we will be analyzing data collected from a national sample of individuals during the 2015-2016 cycle.

This notebook demonstrates application of statistics in Machine Learning using Binary Classification

0.0.1 Import Libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn

import xgboost as xgb
from xgboost import XGBClassifier, XGBRegressor
from xgboost import to_graphviz, plot_importance, plot_tree

%matplotlib inline
sns.set_style('dark')
sns.set(font_scale=1.2)

from sklearn.model_selection import cross_val_score, train_test_split,␣
 ↪GridSearchCV, RandomizedSearchCV
from sklearn.preprocessing import LabelEncoder, StandardScaler, MinMaxScaler,␣
 ↪OneHotEncoder
from sklearn.metrics import confusion_matrix, classification_report,␣
 ↪mean_absolute_error, mean_squared_error,r2_score
from sklearn.metrics import plot_confusion_matrix, plot_precision_recall_curve,␣
 ↪plot_roc_curve, accuracy_score
```

```python
from sklearn.metrics import auc, f1_score, precision_score, recall_score,␣
↪roc_auc_score


import feature_engine.missing_data_imputers as mdi
from feature_engine.outlier_removers import Winsorizer


from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import RandomOverSampler

import warnings
warnings.filterwarnings('ignore')

import pickle
from pickle import dump, load

np.random.seed(0)

from pycaret.classification import *
#from pycaret.clustering import *
#from pycaret.regression import *

pd.set_option('display.max_columns',100)
#pd.set_option('display.max_rows',100)
pd.set_option('display.width', 1000)
```

0.0.2 Data Exploration and Analysis

[2]:
```python
df = pd.read_csv("nhanes_2015_2016.csv")
```

[3]:
```python
df
```

[3]:
```
       SEQN  ALQ101  ALQ110  ALQ130  SMQ020  RIAGENDR  RIDAGEYR  RIDRETH1
DMDCITZN  DMDEDUC2  DMDMARTL  DMDHHSIZ   WTINT2YR  SDMVPSU  SDMVSTRA  INDFMPIR
BPXSY1  BPXDI1  BPXSY2  BPXDI2  BMXWT  BMXHT  BMXBMI  BMXLEG  BMXARML  BMXARMC
BMXWAIST  HIQ210
0     83732     1.0     NaN     1.0       1         1        62         3
1.0       5.0       1.0         2  134671.37         1       125      4.39
128.0    70.0   124.0    64.0   94.8  184.5    27.8    43.3     43.6     35.9
101.1     2.0
1     83733     1.0     NaN     6.0       1         1        53         3
2.0       3.0       3.0         1   24328.56         1       125      1.32
146.0    88.0   140.0    88.0   90.4  171.4    30.8    38.0     40.0     33.2
107.9     NaN
2     83734     1.0     NaN     NaN       1         1        78         3
```

```
1.0       3.0       1.0         2   12400.01        1        131       1.51
138.0    46.0   132.0    44.0   83.4  170.1    28.8    35.6     37.0     31.0
116.5     2.0
3     83735     2.0     1.0     1.0       2         2         56         3
1.0       5.0       6.0         1  102718.00        1        131       5.00
132.0    72.0   134.0    68.0  109.8  160.9    42.4    38.5     37.7     38.3
110.1     2.0
4     83736     2.0     1.0     1.0       2         2         42         4
1.0       4.0       3.0         5   17627.67        2        126       1.23
100.0    70.0   114.0    54.0   55.2  164.9    20.3    37.4     36.0     27.2
80.4     2.0
…     …     …     …     …     …       …       …       …
…       …       …       …        …      …       …       …
…     …     …     …    …    …     …     …     …     …
…     …
5730  93695     2.0     2.0     NaN       1         2         76         3
1.0       3.0       2.0         1   58614.08        2        130       1.43
112.0    48.0   112.0    46.0   59.1  165.8    21.5    38.2     37.0     29.5
95.0     2.0
5731  93696     2.0     2.0     NaN       2         1         26         3
1.0       5.0       1.0         3  122920.60        1        121       2.99
118.0    68.0   116.0    76.0  112.1  182.2    33.8    43.4     41.8     42.3
110.2     2.0
5732  93697     1.0     NaN     1.0       1         2         80         3
1.0       4.0       2.0         1   49050.06        2        132       2.97
154.0    56.0   146.0    58.0   71.7  152.2    31.0    31.3     37.5     28.8
NaN     2.0
5733  93700     NaN     NaN     NaN       1         1         35         3
2.0       1.0       1.0         5   42314.29        1        126       0.00
104.0    62.0   106.0    66.0   78.2  173.3    26.0    40.3     37.5     30.6
98.9     2.0
5734  93702     1.0     NaN     2.0       2         2         24         3
1.0       5.0       5.0         3  107361.91        2        119       3.54
118.0    66.0   114.0    68.0   58.3  165.0    21.4    38.2     33.5     26.2
72.5     2.0

[5735 rows x 28 columns]
```

[4]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5735 entries, 0 to 5734
Data columns (total 28 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   SEQN      5735 non-null   int64
 1   ALQ101    5208 non-null   float64
```

```
 2   ALQ110    1731 non-null   float64
 3   ALQ130    3379 non-null   float64
 4   SMQ020    5735 non-null   int64
 5   RIAGENDR  5735 non-null   int64
 6   RIDAGEYR  5735 non-null   int64
 7   RIDRETH1  5735 non-null   int64
 8   DMDCITZN  5734 non-null   float64
 9   DMDEDUC2  5474 non-null   float64
 10  DMDMARTL  5474 non-null   float64
 11  DMDHHSIZ  5735 non-null   int64
 12  WTINT2YR  5735 non-null   float64
 13  SDMVPSU   5735 non-null   int64
 14  SDMVSTRA  5735 non-null   int64
 15  INDFMPIR  5134 non-null   float64
 16  BPXSY1    5401 non-null   float64
 17  BPXDI1    5401 non-null   float64
 18  BPXSY2    5535 non-null   float64
 19  BPXDI2    5535 non-null   float64
 20  BMXWT     5666 non-null   float64
 21  BMXHT     5673 non-null   float64
 22  BMXBMI    5662 non-null   float64
 23  BMXLEG    5345 non-null   float64
 24  BMXARML   5427 non-null   float64
 25  BMXARMC   5427 non-null   float64
 26  BMXWAIST  5368 non-null   float64
 27  HIQ210    4732 non-null   float64
dtypes: float64(20), int64(8)
memory usage: 1.2 MB
```

[5]:
```
df.describe(include='all')
```

[5]:
```
               SEQN       ALQ101       ALQ110       ALQ130       SMQ020  \
RIAGENDR     RIDAGEYR     RIDRETH1     DMDCITZN     DMDEDUC2     DMDMARTL
DMDHHSIZ       WTINT2YR      SDMVPSU     SDMVSTRA     INDFMPIR       BPXSY1
BPXDI1       BPXSY2       BPXDI2        BMXWT        BMXHT       BMXBMI
BMXLEG      BMXARML      BMXARMC     BMXWAIST       HIQ210
count   5735.000000  5208.000000  1731.000000  3379.000000  5735.000000
5735.000000  5735.000000  5735.000000  5734.000000  5474.000000  5474.000000
5735.000000    5735.000000  5735.000000  5735.000000  5134.000000  5401.000000
5401.000000  5535.000000  5535.000000  5666.000000  5673.000000  5662.000000
5345.000000  5427.000000  5427.000000  5368.000000  4732.000000
mean   88678.583435     1.336406     1.587522     3.911512     1.607149
1.518919    48.052310     3.042371     1.185385     3.441725     2.628608
3.323801   40312.412352     1.487881   126.236617     2.403204   125.084614
69.516386   124.783017    69.346703    81.342676   166.142834    29.382197
38.576782    37.146987    33.112235    99.567213     1.915469
std     2882.139237     0.505514     0.623940    34.341839     0.571975
```

```
0.499686    18.431011     1.296793     0.491678     1.309700     2.366786
1.724670  38768.921774     0.499897     4.244406     1.601995    18.480873
12.881575    18.527012    13.022829    21.764409    10.079264     7.095921
3.873018     2.800784     5.268027    16.844109     0.414845
min     83732.000000     1.000000     1.000000     1.000000     1.000000
1.000000    18.000000     1.000000     1.000000     1.000000     1.000000
1.000000   5330.960000     1.000000   119.000000     0.000000    82.000000
0.000000    84.000000     0.000000    32.400000   129.700000    14.500000
26.000000    28.200000    17.100000    58.700000     1.000000
25%     86164.000000     1.000000     1.000000     1.000000     1.000000
1.000000    32.000000     2.000000     1.000000     3.000000     1.000000
2.000000  17164.085000     1.000000   123.000000     1.060000   112.000000
62.000000   112.000000    62.000000    65.900000   158.700000    24.300000
36.000000    35.200000    29.500000    87.600000     2.000000
50%     88668.000000     1.000000     2.000000     2.000000     2.000000
2.000000    48.000000     3.000000     1.000000     4.000000     1.000000
3.000000  24654.860000     1.000000   126.000000     1.980000   122.000000
70.000000   122.000000    70.000000    78.200000   166.000000    28.300000
38.600000    37.100000    32.700000    98.300000     2.000000
75%     91178.500000     2.000000     2.000000     3.000000     2.000000
2.000000    63.000000     4.000000     1.000000     4.750000     5.000000
5.000000  42862.305000     2.000000   130.000000     3.740000   134.000000
78.000000   134.000000    78.000000    92.700000   173.500000    33.000000
41.200000    39.000000    36.200000   109.300000     2.000000
max     93702.000000     9.000000     9.000000   999.000000     9.000000
2.000000    80.000000     5.000000     9.000000     9.000000    77.000000
7.000000 233755.840000     2.000000   133.000000     5.000000   236.000000
120.000000   238.000000   144.000000   198.900000   202.700000    67.300000
51.500000    47.400000    58.400000   171.600000     9.000000
```

