In [123…
```
#Libraries
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt # this is used for the plot the graph
import os
import seaborn as sns # used for plot interactive graph.
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn import metrics
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.cluster import KMeans
from sklearn.metrics import confusion_matrix
import sklearn.metrics.cluster as smc
from sklearn.model_selection import KFold


from matplotlib import pyplot
import itertools

%matplotlib inline

import random
```

1. Basic Statistics

In [124…
```
#Read in data
hd = pd.read_csv('healthcare-dataset-stroke-data.csv')
hd.head()
```

Out[124…

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glu
0	9046	Male	67.0	0	1	Yes	Private	Urban	
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	
2	31112	Male	80.0	0	1	Yes	Private	Rural	
3	60182	Female	49.0	0	0	Yes	Private	Urban	
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	

In [125…
```
hd.describe()
```

Out[125…

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	str
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	4909.000000	5110.000
mean	36517.829354	43.226614	0.097456	0.054012	106.147677	28.893237	0.048
std	21161.721625	22.612647	0.296607	0.226063	45.283560	7.854067	0.215

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	str
min	67.000000	0.080000	0.000000	0.000000	55.120000	10.300000	0.000
25%	17741.250000	25.000000	0.000000	0.000000	77.245000	23.500000	0.000
50%	36932.000000	45.000000	0.000000	0.000000	91.885000	28.100000	0.000
75%	54682.000000	61.000000	0.000000	0.000000	114.090000	33.100000	0.000
max	72940.000000	82.000000	1.000000	1.000000	271.740000	97.600000	1.000

In [126…
```
hd.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5110 entries, 0 to 5109
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 5110 non-null   int64  
 1   gender             5110 non-null   object 
 2   age                5110 non-null   float64
 3   hypertension       5110 non-null   int64  
 4   heart_disease      5110 non-null   int64  
 5   ever_married       5110 non-null   object 
 6   work_type          5110 non-null   object 
 7   Residence_type     5110 non-null   object 
 8   avg_glucose_level  5110 non-null   float64
 9   bmi                4909 non-null   float64
 10  smoking_status     5110 non-null   object 
 11  stroke             5110 non-null   int64  
dtypes: float64(3), int64(4), object(5)
memory usage: 479.2+ KB
```

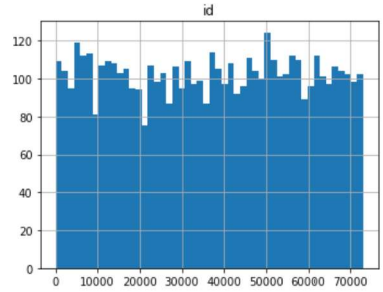
In [201…
```
hd['bmi'].mean()
```

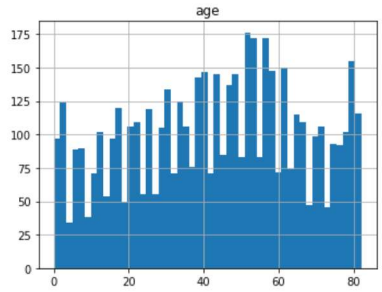
Out[201…
```
28.862035225049
```

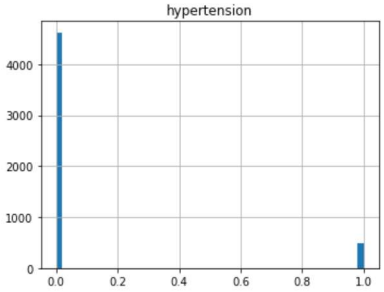
In [202…
```
hd['bmi'].median()
```

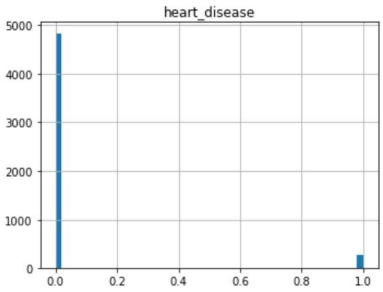
Out[202…
```
28.1
```

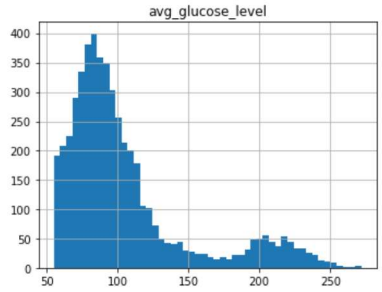
In [127…
```
hd.hist(bins=50, figsize=(20,15))
plt.show()
```