[6]:
```
df.shape
```

[6]:
```
(5735, 28)
```

[7]:
```
df.columns
```

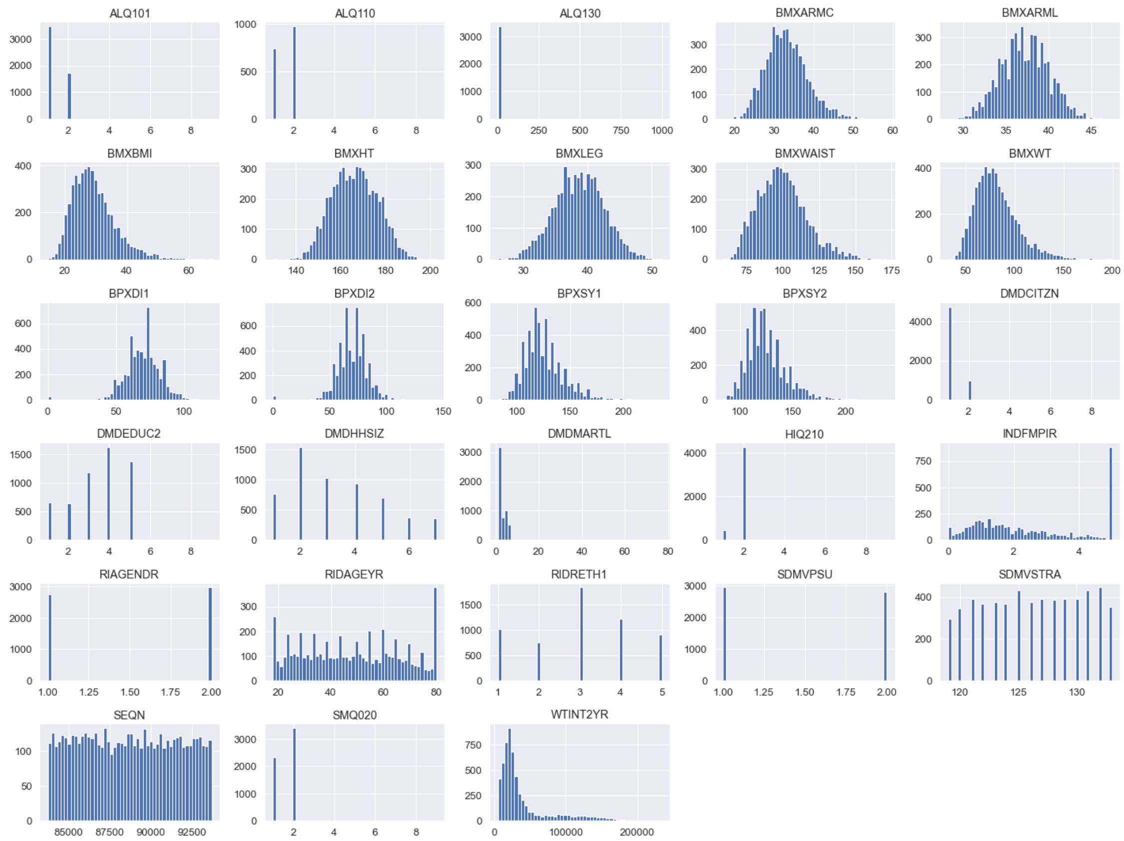
[7]:
```
Index(['SEQN', 'ALQ101', 'ALQ110', 'ALQ130', 'SMQ020', 'RIAGENDR', 'RIDAGEYR',
'RIDRETH1', 'DMDCITZN', 'DMDEDUC2', 'DMDMARTL', 'DMDHHSIZ', 'WTINT2YR',
'SDMVPSU', 'SDMVSTRA', 'INDFMPIR', 'BPXSY1', 'BPXDI1', 'BPXSY2', 'BPXDI2',
'BMXWT', 'BMXHT', 'BMXBMI', 'BMXLEG', 'BMXARML', 'BMXARMC', 'BMXWAIST',
'HIQ210'], dtype='object')
```

[ ]:

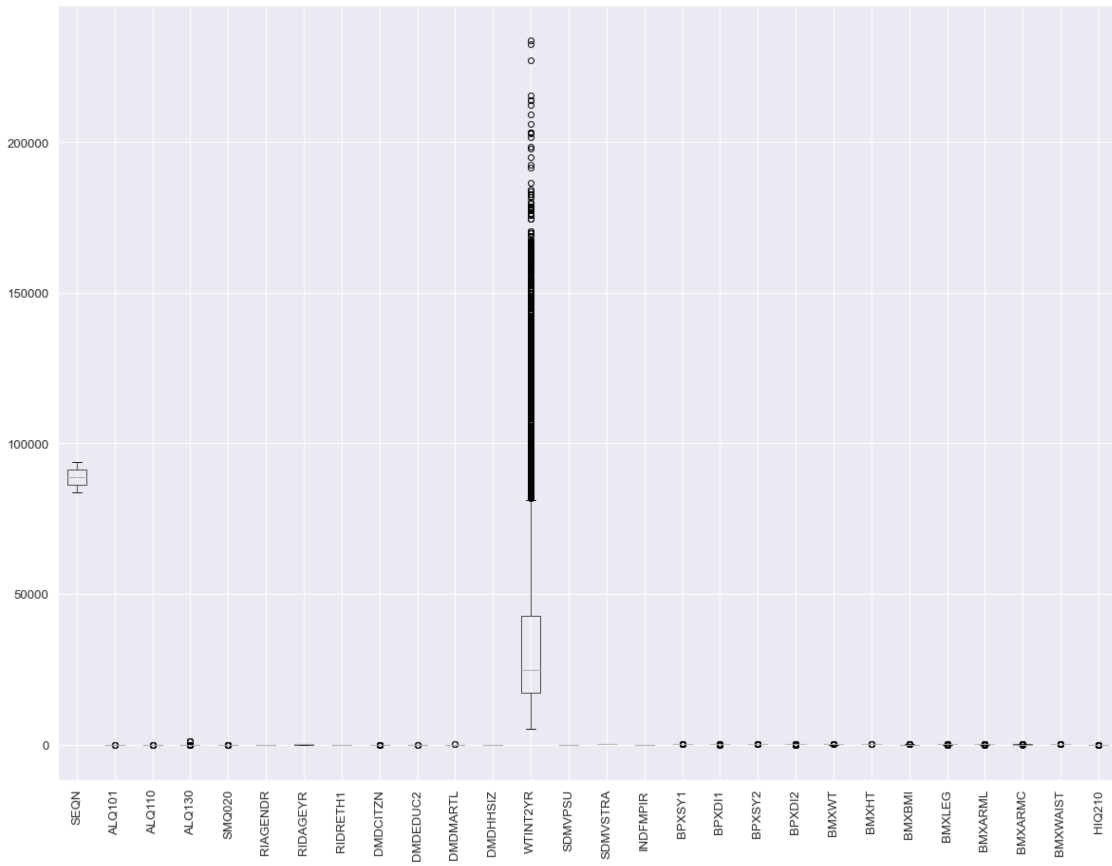
0.0.3 Data Visualization

0.0.4 Univariate Data Exploration

[8]:
```
df.hist(bins=50, figsize=(20,15))
plt.tight_layout()
plt.show()
```

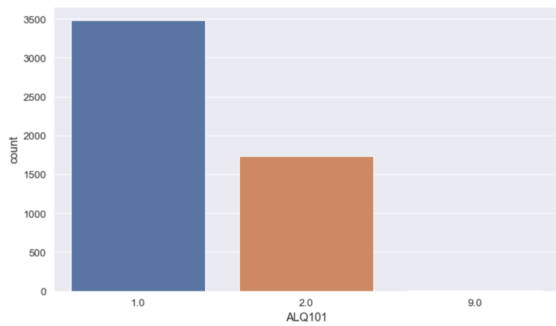


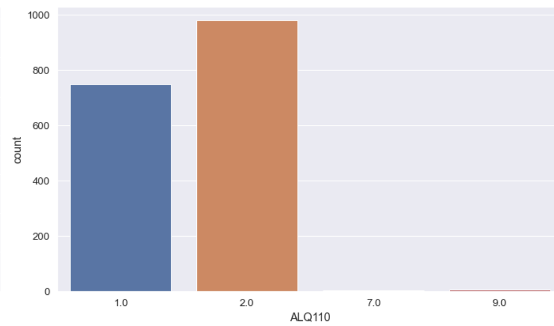
[9]:
```
df.boxplot(figsize=(20,15))
plt.xticks(rotation = 90)
plt.show()
```

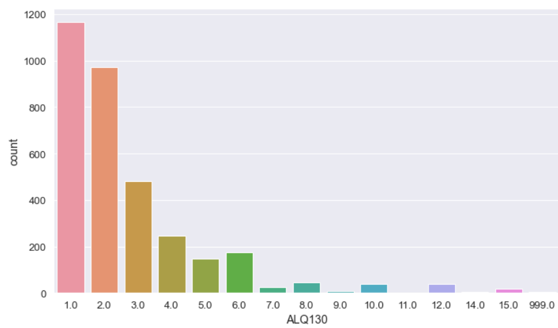


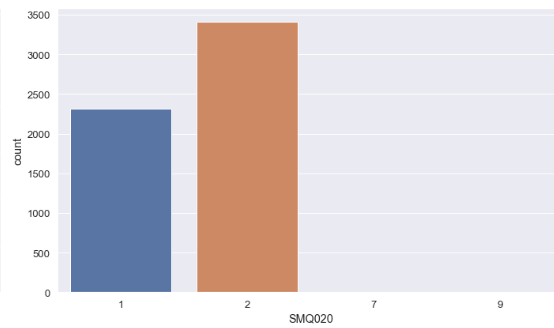
[10]:
```
fig = plt.figure(figsize=(20,40))

plt.subplot(7,2,1)
plt.title("")
sns.countplot(df.ALQ101)

plt.subplot(7,2,2)
plt.title("")
sns.countplot(df.ALQ110)

plt.subplot(7,2,3)
plt.title("")
sns.countplot(df.ALQ130)

plt.subplot(7,2,4)
plt.title("")
sns.countplot(df.SMQ020)

plt.subplot(7,2,5)
plt.title("")
```

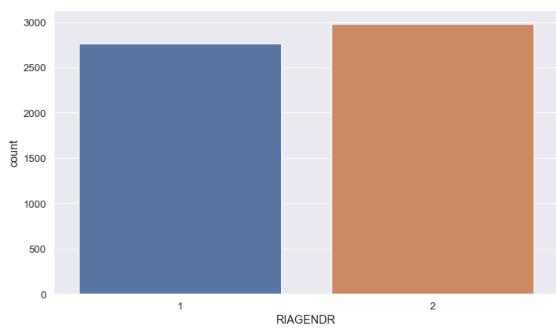
```
sns.countplot(df.RIAGENDR)

plt.subplot(7,2,6)
plt.title("")
sns.countplot(df.RIDRETH1)

plt.subplot(7,2,7)
plt.title("")
sns.countplot(df.DMDHHSIZ)

plt.subplot(7,2,8)
plt.title("")
sns.countplot(df.SDMVPSU)

plt.subplot(7,2,9)
plt.title("")
sns.countplot(df.HIQ210)

plt.tight_layout()
plt.show()
```

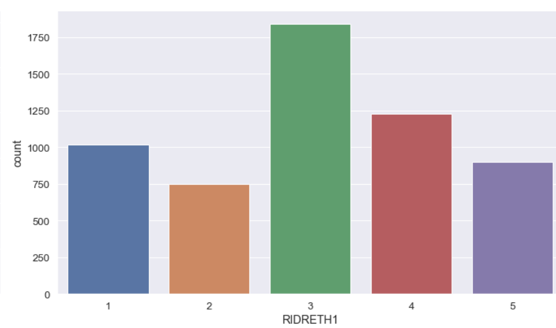

count
0
500
1000
1500
2000
2500
3000
3500
1.0
2.0
9.0
ALQ101

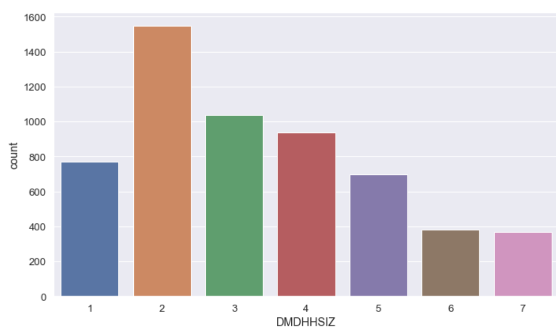

count
0
200
400
600
800
1000
1.0
2.0
7.0
9.0
ALQ110


count
0
200
400
600
800
1000
1200
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0
10.0
11.0
12.0
14.0
15.0
999.0
ALQ130

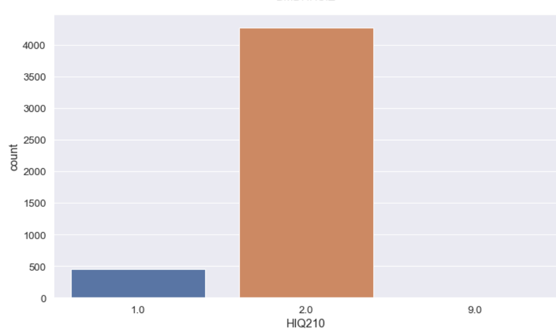

count
0
500
1000
1500
2000
2500
3000
3500
1
2
7
9
SMQ020


count
0
500
1000
1500
2000
2500
3000
1
2
RIAGENDR


count
0
250
500
750
1000
1250
1500
1750
1
2
3
4
5
RIDRETH1


count
0
200
400
600
800
1000
1200
1400
1600
1
2
3
4
5
6
7
DMDHHSIZ


count
0
500
1000
1500
2000
2500
3000
1
2
SDMVPSU


count
0
500
1000
1500
2000
2500
3000
3500
4000
1.0
2.0
9.0
HIQ210

0.0.5 Correlation

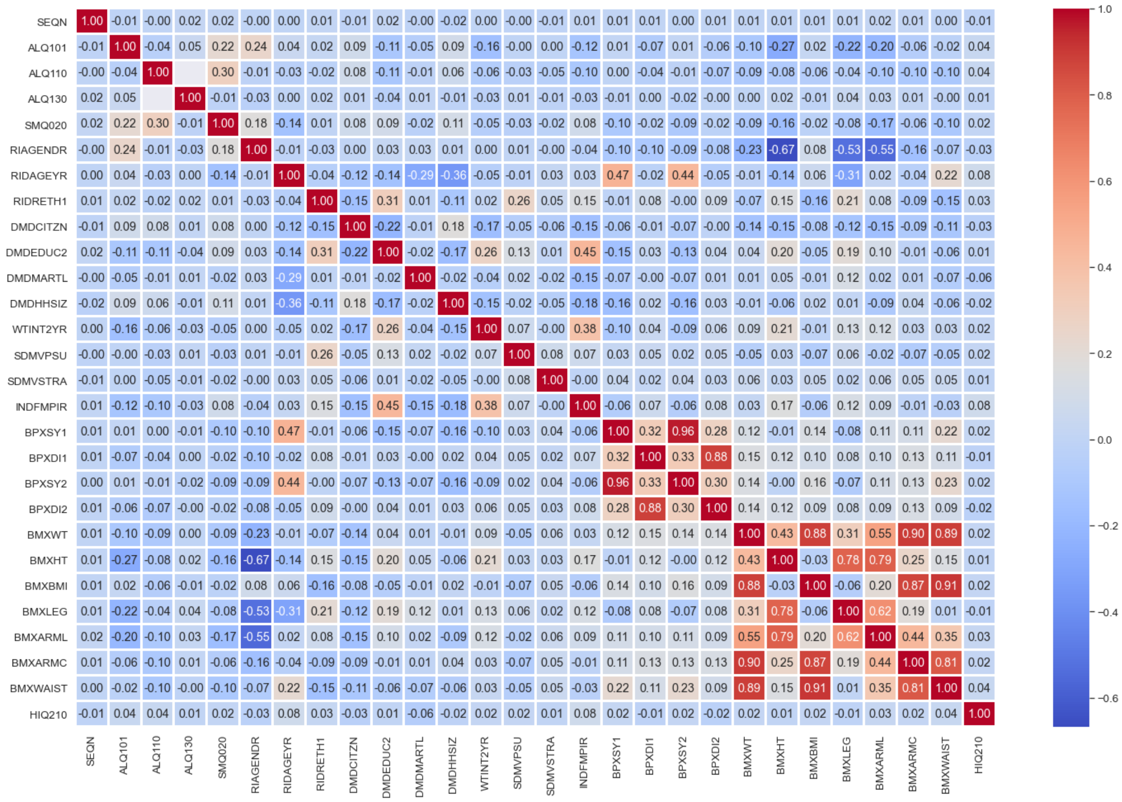
[11]:
```
df.corr()
```

[11]:
```
                SEQN    ALQ101    ALQ110    ALQ130    SMQ020  RIAGENDR  RIDAGEYR  \
RIDRETH1  DMDCITZN  DMDEDUC2  DMDMARTL  DMDHHSIZ  WTINT2YR   SDMVPSU  SDMVSTRA  \
INDFMPIR    BPXSY1    BPXDI1    BPXSY2    BPXDI2     BMXWT     BMXHT    BMXBMI  \
BMXLEG   BMXARML   BMXARMC  BMXWAIST    HIQ210
SEQN      1.000000 -0.006562 -0.002206  0.021034  0.017550 -0.002453  0.001928
0.012015 -0.008718  0.015089 -0.004677 -0.024727  0.000342 -0.004062 -0.006251
0.011142  0.008902  0.005594  0.001039  0.008245  0.009078  0.005313  0.008570
0.013064  0.016829  0.011559  0.000100 -0.008177
ALQ101   -0.006562  1.000000 -0.039246  0.045931  0.224375  0.244817  0.043776
0.024871  0.087437 -0.111179 -0.050906  0.088915 -0.156842 -0.000224  0.002463
-0.124764  0.011492 -0.069583  0.011007 -0.061002 -0.102120 -0.274201  0.023780
-0.220374 -0.198496 -0.060171 -0.018680  0.038166
ALQ110   -0.002206 -0.039246  1.000000       NaN  0.295484 -0.011644 -0.030886
-0.018448  0.081828 -0.111392 -0.009649  0.062514 -0.064570 -0.030140 -0.047782
-0.104446  0.001245 -0.042326 -0.012871 -0.074995 -0.088962 -0.080150 -0.061517
-0.037318 -0.096338 -0.095476 -0.102949  0.041510
ALQ130    0.021034  0.045931       NaN  1.000000 -0.012636 -0.031485  0.003097
0.016002  0.012860 -0.041795  0.014880 -0.012428 -0.027818  0.012380 -0.012612
-0.029824 -0.011648  0.000658 -0.023374 -0.001259  0.002875  0.024239 -0.008138
0.036626  0.029154  0.011710 -0.003915  0.006212
SMQ020    0.017550  0.224375  0.295484 -0.012636  1.000000  0.177643 -0.139940
0.006692  0.075463  0.091573 -0.024573  0.105990 -0.049887 -0.029157 -0.021329
0.083277 -0.098235 -0.023058 -0.087810 -0.017253 -0.091926 -0.164602 -0.021695
-0.079360 -0.166316 -0.058284 -0.101800  0.015915
RIAGENDR -0.002453  0.244817 -0.011644 -0.031485  0.177643  1.000000 -0.014613
-0.027209  0.003889  0.028226  0.026958  0.014847  0.003722  0.007725 -0.004619
-0.041172 -0.100583 -0.095073 -0.094670 -0.082555 -0.230864 -0.667212  0.081811
-0.528197 -0.552607 -0.157442 -0.069071 -0.026879
RIDAGEYR  0.001928  0.043776 -0.030886  0.003097 -0.139940 -0.014613  1.000000
-0.042209 -0.118094 -0.140115 -0.286758 -0.363930 -0.047806 -0.011686  0.029180
0.028044  0.469233 -0.017459  0.443336 -0.053636 -0.010378 -0.144614  0.059597
-0.310151  0.023039 -0.041358  0.223114  0.080909
RIDRETH1  0.012015  0.024871 -0.018448  0.016002  0.006692 -0.027209 -0.042209
1.000000 -0.153333  0.308585  0.007986 -0.113354  0.015321  0.256500  0.054039
0.151841 -0.008399  0.079469 -0.000573  0.087175 -0.065482  0.149536 -0.155929
0.207387  0.075217 -0.088325 -0.150374  0.028450
DMDCITZN -0.008718  0.087437  0.081828  0.012860  0.075463  0.003889 -0.118094
-0.153333  1.000000 -0.215853 -0.011805  0.179095 -0.166302 -0.051599 -0.055125
-0.154238 -0.063834 -0.007891 -0.067105 -0.003437 -0.136959 -0.147733 -0.079562
-0.121425 -0.154126 -0.087352 -0.111723 -0.033559
DMDEDUC2  0.015089 -0.111179 -0.111392 -0.041795  0.091573  0.028226 -0.140115
0.308585 -0.215853  1.000000 -0.018743 -0.172849  0.264202  0.130371  0.012027
0.452827 -0.147522  0.027927 -0.131038  0.039210  0.043743  0.198037 -0.052961
```

```
0.193211  0.101462 -0.005829 -0.062220  0.009331
DMDMARTL -0.004677 -0.050906 -0.009649  0.014880 -0.024573  0.026958 -0.286758
0.007986 -0.011805 -0.018743  1.000000 -0.024617 -0.042558  0.023626 -0.018810
-0.154666 -0.068521 -0.003057 -0.067161  0.010237  0.007163  0.045104 -0.009370
0.120895  0.020497  0.005516 -0.067895 -0.055831
DMDHHSIZ -0.024727  0.088915  0.062514 -0.012428  0.105990  0.014847 -0.363930
-0.113354  0.179095 -0.172849 -0.024617  1.000000 -0.145241 -0.018002 -0.047039
-0.182329 -0.163461  0.017016 -0.159825  0.028106 -0.007254 -0.061131  0.019132
0.010790 -0.089021  0.038489 -0.058631 -0.015397
WTINT2YR  0.000342 -0.156842 -0.064570 -0.027818 -0.049887  0.003722 -0.047806
0.015321 -0.166302  0.264202 -0.042558 -0.145241  1.000000  0.067694 -0.000166
0.383668 -0.104422  0.042768 -0.085959  0.056078  0.087786  0.206175 -0.005600
0.125168  0.124056  0.029703  0.032498  0.022963
SDMVPSU  -0.004062 -0.000224 -0.030140  0.012380 -0.029157  0.007725 -0.011686
0.256500 -0.051599  0.130371  0.023626 -0.018002  0.067694  1.000000  0.075944
0.073119  0.026000  0.047081  0.016482  0.045665 -0.045650  0.026988 -0.065851
0.058874 -0.024464 -0.068062 -0.054145  0.019173
SDMVSTRA -0.006251  0.002463 -0.047782 -0.012612 -0.021329 -0.004619  0.029180
0.054039 -0.055125  0.012027 -0.018810 -0.047039 -0.000166  0.075944  1.000000
-0.003002  0.036356  0.016784  0.044967  0.029184  0.055407  0.026260  0.045612
0.022447  0.059425  0.049342  0.054042  0.007649
INDFMPIR  0.011142 -0.124764 -0.104446 -0.029824  0.083277 -0.041172  0.028044
0.151841 -0.154238  0.452827 -0.154666 -0.182329  0.383668  0.073119 -0.003002
1.000000 -0.062853  0.068295 -0.060583  0.075744  0.029321  0.165772 -0.056020
0.124025  0.087370 -0.007759 -0.032376  0.077823
BPXSY1    0.008902  0.011492  0.001245 -0.011648 -0.098235 -0.100583  0.469233
-0.008399 -0.063834 -0.147522 -0.068521 -0.163461 -0.104422  0.026000  0.036356
-0.062853  1.000000  0.316531  0.962287  0.277681  0.122512 -0.007911  0.135201
-0.081020  0.106399  0.105323  0.218537  0.023539
BPXDI1    0.005594 -0.069583 -0.042326  0.000658 -0.023058 -0.095073 -0.017459
0.079469 -0.007891  0.027927 -0.003057  0.017016  0.042768  0.047081  0.016784
0.068295  0.316531  1.000000  0.329843  0.884722  0.147788  0.119566  0.098179
0.082923  0.096194  0.134682  0.108333 -0.012501
BPXSY2    0.001039  0.011007 -0.012871 -0.023374 -0.087810 -0.094670  0.443336
-0.000573 -0.067105 -0.131038 -0.067161 -0.159825 -0.085959  0.016482  0.044967
-0.060583  0.962287  0.329843  1.000000  0.303847  0.143145 -0.002782  0.155575
-0.072075  0.113354  0.127892  0.229765  0.017146
BPXDI2    0.008245 -0.061002 -0.074995 -0.001259 -0.017253 -0.082555 -0.053636
0.087175 -0.003437  0.039210  0.010237  0.028106  0.056078  0.045665  0.029184
0.075744  0.277681  0.884722  0.303847  1.000000  0.141474  0.115055  0.094868
0.078653  0.088656  0.132322  0.093982 -0.023526
BMXWT     0.009078 -0.102120 -0.088962  0.002875 -0.091926 -0.230864 -0.010378
-0.065482 -0.136959  0.043743  0.007163 -0.007254  0.087786 -0.045650  0.055407
0.029321  0.122512  0.147788  0.143145  0.141474  1.000000  0.431386  0.884133
0.308479  0.546099  0.901598  0.891750  0.022857
BMXHT     0.005313 -0.274201 -0.080150  0.024239 -0.164602 -0.667212 -0.144614
0.149536 -0.147733  0.198037  0.045104 -0.061131  0.206175  0.026988  0.026260
```

```
0.165772 -0.007911  0.119566 -0.002782  0.115055  0.431386  1.000000 -0.025978
0.784273  0.792612  0.254445  0.148385  0.005872
BMXBMI    0.008570  0.023780 -0.061517 -0.008138 -0.021695  0.081811  0.059597
-0.155929 -0.079562 -0.052961 -0.009370  0.019132 -0.005600 -0.065851  0.045612
-0.056020  0.135201  0.098179  0.155575  0.094868  0.884133 -0.025978  1.000000
-0.061293  0.204285  0.874817  0.910781  0.019019
BMXLEG    0.013064 -0.220374 -0.037318  0.036626 -0.079360 -0.528197 -0.310151
0.207387 -0.121425  0.193211  0.120895  0.010790  0.125168  0.058874  0.022447
0.124025 -0.081020  0.082923 -0.072075  0.078653  0.308479  0.784273 -0.061293
1.000000  0.624537  0.190968  0.008828 -0.007347
BMXARML   0.016829 -0.198496 -0.096338  0.029154 -0.166316 -0.552607  0.023039
0.075217 -0.154126  0.101462  0.020497 -0.089021  0.124056 -0.024464  0.059425
0.087370  0.106399  0.096194  0.113354  0.088656  0.546099  0.792612  0.204285
0.624537  1.000000  0.441430  0.354386  0.034269
BMXARMC   0.011559 -0.060171 -0.095476  0.011710 -0.058284 -0.157442 -0.041358
-0.088325 -0.087352 -0.005829  0.005516  0.038489  0.029703 -0.068062  0.049342
-0.007759  0.105323  0.134682  0.127892  0.132322  0.901598  0.254445  0.874817
0.190968  0.441430  1.000000  0.814188  0.016785
BMXWAIST  0.000100 -0.018680 -0.102949 -0.003915 -0.101800 -0.069071  0.223114
-0.150374 -0.111723 -0.062220 -0.067895 -0.058631  0.032498 -0.054145  0.054042
-0.032376  0.218537  0.108333  0.229765  0.093982  0.891750  0.148385  0.910781
0.008828  0.354386  0.814188  1.000000  0.041161
HIQ210   -0.008177  0.038166  0.041510  0.006212  0.015915 -0.026879  0.080909
0.028450 -0.033559  0.009331 -0.055831 -0.015397  0.022963  0.019173  0.007649
0.077823  0.023539 -0.012501  0.017146 -0.023526  0.022857  0.005872  0.019019
-0.007347  0.034269  0.016785  0.041161  1.000000
```