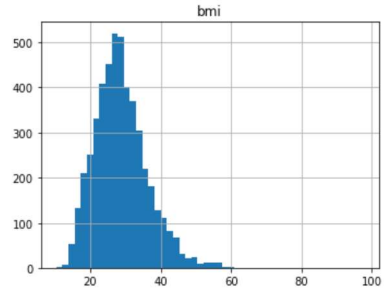


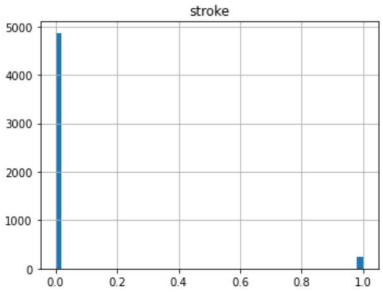








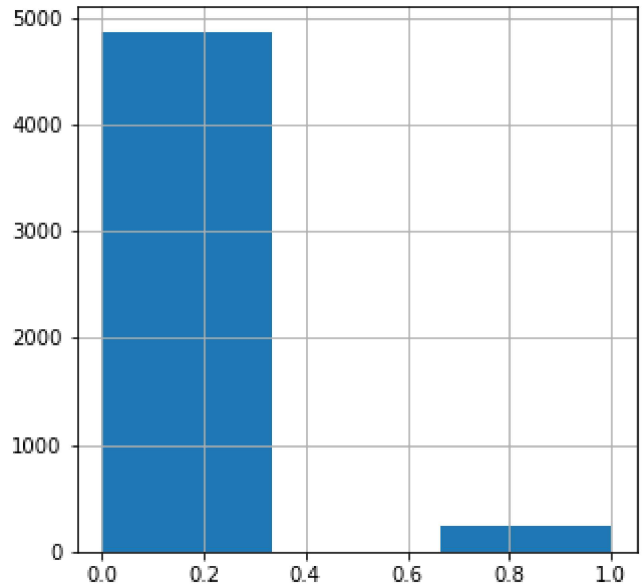




In [ ]:

In [128…
```
hd['stroke'].hist(bins=3, figsize=(5,5))
hd['stroke'].value_counts()
```

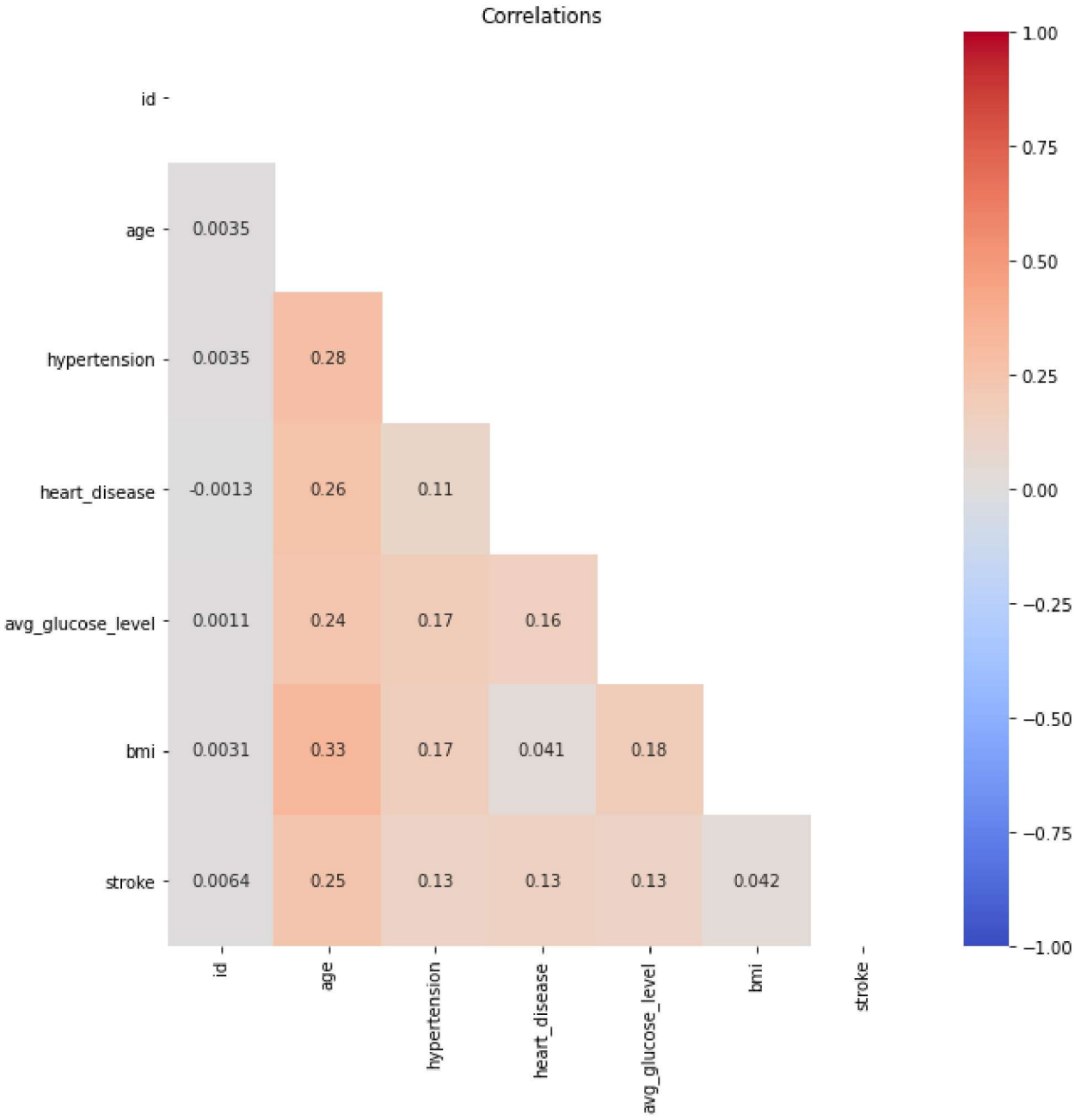
Out[128…
```
0    4861
1     249
Name: stroke, dtype: int64
```