[12]:
```python
plt.figure(figsize=(25,16))
sns.heatmap(df.corr(),cmap="coolwarm",annot=True,fmt='.2f',linewidths=2)
plt.show()
```



0.0.6 Data Preprocessing

0.0.7 Drop unwanted features

[13]:
```
df.columns
```

[13]:
```
Index(['SEQN', 'ALQ101', 'ALQ110', 'ALQ130', 'SMQ020', 'RIAGENDR', 'RIDAGEYR',
'RIDRETH1', 'DMDCITZN', 'DMDEDUC2', 'DMDMARTL', 'DMDHHSIZ', 'WTINT2YR',
'SDMVPSU', 'SDMVSTRA', 'INDFMPIR', 'BPXSY1', 'BPXDI1', 'BPXSY2', 'BPXDI2',
'BMXWT', 'BMXHT', 'BMXBMI', 'BMXLEG', 'BMXARML', 'BMXARMC', 'BMXWAIST',
'HIQ210'], dtype='object')
```

[14]:
```
df.drop(['SEQN', 'ALQ101', 'ALQ110', 'ALQ130'],axis=1,inplace=True)
```

[15]:
```
df
```

[15]:
```
      SMQ020  RIAGENDR  RIDAGEYR  RIDRETH1  DMDCITZN  DMDEDUC2  DMDMARTL  \
DMDHHSIZ   WTINT2YR  SDMVPSU  SDMVSTRA  INDFMPIR  BPXSY1  BPXDI1  BPXSY2  BPXDI2  \
BMXWT  BMXHT  BMXBMI  BMXLEG  BMXARML  BMXARMC  BMXWAIST  HIQ210
0          1         1        62         3       1.0       5.0       1.0
2  134671.37         1       125      4.39    128.0      70.0    124.0      64.0    94.8
184.5     27.8     43.3     43.6     35.9     101.1      2.0
```

```
1           1          1         53          3        2.0        3.0        3.0
1   24328.56          1        125        1.32    146.0      88.0    140.0      88.0    90.4
171.4     30.8     38.0      40.0      33.2     107.9       NaN
2           1          1         78          3        1.0        3.0        1.0
2   12400.01          1        131        1.51    138.0      46.0    132.0      44.0    83.4
170.1     28.8     35.6      37.0      31.0     116.5       2.0
3           2          2         56          3        1.0        5.0        6.0
1  102718.00          1        131        5.00    132.0      72.0    134.0      68.0   109.8
160.9     42.4     38.5      37.7      38.3     110.1       2.0
4           2          2         42          4        1.0        4.0        3.0
5   17627.67          2        126        1.23    100.0      70.0    114.0      54.0    55.2
164.9     20.3     37.4      36.0      27.2      80.4       2.0
…       …        …        …        …        …        …        …
…         …       …        …         …       …      …      …      …
…    …     …      …      …       …        …      …
5730        1          2         76          3        1.0        3.0        2.0
1   58614.08          2        130        1.43    112.0      48.0    112.0      46.0    59.1
165.8     21.5     38.2      37.0      29.5      95.0       2.0
5731        2          1         26          3        1.0        5.0        1.0
3  122920.60          1        121        2.99    118.0      68.0    116.0      76.0   112.1
182.2     33.8     43.4      41.8      42.3     110.2       2.0
5732        1          2         80          3        1.0        4.0        2.0
1   49050.06          2        132        2.97    154.0      56.0    146.0      58.0    71.7
152.2     31.0     31.3      37.5      28.8       NaN       2.0
5733        1          1         35          3        2.0        1.0        1.0
5   42314.29          1        126        0.00    104.0      62.0    106.0      66.0    78.2
173.3     26.0     40.3      37.5      30.6      98.9       2.0
5734        2          2         24          3        1.0        5.0        5.0
3  107361.91          2        119        3.54    118.0      66.0    114.0      68.0    58.3
165.0     21.4     38.2      33.5      26.2      72.5       2.0

[5735 rows x 24 columns]
```

0.0.8 Treat Missing Values

[16]:
```python
df.isnull().sum()
```

[16]:
```
SMQ020        0
RIAGENDR      0
RIDAGEYR      0
RIDRETH1      0
DMDCITZN      1
DMDEDUC2    261
DMDMARTL    261
DMDHHSIZ      0
WTINT2YR      0
SDMVPSU       0
```

```
SDMVSTRA       0
INDFMPIR     601
BPXSY1       334
BPXDI1       334
BPXSY2       200
BPXDI2       200
BMXWT         69
BMXHT         62
BMXBMI        73
BMXLEG       390
BMXARML      308
BMXARMC      308
BMXWAIST     367
HIQ210      1003
dtype: int64
```

[17]:
```
df.dropna(inplace=True)
```

[18]:
```
df
```

[18]:
```
      SMQ020  RIAGENDR  RIDAGEYR  RIDRETH1  DMDCITZN  DMDEDUC2  DMDMARTL
DMDHHSIZ   WTINT2YR  SDMVPSU  SDMVSTRA  INDFMPIR  BPXSY1  BPXDI1  BPXSY2  BPXDI2
BMXWT  BMXHT  BMXBMI  BMXLEG  BMXARML  BMXARMC  BMXWAIST  HIQ210
0          1         1        62         3       1.0       5.0       1.0
2  134671.37         1       125      4.39    128.0     70.0   124.0    64.0   94.8
184.5    27.8    43.3     43.6     35.9     101.1     2.0
2          1         1        78         3       1.0       3.0       1.0
2   12400.01         1       131      1.51    138.0     46.0   132.0    44.0   83.4
170.1    28.8    35.6     37.0     31.0     116.5     2.0
3          2         2        56         3       1.0       5.0       6.0
1  102718.00         1       131      5.00    132.0     72.0   134.0    68.0  109.8
160.9    42.4    38.5     37.7     38.3     110.1     2.0
4          2         2        42         4       1.0       4.0       3.0
5   17627.67         2       126      1.23    100.0     70.0   114.0    54.0   55.2
164.9    20.3    37.4     36.0     27.2      80.4     2.0
7          2         2        32         1       2.0       4.0       1.0
4   22744.36         1       125      1.03    120.0     70.0   114.0    70.0   64.5
151.3    28.2    34.1     33.1     31.5      93.3     2.0
…       …       …       …       …       …       …       …
…       …       …       …       …       …       …       …       …
…    …     …      …      …      …       …      …
5729       2         1        25         5       2.0       5.0       5.0
7   13525.39         2       133      1.59    112.0     80.0   112.0    76.0   39.2
136.5    21.0    33.6     29.7     23.8      75.4     2.0
5730       1         2        76         3       1.0       3.0       2.0
1   58614.08         2       130      1.43    112.0     48.0   112.0    46.0   59.1
165.8    21.5    38.2     37.0     29.5      95.0     2.0
```

```
5731        2         1         26         3       1.0       5.0       1.0
3  122920.60         1        121       2.99    118.0     68.0    116.0     76.0   112.1
182.2     33.8     43.4     41.8     42.3     110.2      2.0
5733        1         1         35         3       2.0       1.0       1.0
5   42314.29         1        126       0.00    104.0     62.0    106.0     66.0    78.2
173.3     26.0     40.3     37.5     30.6      98.9      2.0
5734        2         2         24         3       1.0       5.0       5.0
3  107361.91         2        119       3.54    118.0     66.0    114.0     68.0    58.3
165.0     21.4     38.2     33.5     26.2      72.5      2.0

[3572 rows x 24 columns]
```

[19]:
```python
df.reset_index(inplace=True,drop=True)
```

[20]:
```python
df
```

[20]:
```
      SMQ020  RIAGENDR  RIDAGEYR  RIDRETH1  DMDCITZN  DMDEDUC2  DMDMARTL
DMDHHSIZ   WTINT2YR  SDMVPSU  SDMVSTRA  INDFMPIR  BPXSY1  BPXDI1  BPXSY2  BPXDI2
BMXWT   BMXHT   BMXBMI   BMXLEG   BMXARML   BMXARMC   BMXWAIST   HIQ210
0           1         1         62         3       1.0       5.0       1.0
2  134671.37         1        125       4.39    128.0     70.0    124.0     64.0    94.8
184.5     27.8     43.3     43.6     35.9     101.1      2.0
1           1         1         78         3       1.0       3.0       1.0
2   12400.01         1        131       1.51    138.0     46.0    132.0     44.0    83.4
170.1     28.8     35.6     37.0     31.0     116.5      2.0
2           2         2         56         3       1.0       5.0       6.0
1  102718.00         1        131       5.00    132.0     72.0    134.0     68.0   109.8
160.9     42.4     38.5     37.7     38.3     110.1      2.0
3           2         2         42         4       1.0       4.0       3.0
5   17627.67         2        126       1.23    100.0     70.0    114.0     54.0    55.2
164.9     20.3     37.4     36.0     27.2      80.4      2.0
4           2         2         32         1       2.0       4.0       1.0
4   22744.36         1        125       1.03    120.0     70.0    114.0     70.0    64.5
151.3     28.2     34.1     33.1     31.5      93.3      2.0
…      …        …        …        …        …        …        …
…        …       …        …        …      …      …      …      …
…    …     …     …     …     …     …      …
3567        2         1         25         5       2.0       5.0       5.0
7   13525.39         2        133       1.59    112.0     80.0    112.0     76.0    39.2
136.5     21.0     33.6     29.7     23.8      75.4      2.0
3568        1         2         76         3       1.0       3.0       2.0
1   58614.08         2        130       1.43    112.0     48.0    112.0     46.0    59.1
165.8     21.5     38.2     37.0     29.5      95.0      2.0
3569        2         1         26         3       1.0       5.0       1.0
3  122920.60         1        121       2.99    118.0     68.0    116.0     76.0   112.1
182.2     33.8     43.4     41.8     42.3     110.2      2.0
3570        1         1         35         3       2.0       1.0       1.0
```

```
5   42314.29        1       126       0.00    104.0     62.0    106.0     66.0    78.2
173.3    26.0    40.3     37.5     30.6      98.9     2.0
3571        2          2         24          3       1.0       5.0       5.0
3   107361.91        2       119       3.54    118.0     66.0    114.0     68.0    58.3
165.0    21.4    38.2     33.5     26.2      72.5     2.0

[3572 rows x 24 columns]
```

[21]:
```python
df.isnull().sum()
```

[21]:
```
SMQ020      0
RIAGENDR    0
RIDAGEYR    0
RIDRETH1    0
DMDCITZN    0
DMDEDUC2    0
DMDMARTL    0
DMDHHSIZ    0
WTINT2YR    0
SDMVPSU     0
SDMVSTRA    0
INDFMPIR    0
BPXSY1      0
BPXDI1      0
BPXSY2      0
BPXDI2      0
BMXWT       0
BMXHT       0
BMXBMI      0
BMXLEG      0
BMXARML     0
BMXARMC     0
BMXWAIST    0
HIQ210      0
dtype: int64
```

0.0.9 Treat Data Types

[22]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3572 entries, 0 to 3571
Data columns (total 24 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   SMQ020    3572 non-null   int64
 1   RIAGENDR  3572 non-null   int64
```

```
 2   RIDAGEYR  3572 non-null   int64
 3   RIDRETH1  3572 non-null   int64
 4   DMDCITZN  3572 non-null   float64
 5   DMDEDUC2  3572 non-null   float64
 6   DMDMARTL  3572 non-null   float64
 7   DMDHHSIZ  3572 non-null   int64
 8   WTINT2YR  3572 non-null   float64
 9   SDMVPSU   3572 non-null   int64
 10  SDMVSTRA  3572 non-null   int64
 11  INDFMPIR  3572 non-null   float64
 12  BPXSY1    3572 non-null   float64
 13  BPXDI1    3572 non-null   float64
 14  BPXSY2    3572 non-null   float64
 15  BPXDI2    3572 non-null   float64
 16  BMXWT     3572 non-null   float64
 17  BMXHT     3572 non-null   float64
 18  BMXBMI    3572 non-null   float64
 19  BMXLEG    3572 non-null   float64
 20  BMXARML   3572 non-null   float64
 21  BMXARMC   3572 non-null   float64
 22  BMXWAIST  3572 non-null   float64
 23  HIQ210    3572 non-null   float64
dtypes: float64(17), int64(7)
memory usage: 669.9 KB
```

[23]:
```
#Convert categorical features to objects first
df[['SMQ020','RIAGENDR','RIDRETH1','DMDHHSIZ','SDMVPSU']] =␣
↪df[['SMQ020','RIAGENDR','RIDRETH1','DMDHHSIZ','SDMVPSU']].astype(object)
```

[24]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3572 entries, 0 to 3571
Data columns (total 24 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   SMQ020    3572 non-null   object
 1   RIAGENDR  3572 non-null   object
 2   RIDAGEYR  3572 non-null   int64
 3   RIDRETH1  3572 non-null   object
 4   DMDCITZN  3572 non-null   float64
 5   DMDEDUC2  3572 non-null   float64
 6   DMDMARTL  3572 non-null   float64
 7   DMDHHSIZ  3572 non-null   object
 8   WTINT2YR  3572 non-null   float64
 9   SDMVPSU   3572 non-null   object
 10  SDMVSTRA  3572 non-null   int64
 11  INDFMPIR  3572 non-null   float64
```

```
 12  BPXSY1    3572 non-null   float64
 13  BPXDI1    3572 non-null   float64
 14  BPXSY2    3572 non-null   float64
 15  BPXDI2    3572 non-null   float64
 16  BMXWT     3572 non-null   float64
 17  BMXHT     3572 non-null   float64
 18  BMXBMI    3572 non-null   float64
 19  BMXLEG    3572 non-null   float64
 20  BMXARML   3572 non-null   float64
 21  BMXARMC   3572 non-null   float64
 22  BMXWAIST  3572 non-null   float64
 23  HIQ210    3572 non-null   float64
dtypes: float64(17), int64(2), object(5)
memory usage: 669.9+ KB
```

0.0.10 Treat Duplicate Values

[25]:
```
df.duplicated(keep='first').sum()
```

[25]:
```
0
```

0.0.11 Perform one hot encoding

[26]:
```
df2 = pd.get_dummies(df, drop_first=True)
```

[27]:
```
df2
```

[27]:
```
      RIDAGEYR  DMDCITZN  DMDEDUC2  DMDMARTL   WTINT2YR  SDMVSTRA  INDFMPIR  
BPXSY1  BPXDI1  BPXSY2  BPXDI2  BMXWT  BMXHT  BMXBMI  BMXLEG  BMXARML  BMXARMC  
BMXWAIST  HIQ210  SMQ020_2  SMQ020_9  RIAGENDR_2  RIDRETH1_2  RIDRETH1_3  
RIDRETH1_4  RIDRETH1_5  DMDHHSIZ_2  DMDHHSIZ_3  DMDHHSIZ_4  DMDHHSIZ_5  
DMDHHSIZ_6  DMDHHSIZ_7  SDMVPSU_2  
0           62       1.0       5.0       1.0  134671.37       125      4.39  
128.0    70.0   124.0    64.0   94.8  184.5    27.8    43.3     43.6     35.9  
101.1     2.0         0         0           0           0           1  
0           0           1           0           0           0           0  
0         0  
1           78       1.0       3.0       1.0   12400.01       131      1.51  
138.0    46.0   132.0    44.0   83.4  170.1    28.8    35.6     37.0     31.0  
116.5     2.0         0         0           0           0           1  
0           0           1           0           0           0           0  
0         0  
2           56       1.0       5.0       6.0  102718.00       131      5.00  
132.0    72.0   134.0    68.0  109.8  160.9    42.4    38.5     37.7     38.3  
110.1     2.0         1         0           1           0           1  
0           0           0           0           0           0           0  
0         0  
```

```
3           42       1.0       4.0       3.0    17627.67       126      1.23
100.0    70.0    114.0     54.0    55.2   164.9     20.3     37.4      36.0      27.2
80.4     2.0         1         0          1          0          0          1
0           0          0          0          1          0          0
1
4           32       2.0       4.0       1.0    22744.36       125      1.03
120.0    70.0    114.0     70.0    64.5   151.3     28.2     34.1      33.1      31.5
93.3     2.0         1         0          1          0          0          0
0           0          0          1          0          0          0
0
…       …       …       …       …       …       …       …
…     …     …     …     …     …     …     …     …     …
…     …      …      …      …      …      …      …
…      …      …      …      …      …      …
…
3567        25       2.0       5.0       5.0    13525.39       133      1.59
112.0    80.0    112.0     76.0    39.2   136.5     21.0     33.6      29.7      23.8
75.4     2.0         1         0          0          0          0          0
1           0          0          0          0          0          1
1
3568        76       1.0       3.0       2.0    58614.08       130      1.43
112.0    48.0    112.0     46.0    59.1   165.8     21.5     38.2      37.0      29.5
95.0     2.0         0         0          1          0          1          0
0           0          0          0          0          0          0
1
3569        26       1.0       5.0       1.0   122920.60       121      2.99
118.0    68.0    116.0     76.0   112.1   182.2     33.8     43.4      41.8      42.3
110.2     2.0         1         0          0          0          1
0           0          0          1          0          0          0
0          0
3570        35       2.0       1.0       1.0    42314.29       126      0.00
104.0    62.0    106.0     66.0    78.2   173.3     26.0     40.3      37.5      30.6
98.9     2.0         0         0          0          0          1          0
0           0          0          0          1          0          0
0
3571        24       1.0       5.0       5.0   107361.91       119      3.54
118.0    66.0    114.0     68.0    58.3   165.0     21.4     38.2      33.5      26.2
72.5     2.0         1         0          1          0          1          0
0           0          1          0          0          0          0
1

[3572 rows x 33 columns]
```