In [129…
```
#NOTE: code tutorial for diaganol heatmap taken from https://heartbeat.fritz.ai/seaborn
matrix = np.triu(hd.corr())
```

```
fig, ax = plt.subplots(figsize=(10,10))
plt.title("Correlations")
sns.heatmap(hd.corr(), annot = True, mask=matrix, vmin=-1, vmax=1, center= 0, cmap= 'co
```

Out[129… <AxesSubplot:title={'center':'Correlations'}>



Meaningful positive correlations between ageXstroke, hypertensionXstroke, heart_diseaseXstroke. Small + correlation between bmiXstroke. Id should be dropped.

2. Data Pipeline

In [130…
```
#Drop id as it is arbitrary and only used to help store/catalog the input data
hd = hd.drop('id', axis=1)
hd.head()
```

Out[130…

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_lev

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_lev
0	Male	67.0	0	1	Yes	Private	Urban	228.6
1	Female	61.0	0	0	Yes	Self-employed	Rural	202.2
2	Male	80.0	0	1	Yes	Private	Rural	105.9
3	Female	49.0	0	0	Yes	Private	Urban	171.2
4	Female	79.0	1	0	Yes	Self-employed	Rural	174.1

In [131…
```
#what features do we need to impute due to nan values
hd.isnull().sum()
```

Out[131…
```
gender                 0
age                    0
hypertension           0
heart_disease          0
ever_married           0
work_type              0
Residence_type         0
avg_glucose_level      0
bmi                  201
smoking_status         0
stroke                 0
dtype: int64
```

In [132…
```
#bmi is only missing ~4% of its values
hd.isnull().sum()['bmi']/hd['bmi'].size
#impute with median to avoid outlier bmi from biasing
```

Out[132…
```
0.03933463796477495
```

In [133…
```
hd['gender'].value_counts()
#there's only one other gender in the entire dataset, should I just ignore the 'other'
```

Out[133…
```
Female    2994
Male      2115
Other        1
Name: gender, dtype: int64
```

In [134…
```
hd['smoking_status'].value_counts()
```

Out[134…
```
never smoked       1892
Unknown            1544
formerly smoked     885
smokes              789
Name: smoking_status, dtype: int64
```

imputation --> augmentation --> scaling split -> balance training, do not balance test

Feature Augmentation:

```
weight_glucose = avg_glucose_level * bmi //if overweight and high blood
sugar, correlated with diabetes and stroke
```

```
hypertension_heart_disease = hyper_tension*heart_disease //as both are
boolean, result is also boolean
```

Numerical features:

```
age, avg_glucose_level, bmi, weight_glucose --> numerical scaler
```

Categorical features:

```
gender, ever_married, residence_type, smoking_status --> lable encoding
(females more likely for stroke, and only one 'other' gender in dataset
hypertension, heart_disease, hypertension_heart_disease --> leave as is
work_type --> OHE
```

In [135…
```
#impute BMI with median
missing_col = ['bmi']
for i in missing_col:
    hd.loc[hd.loc[:, i].isnull(), i] = hd.loc[:,i].median()
hd['bmi'].isnull().sum()
```

Out[135… 0

In [136…
```
#augment features
hd['weight_glucose'] = hd['avg_glucose_level'] * hd['bmi']
hd['hypertension_heart_disease'] = hd['hypertension'] * hd['heart_disease']
hd.head()
```

Out[136…

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_lev
0	Male	67.0	0	1	Yes	Private	Urban	228.6
1	Female	61.0	0	0	Yes	Self-employed	Rural	202.2
2	Male	80.0	0	1	Yes	Private	Rural	105.9
3	Female	49.0	0	0	Yes	Private	Urban	171.2
4	Female	79.0	1	0	Yes	Self-employed	Rural	174.1

In [137…
```
numerical_features = ['age', 'avg_glucose_level', 'bmi', 'weight_glucose']
cat_features_ohe = ['work_type' ]
cat_features_le = ['gender', 'ever_married', 'Residence_type', 'smoking_status' , 'hype
#leave the rest as is
```

In [138…
```
#label encode some cat features
from sklearn.preprocessing import OrdinalEncoder
for i in cat_features_le:
```

```
    ord_enc = OrdinalEncoder()
    hd[i] = ord_enc.fit_transform(hd[[i]])
hd.head()
```

Out[138…

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_lev
0	1.0	67.0	0.0	1.0	1.0	Private	1.0	228.6
1	0.0	61.0	0.0	0.0	1.0	Self-employed	0.0	202.2
2	1.0	80.0	0.0	1.0	1.0	Private	0.0	105.9
3	0.0	49.0	0.0	0.0	1.0	Private	1.0	171.2
4	0.0	79.0	1.0	0.0	1.0	Self-employed	0.0	174.1

In [139…

```
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder

from sklearn.base import BaseEstimator, TransformerMixin
from sklearn import preprocessing
```

In [140…

```
#scale numerical features and one hot encode the rest of categorical vars

hd_features = hd.drop('stroke', axis=1)
hd_label = hd['stroke']



num_pipeline = Pipeline([
    ('std_scaler', StandardScaler()),
])

full_pipeline = ColumnTransformer([
    ("num", num_pipeline, numerical_features),
    ("cat_ohe", OneHotEncoder(), cat_features_ohe),
    ('nothing', 'passthrough' , cat_features_le)
])

hd_features.shape
```

Out[140… (5110, 12)

In [141…

```
#finish data pipeline
hd_prepared_unbalanced = full_pipeline.fit_transform(hd_features)
hd_prepared_unbalanced[1]
```

Out[141…

```
array([ 0.78607007,  2.12155854, -0.09898092,  1.42650907,  0.        ,
        0.        ,  0.        ,  1.        ,  0.        ,  0.        ,
        1.        ,  0.        ,  2.        ,  0.        ,  0.        ,
        0.        ])
```

In [142…
```
hd_prepared_unbalanced.shape
```

Out[142… (5110, 16)

3. Basic Logistic Regression

In [143…
```
#split data into train and test
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(hd_prepared_unbalanced, hd_label, t
print (X_train.shape, y_train.shape)
print (X_test.shape, y_test.shape)
```

```
(4088, 16) (4088,)
(1022, 16) (1022,)
```

In [144…
```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
log_reg = LogisticRegression(solver='liblinear')
log_reg.fit(X_train, y_train)
predicted = log_reg.predict(X_test)
score = log_reg.predict_proba(X_test)[:,1]
log_reg_preds = predicted
```