[28]:
```
df2.columns
```

[28]:
```
Index(['RIDAGEYR', 'DMDCITZN', 'DMDEDUC2', 'DMDMARTL', 'WTINT2YR', 'SDMVSTRA',
'INDFMPIR', 'BPXSY1', 'BPXDI1', 'BPXSY2', 'BPXDI2', 'BMXWT', 'BMXHT', 'BMXBMI',
```

```
'BMXLEG', 'BMXARML', 'BMXARMC', 'BMXWAIST', 'HIQ210', 'SMQ020_2', 'SMQ020_9',
'RIAGENDR_2', 'RIDRETH1_2', 'RIDRETH1_3', 'RIDRETH1_4', 'RIDRETH1_5',
'DMDHHSIZ_2', 'DMDHHSIZ_3', 'DMDHHSIZ_4', 'DMDHHSIZ_5', 'DMDHHSIZ_6',
'DMDHHSIZ_7', 'SDMVPSU_2'], dtype='object')
```

[29]:
```
df2 = df2[['RIDAGEYR', 'DMDCITZN', 'DMDEDUC2', 'DMDMARTL', 'WTINT2YR',␣
↪'SDMVSTRA', 'INDFMPIR', 'BPXSY1', 'BPXDI1', 'BPXSY2', 'BPXDI2', 'BMXWT',␣
↪'BMXHT', 'BMXBMI', 'BMXLEG',
           'BMXARML', 'BMXARMC', 'BMXWAIST', 'SMQ020_2', 'SMQ020_9',␣
↪'RIAGENDR_2', 'RIDRETH1_2', 'RIDRETH1_3', 'RIDRETH1_4', 'RIDRETH1_5',␣
↪'DMDHHSIZ_2', 'DMDHHSIZ_3', 'DMDHHSIZ_4',
           'DMDHHSIZ_5', 'DMDHHSIZ_6', 'DMDHHSIZ_7', 'SDMVPSU_2','HIQ210']]
```

[30]:
```
df2
```

[30]:
```
      RIDAGEYR  DMDCITZN  DMDEDUC2  DMDMARTL   WTINT2YR  SDMVSTRA  INDFMPIR
BPXSY1  BPXDI1  BPXSY2  BPXDI2  BMXWT  BMXHT  BMXBMI  BMXLEG  BMXARML  BMXARMC
BMXWAIST  SMQ020_2  SMQ020_9  RIAGENDR_2  RIDRETH1_2  RIDRETH1_3  RIDRETH1_4
RIDRETH1_5  DMDHHSIZ_2  DMDHHSIZ_3  DMDHHSIZ_4  DMDHHSIZ_5  DMDHHSIZ_6
DMDHHSIZ_7  SDMVPSU_2  HIQ210
0            62       1.0       5.0       1.0  134671.37       125      4.39
128.0    70.0   124.0     64.0   94.8  184.5    27.8    43.3     43.6     35.9
101.1         0         0           0           0           1           0
0            1          0           0           0           0           0
0      2.0
1            78       1.0       3.0       1.0   12400.01       131      1.51
138.0    46.0   132.0     44.0   83.4  170.1    28.8    35.6     37.0     31.0
116.5         0         0           0           0           1           0
0            1          0           0           0           0           0
0      2.0
2            56       1.0       5.0       6.0  102718.00       131      5.00
132.0    72.0   134.0     68.0  109.8  160.9    42.4    38.5     37.7     38.3
110.1         1         0           1           0           1           0
0            0          0           0           0           0           0
0      2.0
3            42       1.0       4.0       3.0   17627.67       126      1.23
100.0    70.0   114.0     54.0   55.2  164.9    20.3    37.4     36.0     27.2
80.4         1         0           1           0           0           1
0            0          0           0           1           0           0
1      2.0
4            32       2.0       4.0       1.0   22744.36       125      1.03
120.0    70.0   114.0     70.0   64.5  151.3    28.2    34.1     33.1     31.5
93.3         1         0           1           0           0           0
0            0          0           1           0           0           0
0      2.0
…        …        …        …        …         …        …        …
…      …      …      …      …     …      …      …       …       …
```

```
…       …       …         …         …         …         …
…         …         …         …         …         …         …
…     …
3567         25        2.0        5.0        5.0   13525.39        133       1.59
112.0     80.0    112.0     76.0    39.2  136.5     21.0     33.6      29.7      23.8
75.4          1          0           0           0           0           0
1            0            0            0            0            0            1
1     2.0
3568         76        1.0        3.0        2.0   58614.08        130       1.43
112.0     48.0    112.0     46.0    59.1  165.8     21.5     38.2      37.0      29.5
95.0          0          0           1           0           1           0
0            0            0            0            0            0            0
1     2.0
3569         26        1.0        5.0        1.0  122920.60        121       2.99
118.0     68.0    116.0     76.0   112.1  182.2     33.8     43.4      41.8      42.3
110.2          1          0           0           0           1           0
0            0            1            0            0            0            0
0     2.0
3570         35        2.0        1.0        1.0   42314.29        126       0.00
104.0     62.0    106.0     66.0    78.2  173.3     26.0     40.3      37.5      30.6
98.9          0          0           0           0           1           0
0            0            0            0            1            0            0
0     2.0
3571         24        1.0        5.0        5.0  107361.91        119       3.54
118.0     66.0    114.0     68.0    58.3  165.0     21.4     38.2      33.5      26.2
72.5          1          0           1           0           1           0
0            0            1            0            0            0            0
1     2.0

[3572 rows x 33 columns]
```

[31]:
```
df2["HIQ210"].value_counts()
```

[31]:
```
2.0    3196
1.0     374
9.0       2
Name: HIQ210, dtype: int64
```

[32]:
```
df3 = df2[df2["HIQ210"]!=9.0]
```

[33]:
```
df3
```

[33]:
```
      RIDAGEYR  DMDCITZN  DMDEDUC2  DMDMARTL   WTINT2YR  SDMVSTRA  INDFMPIR
BPXSY1  BPXDI1  BPXSY2  BPXDI2  BMXWT  BMXHT  BMXBMI  BMXLEG  BMXARML  BMXARMC
BMXWAIST  SMQ020_2  SMQ020_9  RIAGENDR_2  RIDRETH1_2  RIDRETH1_3  RIDRETH1_4
RIDRETH1_5  DMDHHSIZ_2  DMDHHSIZ_3  DMDHHSIZ_4  DMDHHSIZ_5  DMDHHSIZ_6
DMDHHSIZ_7  SDMVPSU_2  HIQ210
```

```
0           62        1.0       5.0       1.0  134671.37       125      4.39
128.0    70.0   124.0    64.0   94.8  184.5    27.8    43.3     43.6     35.9
101.1        0         0          0          0          1          0
0           1          0          0          0          0          0
0      2.0
1           78        1.0       3.0       1.0   12400.01       131      1.51
138.0    46.0   132.0    44.0   83.4  170.1    28.8    35.6     37.0     31.0
116.5        0         0          0          0          1          0
0           1          0          0          0          0          0
0      2.0
2           56        1.0       5.0       6.0  102718.00       131      5.00
132.0    72.0   134.0    68.0  109.8  160.9    42.4    38.5     37.7     38.3
110.1        1         0          1          0          1          0
0           0          0          0          0          0          0
0      2.0
3           42        1.0       4.0       3.0   17627.67       126      1.23
100.0    70.0   114.0    54.0   55.2  164.9    20.3    37.4     36.0     27.2
80.4         1         0          1          0          0          1
0           0          0          0          1          0          0
1      2.0
4           32        2.0       4.0       1.0   22744.36       125      1.03
120.0    70.0   114.0    70.0   64.5  151.3    28.2    34.1     33.1     31.5
93.3         1         0          1          0          0          0
0           0          0          1          0          0          0
0      2.0
…        …        …        …        …        …        …        …
…     …     …     …     …     …     …     …     …     …
…       …        …         …         …         …         …
…         …          …          …          …          …          …
…     …
3567        25        2.0       5.0       5.0   13525.39       133      1.59
112.0    80.0   112.0    76.0   39.2  136.5    21.0    33.6     29.7     23.8
75.4         1         0          0          0          0          0
1           0          0          0          0          0          1
1      2.0
3568        76        1.0       3.0       2.0   58614.08       130      1.43
112.0    48.0   112.0    46.0   59.1  165.8    21.5    38.2     37.0     29.5
95.0         0         0          1          0          1          0
0           0          0          0          0          0          0
1      2.0
3569        26        1.0       5.0       1.0  122920.60       121      2.99
118.0    68.0   116.0    76.0  112.1  182.2    33.8    43.4     41.8     42.3
110.2        1         0          0          0          1          0
0           0          1          0          0          0          0
0      2.0
3570        35        2.0       1.0       1.0   42314.29       126      0.00
104.0    62.0   106.0    66.0   78.2  173.3    26.0    40.3     37.5     30.6
```

```
98.9          0         0           0           0           1           0
0           0           0           0           1           0           0
0     2.0
3571        24        1.0        5.0        5.0  107361.91        119       3.54
118.0     66.0    114.0     68.0    58.3   165.0     21.4     38.2     33.5     26.2
72.5          1         0           1           0           1           0
0           0           1           0           0           0           0
1     2.0

[3570 rows x 33 columns]
```