In [145…
```
print(f"Accuracy: {metrics.accuracy_score(y_test, log_reg_preds)}")
print(f"Precision: {metrics.precision_score(y_test, log_reg_preds)}")
print(f"Recall: {metrics.recall_score(y_test, log_reg_preds)}")
print(f"F1 Score: {metrics.f1_score(y_test, log_reg_preds)}")

###issue with unbalanced data, predicts everything as no stroke
```

```
Accuracy: 0.9422700587084148
Precision: 0.0
Recall: 0.0
F1 Score: 0.0
C:\Users\dyera\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1248: Unde
finedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted sa
mples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [146…
```
hd_unbalanced = pd.concat([pd.DataFrame(hd_prepared_unbalanced), pd.DataFrame(hd_label)
hd_unbalanced.head()
```

Out[146…

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	stro
0	1.051434	2.706375	1.005086	2.924147	0.0	0.0	1.0	0.0	0.0	1.0	1.0	1.0	1.0	0.0	1.0	0.0	
1	0.786070	2.121559	-0.098981	1.426509	0.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	2.0	0.0	0.0	0.0	
2	1.626390	-0.005028	0.472536	0.178622	0.0	0.0	1.0	0.0	0.0	1.0	1.0	0.0	2.0	0.0	1.0	0.0	
3	0.255342	1.437358	0.719327	1.542517	0.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	3.0	0.0	0.0	0.0	
4	1.582163	1.501184	-0.631531	0.588964	0.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	2.0	1.0	0.0	0.0	

In [147…
```
#seems like the model gets a very low mse rate as it is heavily biased towards no strok
#to fix this, I will balance the dataset

#code taken from https://towardsdatascience.com/having-an-imbalanced-dataset-here-is-ho
```

```
from imblearn import under_sampling
from imblearn import over_sampling
from imblearn.over_sampling import SMOTE

# Resample the minority class. You can change the strategy to 'auto' if you are not sur
sm = SMOTE(sampling_strategy='minority', random_state=7)

# Fit the model to generate the data.
#oversampled_trainX, oversampled_trainY = sm.fit_resample(hd_unbalanced.drop('stroke',
oversampled_trainX, oversampled_trainY = sm.fit_resample(X_train, y_train)
oversampled_train = pd.concat([pd.DataFrame(oversampled_trainY), pd.DataFrame(oversampl
```

In [148…

```
log_reg = LogisticRegression(solver='liblinear')
log_reg.fit(oversampled_trainX, oversampled_trainY)
predicted = log_reg.predict(X_test)
score = log_reg.predict_proba(X_test)[:,1]
log_reg_preds = predicted
print(f"Accuracy: {metrics.accuracy_score(y_test, log_reg_preds)}")
print(f"Precision: {metrics.precision_score(y_test, log_reg_preds)}")
print(f"Recall: {metrics.recall_score(y_test, log_reg_preds)}")
print(f"F1 Score: {metrics.f1_score(y_test, log_reg_preds)}")
```

```
Accuracy: 0.738747553816047
Precision: 0.15562913907284767
Recall: 0.7966101694915254
F1 Score: 0.260387811634349
```

In [149…

```
##statistical modeling for feature selection
import statsmodels.api as sm

# build the OLS model (ordinary least squares) from the training data
stats = sm.OLS(hd_label, hd_prepared_unbalanced)

# do the fit and save regression info (parameters, etc) in results_stats
results_stats = stats.fit()
```

In [150…

```
print(results_stats.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 stroke   R-squared:                       0.085
Model:                            OLS   Adj. R-squared:                  0.082
Method:                 Least Squares   F-statistic:                     31.50
Date:                Mon, 31 May 2021   Prob (F-statistic):           6.51e-87
Time:                        21:44:27   Log-Likelihood:                823.41
No. Observations:                5110   AIC:                            -1615.
Df Residuals:                    5094   BIC:                            -1510.
Df Model:                          15
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
x1             0.0700      0.005     14.406      0.000       0.060       0.079
x2            -0.0046      0.012     -0.380      0.704      -0.028       0.019
x3            -0.0162      0.008     -2.139      0.032      -0.031      -0.001
x4             0.0229      0.015      1.567      0.117      -0.006       0.052
x5             0.0487      0.012      4.091      0.000       0.025       0.072
x6             0.0832      0.045      1.857      0.063      -0.005       0.171
x7             0.0633      0.009      6.882      0.000       0.045       0.081
x8             0.0434      0.011      3.848      0.000       0.021       0.066
x9             0.1095      0.013      8.735      0.000       0.085       0.134
x10           -0.0009      0.006     -0.157      0.875      -0.013       0.011
```

```
x11           -0.0343      0.009     -4.005      0.000      -0.051      -0.018
x12            0.0055      0.006      0.944      0.345      -0.006       0.017
x13           -0.0017      0.003     -0.562      0.574      -0.008       0.004
x14            0.0397      0.011      3.633      0.000       0.018       0.061
x15            0.0543      0.015      3.573      0.000       0.025       0.084
x16           -0.0127      0.031     -0.406      0.685      -0.074       0.049
==============================================================================
Omnibus:                     3801.863   Durbin-Watson:                   0.173
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            47434.704
Skew:                           3.645   Prob(JB):                         0.00
Kurtosis:                      16.024   Cond. No.                         32.0
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
```

4. Principal Component Analysis (PCA)

In [151…
```
from sklearn import decomposition

pca = decomposition.PCA(n_components=6)
hd_unbalanced_label = hd_unbalanced['stroke']
hd_unbalanced_features = hd_unbalanced.drop('stroke', axis=1)
hd_pca = pca.fit_transform(hd_unbalanced_features)
```

In [152…
```
hd_pca.shape
```

Out[152…
```
(5110, 6)
```

In [153…
```
hd_pca
```

Out[153…
```
array([[ 3.75652956,  2.03862158, -0.0156282 , -0.36403933, -0.47095928,
        -0.45024525],
       [ 2.28571697,  0.80695305, -0.81279654, -1.09693869,  0.62511791,
         0.4788159 ],
       [ 1.22520312, -1.03201303,  0.59187467, -0.61589837, -0.47323799,
         0.58980588],
       ...,
       [-0.23491173, -0.74796311, -0.15499294,  0.31877295,  0.79487574,
         0.51422793],
       [ 0.89707368,  0.99563627, -0.23080413, -0.79972333, -0.69142489,
         0.52811049],
       [-0.96920177,  0.51329231,  1.0900334 , -0.37968008,  0.48477922,
        -0.52462224]])
```

In [154…
```
#shrunk from 16->6 features
```

5. Ensemble Method - bagging

In [155…
```
X_train, X_test, y_train, y_test = train_test_split(hd_pca, hd_unbalanced_label, test_s
```

In [156…
```
# Resample the minority class. You can change the strategy to 'auto' if you are not sur
sm = SMOTE(sampling_strategy='minority', random_state=7)

# Fit the model to generate the data.
```

```
oversampled_trainX, oversampled_trainY = sm.fit_resample(X_train, y_train)
oversampled_train = pd.concat([pd.DataFrame(oversampled_trainY), pd.DataFrame(oversampl
```

In [157…
```
from sklearn import model_selection
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier
from imblearn.ensemble import BalancedBaggingClassifier
```

In [159…
```
bc = BaggingClassifier(base_estimator=DecisionTreeClassifier(), random_state=0)
bc.fit(oversampled_trainX, oversampled_trainY)
predictions = bc.predict(X_test)
log_reg_preds = predictions
print(f"Accuracy: {metrics.accuracy_score(y_test, log_reg_preds)}")
print(f"Precision: {metrics.precision_score(y_test, log_reg_preds)}")
print(f"Recall: {metrics.recall_score(y_test, log_reg_preds)}")
print(f"F1 Score: {metrics.f1_score(y_test, log_reg_preds)}")
```

```
Accuracy: 0.8874755381604696
Precision: 0.1375
Recall: 0.19298245614035087
F1 Score: 0.16058394160583941
```

In [160…
```
bc = BalancedBaggingClassifier(base_estimator=DecisionTreeClassifier(),replacement=True
bc.fit(oversampled_trainX, oversampled_trainY)
predictions = bc.predict(X_test)
log_reg_preds = predictions
print(f"Accuracy: {metrics.accuracy_score(y_test, log_reg_preds)}")
print(f"Precision: {metrics.precision_score(y_test, log_reg_preds)}")
print(f"Recall: {metrics.recall_score(y_test, log_reg_preds)}")
print(f"F1 Score: {metrics.f1_score(y_test, log_reg_preds)}")
```