[34]:
```
df3["HIQ210"].value_counts()
```

[34]:
```
2.0    3196
1.0     374
Name: HIQ210, dtype: int64
```

0.0.12 Create and save processed dataset

[35]:
```
df3.to_csv("nhnestrain.csv",index=False)
```

[36]:
```
df3.shape
```

[36]:
```
(3570, 33)
```

0.0.13 Train Test Split

[37]:
```
X = df3.iloc[:,0:32]
y = df3.iloc[:,32]
```

0.0.14 Treat Imbalance Data

[38]:
```
y.value_counts()
```

[38]:
```
2.0    3196
1.0     374
Name: HIQ210, dtype: int64
```

[39]:
```
ros = RandomOverSampler(sampling_strategy='all',random_state=0)
```

[40]:
```
new_X, new_y = ros.fit_resample(X, y)
```

[41]:
```
new_y.value_counts()
```

[41]:
```
1.0    3196
2.0    3196
```

```
Name: HIQ210, dtype: int64
```

[42]:
```
new_X
```

[42]:
```
      RIDAGEYR  DMDCITZN  DMDEDUC2  DMDMARTL   WTINT2YR  SDMVSTRA  INDFMPIR
BPXSY1  BPXDI1  BPXSY2  BPXDI2  BMXWT  BMXHT  BMXBMI  BMXLEG  BMXARML  BMXARMC
BMXWAIST  SMQ020_2  SMQ020_9  RIAGENDR_2  RIDRETH1_2  RIDRETH1_3  RIDRETH1_4
RIDRETH1_5  DMDHHSIZ_2  DMDHHSIZ_3  DMDHHSIZ_4  DMDHHSIZ_5  DMDHHSIZ_6
DMDHHSIZ_7  SDMVPSU_2
0           62       1.0       5.0       1.0  134671.37       125      4.39
128.0    70.0   124.0    64.0   94.8  184.5    27.8    43.3     43.6     35.9
101.1         0          0           0           0           1           0
0           1          0           0           0           0           0
0
1           78       1.0       3.0       1.0   12400.01       131      1.51
138.0    46.0   132.0    44.0   83.4  170.1    28.8    35.6     37.0     31.0
116.5         0          0           0           0           1           0
0           1          0           0           0           0           0
0
2           56       1.0       5.0       6.0  102718.00       131      5.00
132.0    72.0   134.0    68.0  109.8  160.9    42.4    38.5     37.7     38.3
110.1         1          0           1           0           1           0
0           0          0           0           0           0           0
0
3           42       1.0       4.0       3.0   17627.67       126      1.23
100.0    70.0   114.0    54.0   55.2  164.9    20.3    37.4     36.0     27.2
80.4         1          0           1           0           0           1
0           0          0           0           1           0           0
1
4           32       2.0       4.0       1.0   22744.36       125      1.03
120.0    70.0   114.0    70.0   64.5  151.3    28.2    34.1     33.1     31.5
93.3         1          0           1           0           0           0
0           0          0           1           0           0           0
0
…        …        …        …        …        …        …        …
…     …     …     …     …     …     …     …      …      …
…       …       …         …         …         …         …
…         …         …         …         …         …         …
…
6387        28       1.0       4.0       6.0   71202.21       130      2.38
144.0    58.0   148.0    60.0   89.0  186.3    25.6    42.3     38.7     34.4
93.0         1          0           0           0           1           0
0           1          0           0           0           0           0
0
6388        42       1.0       3.0       3.0   27901.72       125      1.27
126.0    88.0   116.0    80.0   81.6  178.7    25.6    41.4     38.3     30.9
92.6         1          0           0           0           1           0
```

```
0           0           0           0           0           0           0
0
6389         34        2.0        1.0        6.0   21932.06        125       0.68
124.0     74.0    112.0     74.0    78.6   154.7     32.8     35.0     37.0     33.5
99.5          1          0          1          0          0          0
0           0           0           0           0           1           0
0
6390         80        1.0        1.0        2.0   36308.09        131       3.23
130.0     62.0    132.0     62.0    67.7   151.0     29.7     36.0     36.0     30.0
96.7          1          0          1          0          1          0
0           0           0           0           0           0           0
0
6391         22        1.0        4.0        5.0   28981.66        122       0.94
90.0    48.0    100.0     54.0    83.5   157.0     33.9     38.0     38.2     36.6
106.2          0          0          1          0          0          1
0           1           0           0           0           0           0
1

[6392 rows x 32 columns]
```

[43]:
```python
new_X.values, new_y.values
```

[43]:
```
(array([[62.,  1.,  5., …,  0.,  0.,  0.],
        [78.,  1.,  3., …,  0.,  0.,  0.],
        [56.,  1.,  5., …,  0.,  0.,  0.],
        …,
        [34.,  2.,  1., …,  1.,  0.,  0.],
        [80.,  1.,  1., …,  0.,  0.,  0.],
        [22.,  1.,  4., …,  0.,  0.,  1.]]),
 array([2., 2., 2., …, 1., 1., 1.]))
```

[44]:
```python
X_train, X_test, y_train, y_test = train_test_split(new_X.values, new_y.values,␣
↪test_size=0.2, random_state=0)
```

[45]:
```python
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[45]:
```
((5113, 32), (1279, 32), (5113,), (1279,))
```

0.0.15 Feature Scaling

[46]:
```python
X_train
```

[46]:
```
array([[55.,  2.,  3., …,  0.,  0.,  0.],
       [23.,  1.,  5., …,  0.,  0.,  1.],
       [23.,  1.,  5., …,  0.,  0.,  1.],
       …,
       [68.,  1.,  4., …,  0.,  0.,  1.],
```

```
        [36.,  2.,  5., …,  0.,  0.,  0.],
        [45.,  1.,  5., …,  0.,  0.,  1.]])
```

[47]:
```python
minmax = MinMaxScaler()
```

[48]:
```python
X_train_scaled = minmax.fit_transform(X_train)
```

[49]:
```python
X_test_scaled = minmax.transform(X_test)
```

[50]:
```python
X_train_scaled
```

[50]:
```
array([[0.58333333, 0.125     , 0.25      , …, 0.        , 0.        ,
        0.        ],
       [0.05      , 0.        , 0.5       , …, 0.        , 0.        ,
        1.        ],
       [0.05      , 0.        , 0.5       , …, 0.        , 0.        ,
        1.        ],
       …,
       [0.8       , 0.        , 0.375     , …, 0.        , 0.        ,
        1.        ],
       [0.26666667, 0.125     , 0.5       , …, 0.        , 0.        ,
        0.        ],
       [0.41666667, 0.        , 0.5       , …, 0.        , 0.        ,
        1.        ]])
```

[51]:
```python
X_test_scaled
```

[51]:
```
array([[0.8       , 0.        , 0.5       , …, 0.        , 0.        ,
        1.        ],
       [0.03333333, 0.        , 0.25      , …, 0.        , 0.        ,
        0.        ],
       [0.33333333, 0.        , 0.125     , …, 0.        , 0.        ,
        0.        ],
       …,
       [0.18333333, 0.        , 0.375     , …, 0.        , 0.        ,
        1.        ],
       [0.96666667, 0.        , 0.5       , …, 0.        , 0.        ,
        0.        ],
       [0.65      , 0.        , 0.25      , …, 0.        , 0.        ,
        0.        ]])
```

[ ]:
```python

```

0.0.16 Model Training

0.0.17 Using XGBoost (Scikit-Learn)

0.0.18 Using RandomSearchCV

[52]:
```
model = XGBClassifier(random_state=0, n_estimators=100, objective='binary:
↪logistic')
```

[53]:
```
parameters = {'max_depth': np.arange(3,10,1),
              'eta': np.arange(0.05,0.3,0.05),
              'n_estimators':np.arange(100,1000,100),
              'min_child_weight': np.arange(1,4,1),
              'gamma':np.arange(0,50,2),
              'subsample':np.arange(0.5,0.9,0.1),
              'colsample_bytree':np.arange(0.5,0.9,0.1)
             }
```

[54]:
```
randm = RandomizedSearchCV(estimator=model, param_distributions = parameters,␣
↪cv = 5, n_iter = 10,
                           n_jobs=-1, scoring='accuracy')
```

[55]:
```
randm.fit(new_X, new_y)
```

[55]:
```
RandomizedSearchCV(cv=5,
                   estimator=XGBClassifier(base_score=None, booster=None,
                                           colsample_bylevel=None,
                                           colsample_bynode=None,
                                           colsample_bytree=None, gamma=None,
                                           gpu_id=None, importance_type='gain',
                                           interaction_constraints=None,
                                           learning_rate=None,
                                           max_delta_step=None, max_depth=None,
                                           min_child_weight=None, missing=nan,
                                           monotone_constraints=None,
                                           n_estimators=100,…
                   param_distributions={'colsample_bytree': array([0.5, 0.6,
0.7, 0.8]),
                                        'eta': array([0.05, 0.1 , 0.15, 0.2 ,
0.25]),
                                        'gamma': array([ 0,  2,  4,  6,  8, 10,
12, 14, 16, 18, 20, 22, 24, 26, 28, 30, 32,
       34, 36, 38, 40, 42, 44, 46, 48]),
                                        'max_depth': array([3, 4, 5, 6, 7, 8,
9]),
                                        'min_child_weight': array([1, 2, 3]),
                                        'n_estimators': array([100, 200, 300,
400, 500, 600, 700, 800, 900]),
```

```
                                        'subsample': array([0.5, 0.6, 0.7,
0.8])},
                   scoring='accuracy')
```

[56]:
```
randm.best_estimator_
```

[56]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.7999999999999999, eta=0.25,
              gamma=0, gpu_id=-1, importance_type='gain',
              interaction_constraints='', learning_rate=0.25, max_delta_step=0,
              max_depth=9, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=900, n_jobs=0,
              num_parallel_tree=1, random_state=0, reg_alpha=0, reg_lambda=1,
              scale_pos_weight=1, subsample=0.7999999999999999,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

[57]:
```
randm.best_score_
```

[57]:
```
0.9759062060662123
```

[58]:
```
randm.best_params_
```

[58]:
```
{'subsample': 0.7999999999999999,
 'n_estimators': 900,
 'min_child_weight': 1,
 'max_depth': 9,
 'gamma': 0,
 'eta': 0.25,
 'colsample_bytree': 0.7999999999999999}
```

0.0.19 Final Tuned Model

[59]:
```
xgbmodel = XGBClassifier(random_state=0, n_estimators=900, objective='binary:
 ↪logistic', eta=0.25,
                         subsample=0.8,␣
 ↪min_child_weight=1,max_depth=9,gamma=0,colsample_bytree=0.8)
```

[60]:
```
xgbmodel.
 ↪fit(X_train_scaled,y_train,eval_set=[(X_test_scaled,y_test)],eval_metric='error',early_stop
```

```
[0]     validation_0-error:0.17983
Will train until validation_0-error hasn't improved in 10 rounds.
[1]     validation_0-error:0.12275
[2]     validation_0-error:0.11962
[3]     validation_0-error:0.12197
[4]     validation_0-error:0.10712
[5]     validation_0-error:0.10321
```

```
[6]     validation_0-error:0.09226
[7]     validation_0-error:0.08522
[8]     validation_0-error:0.08053
[9]     validation_0-error:0.07115
[10]    validation_0-error:0.06802
[11]    validation_0-error:0.06333
[12]    validation_0-error:0.05395
[13]    validation_0-error:0.04769
[14]    validation_0-error:0.04457
[15]    validation_0-error:0.03988
[16]    validation_0-error:0.03831
[17]    validation_0-error:0.03518
[18]    validation_0-error:0.02815
[19]    validation_0-error:0.02737
[20]    validation_0-error:0.02502
[21]    validation_0-error:0.02424
[22]    validation_0-error:0.02267
[23]    validation_0-error:0.02189
[24]    validation_0-error:0.02111
[25]    validation_0-error:0.02267
[26]    validation_0-error:0.02502
[27]    validation_0-error:0.02346
[28]    validation_0-error:0.02267
[29]    validation_0-error:0.02189
[30]    validation_0-error:0.02033
[31]    validation_0-error:0.01798
[32]    validation_0-error:0.01720
[33]    validation_0-error:0.01720
[34]    validation_0-error:0.01642
[35]    validation_0-error:0.01564
[36]    validation_0-error:0.01564
[37]    validation_0-error:0.01407
[38]    validation_0-error:0.01486
[39]    validation_0-error:0.01564
[40]    validation_0-error:0.01407
[41]    validation_0-error:0.01329
[42]    validation_0-error:0.01329
[43]    validation_0-error:0.01329
[44]    validation_0-error:0.01251
[45]    validation_0-error:0.01329
[46]    validation_0-error:0.01329
[47]    validation_0-error:0.01251
[48]    validation_0-error:0.01407
[49]    validation_0-error:0.01407
[50]    validation_0-error:0.01407
[51]    validation_0-error:0.01407
[52]    validation_0-error:0.01407
[53]    validation_0-error:0.01329
```

```
[54]	validation_0-error:0.01407
Stopping. Best iteration:
[44]	validation_0-error:0.01251
```

[60]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.8, eta=0.25, gamma=0,
              gpu_id=-1, importance_type='gain', interaction_constraints='',
              learning_rate=0.25, max_delta_step=0, max_depth=9,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=900, n_jobs=0, num_parallel_tree=1, random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=0.8,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

[61]:
```
y_pred = xgbmodel.predict(X_test_scaled)
```

[62]:
```
y_pred
```

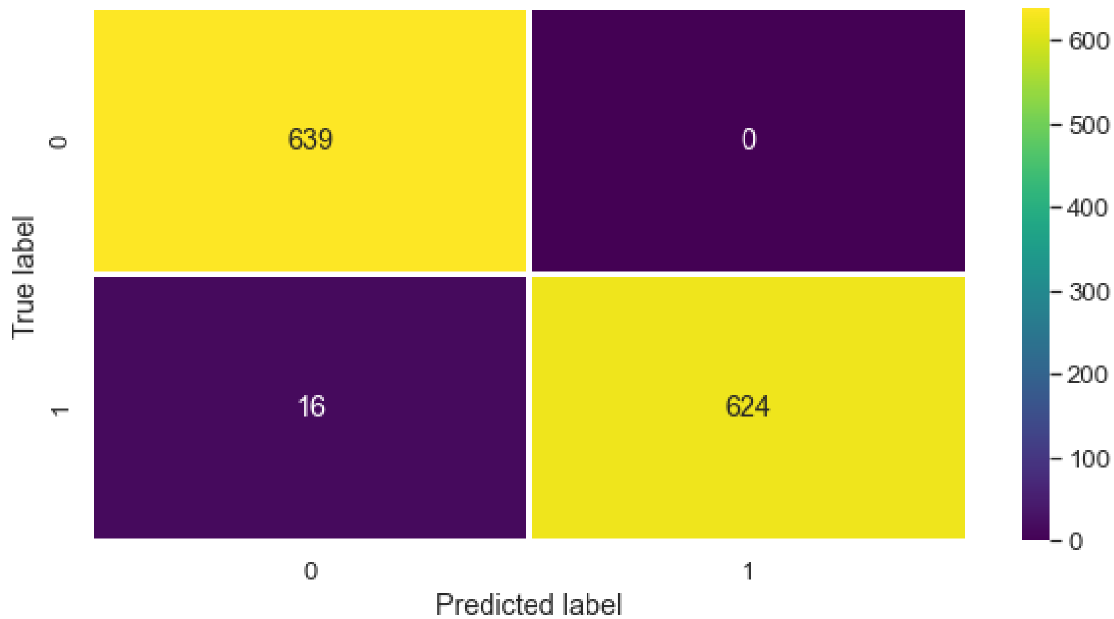
[62]:
```
array([2., 1., 2., …, 1., 1., 1.])
```

0.0.20 Model Evaluation

[63]:
```
cm = confusion_matrix(y_test,y_pred)
cm
```

[63]:
```
array([[639,   0],
       [ 16, 624]], dtype=int64)
```

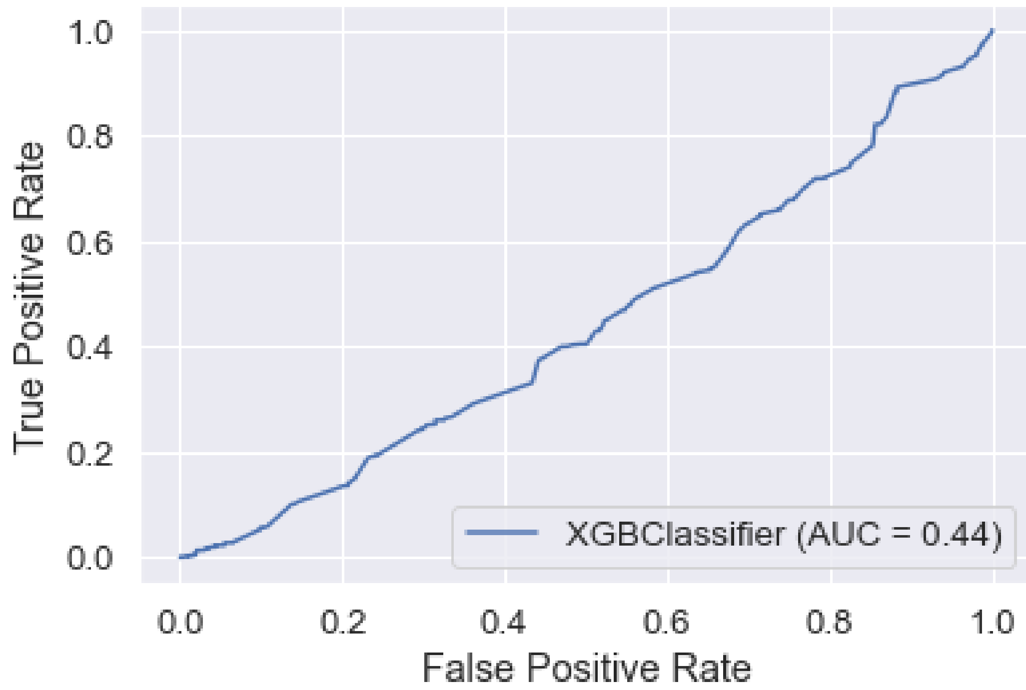
[64]:
```
fig , ax = plt.subplots(figsize=(10,5))
sns.heatmap(cm, annot=True,fmt='.4g',linewidths=2, cmap='viridis')
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()
```



[65]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

         1.0       0.98      1.00      0.99       639
         2.0       1.00      0.97      0.99       640

    accuracy                           0.99      1279
   macro avg       0.99      0.99      0.99      1279
weighted avg       0.99      0.99      0.99      1279
```

[66]:
```
plot_roc_curve(xgbmodel,X_test,y_test)
plt.show()
```




```
[ ]:
```

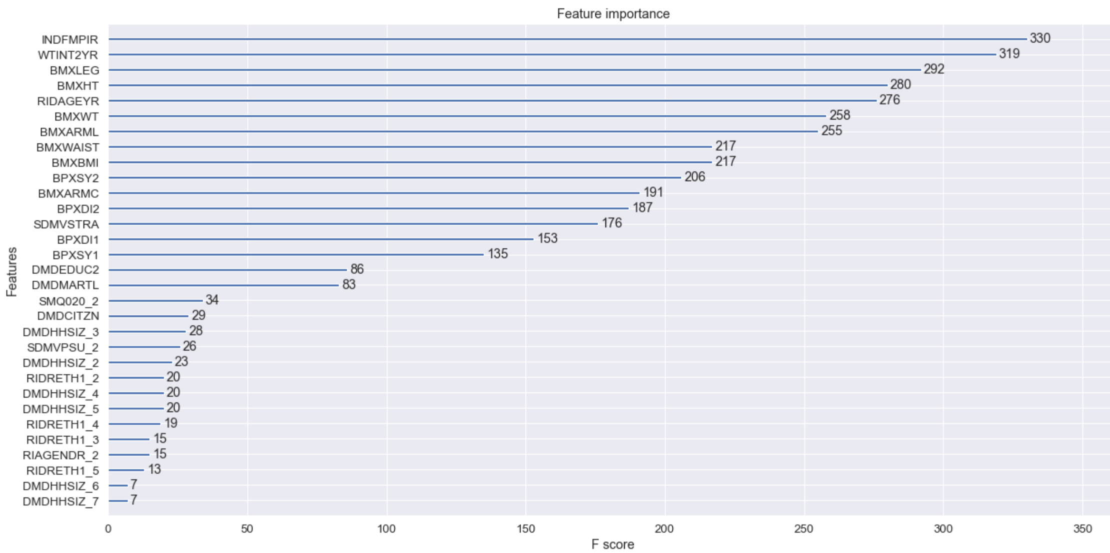
0.0.21 Available importance_types = ['weight', 'gain', 'cover', 'total_gain', 'total_cover']

```
[67]: X.columns
```

```
[67]: Index(['RIDAGEYR', 'DMDCITZN', 'DMDEDUC2', 'DMDMARTL', 'WTINT2YR', 'SDMVSTRA',
       'INDFMPIR', 'BPXSY1', 'BPXDI1', 'BPXSY2', 'BPXDI2', 'BMXWT', 'BMXHT', 'BMXBMI',
       'BMXLEG', 'BMXARML', 'BMXARMC', 'BMXWAIST', 'SMQ020_2', 'SMQ020_9',
       'RIAGENDR_2', 'RIDRETH1_2', 'RIDRETH1_3', 'RIDRETH1_4', 'RIDRETH1_5',
       'DMDHHSIZ_2', 'DMDHHSIZ_3', 'DMDHHSIZ_4', 'DMDHHSIZ_5', 'DMDHHSIZ_6',
       'DMDHHSIZ_7', 'SDMVPSU_2'], dtype='object')
```

```
[68]: xgbmodel.get_booster().feature_names = ['RIDAGEYR', 'DMDCITZN', 'DMDEDUC2',␣
 ↪'DMDMARTL', 'WTINT2YR', 'SDMVSTRA', 'INDFMPIR', 'BPXSY1', 'BPXDI1',␣
 ↪'BPXSY2', 'BPXDI2', 'BMXWT', 'BMXHT', 'BMXBMI', 'BMXLEG', 'BMXARML',␣
 ↪'BMXARMC', 'BMXWAIST', 'SMQ020_2', 'SMQ020_9', 'RIAGENDR_2', 'RIDRETH1_2',␣
 ↪'RIDRETH1_3', 'RIDRETH1_4', 'RIDRETH1_5', 'DMDHHSIZ_2', 'DMDHHSIZ_3',␣
 ↪'DMDHHSIZ_4', 'DMDHHSIZ_5', 'DMDHHSIZ_6', 'DMDHHSIZ_7', 'SDMVPSU_2']
```

```
[69]: fig, ax = plt.subplots(figsize=(20,10))
xgb.plot_importance(xgbmodel.get_booster(),ax=ax)
plt.show()
```



0.0.22 Cross-Validation

[70]:
```
cv = cross_val_score(xgbmodel,new_X,new_y,cv=5,verbose=1,scoring='accuracy')
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:   28.1s finished
```

[71]:
```
cv.mean()
```

[71]: 0.9759062060662123

[ ]:
```

```