```
Accuracy: 0.8796477495107632
Precision: 0.13333333333333333
Recall: 0.21052631578947367
F1 Score: 0.163265306122449
```

6. Neural Net Classifier

In [161…
```
from sklearn.neural_network import MLPClassifier
```

In [190…
```
clf = MLPClassifier(solver='lbfgs', alpha=1e-5, hidden_layer_sizes=(5, 2), random_state
clf.fit(oversampled_trainX, oversampled_trainY)
predictions = clf.predict(X_test)
log_reg_preds = predictions
print(f"Accuracy: {metrics.accuracy_score(y_test, log_reg_preds)}")
print(f"Precision: {metrics.precision_score(y_test, log_reg_preds)}")
print(f"Recall: {metrics.recall_score(y_test, log_reg_preds)}")
print(f"F1 Score: {metrics.f1_score(y_test, log_reg_preds)}")
```

```
Accuracy: 0.7338551859099804
Precision: 0.14285714285714285
Recall: 0.7543859649122807
F1 Score: 0.2402234636871508
```

In [191…
```
clf = MLPClassifier(solver='lbfgs', alpha=1e-5, hidden_layer_sizes=(2, 2), random_state
clf.fit(oversampled_trainX, oversampled_trainY)
predictions = clf.predict(X_test)
log_reg_preds = predictions
print(f"Accuracy: {metrics.accuracy_score(y_test, log_reg_preds)}")
print(f"Precision: {metrics.precision_score(y_test, log_reg_preds)}")
```

```
print(f"Recall: {metrics.recall_score(y_test, log_reg_preds)}")
print(f"F1 Score: {metrics.f1_score(y_test, log_reg_preds)}")
```

```
Accuracy: 0.7113502935420744
Precision: 0.14156626506024098
Recall: 0.8245614035087719
F1 Score: 0.24164524421593833
```

In [192…
```
clf = MLPClassifier(solver='lbfgs', alpha=1e-3, hidden_layer_sizes=(5, 2), random_state
clf.fit(oversampled_trainX, oversampled_trainY)
predictions = clf.predict(X_test)
log_reg_preds = predictions
print(f"Accuracy: {metrics.accuracy_score(y_test, log_reg_preds)}")
print(f"Precision: {metrics.precision_score(y_test, log_reg_preds)}")
print(f"Recall: {metrics.recall_score(y_test, log_reg_preds)}")
print(f"F1 Score: {metrics.f1_score(y_test, log_reg_preds)}")
```

```
Accuracy: 0.7074363992172211
Precision: 0.12422360248447205
Recall: 0.7017543859649122
F1 Score: 0.21108179419525064
```

In [193…
```
clf = MLPClassifier(solver='lbfgs', alpha=1e-5, hidden_layer_sizes=(2, 2), random_state
clf.fit(oversampled_trainX, oversampled_trainY)
predictions = clf.predict(X_test)
log_reg_preds = predictions
print(f"Accuracy: {metrics.accuracy_score(y_test, log_reg_preds)}")
print(f"Precision: {metrics.precision_score(y_test, log_reg_preds)}")
print(f"Recall: {metrics.recall_score(y_test, log_reg_preds)}")
print(f"F1 Score: {metrics.f1_score(y_test, log_reg_preds)}")
```

```
Accuracy: 0.7113502935420744
Precision: 0.14156626506024098
Recall: 0.8245614035087719
F1 Score: 0.24164524421593833
```

In [189…
```
clf = MLPClassifier(solver='lbfgs', alpha=1e-2, hidden_layer_sizes=(2, 2), random_state
clf.fit(oversampled_trainX, oversampled_trainY)
predictions = clf.predict(X_test)
log_reg_preds = predictions
print(f"Accuracy: {metrics.accuracy_score(y_test, log_reg_preds)}")
print(f"Precision: {metrics.precision_score(y_test, log_reg_preds)}")
print(f"Recall: {metrics.recall_score(y_test, log_reg_preds)}")
print(f"F1 Score: {metrics.f1_score(y_test, log_reg_preds)}")
```

```
Accuracy: 0.7103718199608611
Precision: 0.14114114114114115
Recall: 0.8245614035087719
F1 Score: 0.24102564102564106
```

In [188…
```
clf = MLPClassifier(solver='lbfgs', alpha=1e-9, hidden_layer_sizes=(2, 8), random_state
clf.fit(oversampled_trainX, oversampled_trainY)
predictions = clf.predict(X_test)
log_reg_preds = predictions
print(f"Accuracy: {metrics.accuracy_score(y_test, log_reg_preds)}")
print(f"Precision: {metrics.precision_score(y_test, log_reg_preds)}")
print(f"Recall: {metrics.recall_score(y_test, log_reg_preds)}")
print(f"F1 Score: {metrics.f1_score(y_test, log_reg_preds)}")
```

```
Accuracy: 0.6868884540117417
Precision: 0.13774104683195593
Recall: 0.8771929824561403
F1 Score: 0.2380952380952381
```

after playing with the parameters, my best recall occurred with alpha = 1e-9 layers = 2x8

7. Cross Validation

In [183…
```
from sklearn.model_selection import KFold
from sklearn import model_selection
```

In [195…
```
kfold = model_selection.KFold(n_splits=10, random_state=42, shuffle=True)

model_kfold = BalancedBaggingClassifier(base_estimator=DecisionTreeClassifier(),replace

results_kfold = model_selection.cross_val_score(model_kfold, hd_unbalanced_features, hd

print("Accuracy: %.2f%%" % (results_kfold.mean()*100.0))
```

```
Accuracy: 79.84%
```

In [196…
```
kfold = model_selection.KFold(n_splits=10, random_state=42, shuffle=True)

model_kfold = MLPClassifier(solver='lbfgs', alpha=1e-2, hidden_layer_sizes=(2, 2), rand

results_kfold = model_selection.cross_val_score(model_kfold, hd_unbalanced_features, hd

print("Accuracy: %.2f%%" % (results_kfold.mean()*100.0))
```

```
Accuracy: 95.13%
```

8. Best Model

In [203…
```
X_train, X_test, y_train, y_test = train_test_split(hd_pca, hd_unbalanced_label, test_s

sm = SMOTE(sampling_strategy='minority', random_state=7)

# Fit the model to generate the data.
oversampled_trainX, oversampled_trainY = sm.fit_resample(X_train, y_train)
oversampled_train = pd.concat([pd.DataFrame(oversampled_trainY), pd.DataFrame(oversampl
```

In [204…
```
clf = MLPClassifier(solver='lbfgs', alpha=1e-9, hidden_layer_sizes=(2, 8), random_state
clf.fit(oversampled_trainX, oversampled_trainY)
predictions = clf.predict(X_test)
log_reg_preds = predictions
print(f"Accuracy: {metrics.accuracy_score(y_test, log_reg_preds)}")
print(f"Precision: {metrics.precision_score(y_test, log_reg_preds)}")
print(f"Recall: {metrics.recall_score(y_test, log_reg_preds)}")
print(f"F1 Score: {metrics.f1_score(y_test, log_reg_preds)}")
```

```
Accuracy: 0.7367906066536204
Precision: 0.11301369863013698
Recall: 0.7674418604651163
F1 Score: 0.19701492537313434
```

In [205…
```
X_train, X_test, y_train, y_test = train_test_split(hd_unbalanced_features, hd_unbalanc

sm = SMOTE(sampling_strategy='minority', random_state=7)

# Fit the model to generate the data.
```

```
oversampled_trainX, oversampled_trainY = sm.fit_resample(X_train, y_train)
oversampled_train = pd.concat([pd.DataFrame(oversampled_trainY), pd.DataFrame(oversampl
```

In [207…

```
clf = MLPClassifier(solver='lbfgs', alpha=1e-9, hidden_layer_sizes=(2, 9), random_state
clf.fit(oversampled_trainX, oversampled_trainY)
predictions = clf.predict(X_test)
log_reg_preds = predictions
print(f"Accuracy: {metrics.accuracy_score(y_test, log_reg_preds)}")
print(f"Precision: {metrics.precision_score(y_test, log_reg_preds)}")
print(f"Recall: {metrics.recall_score(y_test, log_reg_preds)}")
print(f"F1 Score: {metrics.f1_score(y_test, log_reg_preds)}")
```

```
Accuracy: 0.7407045009784736
Precision: 0.1390728476821192
Recall: 0.8936170212765957
F1 Score: 0.24068767908309452
```

My best model, with a priority on Recall, would be a mlp classifier using the PCA reduced feature space along with SMOTE minority balancing to balance ONLY the training data and NOT the test data

In [ ]: