# kzzhuuzhp

### August 2, 2023

[1]: import numpy as np

```
import pandas as pd
     import matplotlib.pyplot as plt
     import seaborn as sns
     from sklearn.linear_model import LogisticRegression
     from sklearn.preprocessing import StandardScaler
[2]: from google.colab import drive
     drive.mount('/content/drive')
    Mounted at /content/drive
[3]: df=pd.read_csv("/content/drive/MyDrive/mydatasets/C4_framingham.csv")
     df
[3]:
                       education currentSmoker
                                                   cigsPerDay
                                                                BPMeds
           \mathtt{male}
                 age
     0
              1
                   39
                             4.0
                                                0
                                                          0.0
                                                                   0.0
                             2.0
                                                          0.0
     1
              0
                   46
                                                0
                                                                   0.0
     2
                              1.0
                                                         20.0
              1
                   48
                                                1
                                                                   0.0
     3
              0
                   61
                             3.0
                                                         30.0
                                                                   0.0
              0
     4
                   46
                             3.0
                                                1
                                                         23.0
                                                                   0.0
     4233
              1
                   50
                             1.0
                                                          1.0
                                                                   0.0
                                                1
     4234
                   51
                             3.0
                                                1
                                                         43.0
                                                                   0.0
              1
     4235
              0
                   48
                             2.0
                                                1
                                                         20.0
                                                                   NaN
     4236
              0
                                                         15.0
                                                                   0.0
                   44
                              1.0
                                                1
     4237
                   52
                              2.0
                                                          0.0
                                                                   0.0
           prevalentStroke
                             prevalentHyp
                                            diabetes
                                                       totChol
                                                                 sysBP
                                                                        diaBP
                                                                                  BMI
                                                         195.0
     0
                                                    0
                                                                 106.0
                                                                         70.0
                                                                                26.97
     1
                          0
                                         0
                                                    0
                                                         250.0 121.0
                                                                         81.0
                                                                                28.73
     2
                          0
                                         0
                                                    0
                                                         245.0 127.5
                                                                         80.0
                                                                                25.34
     3
                                                         225.0
                          0
                                         1
                                                    0
                                                                150.0
                                                                         95.0
                                                                                28.58
     4
                                                         285.0
                          0
                                         0
                                                    0
                                                                130.0
                                                                         84.0
                                                                                23.10
                                                         313.0
                                                                179.0
     4233
                          0
                                         1
                                                    0
                                                                         92.0
                                                                                25.97
     4234
                          0
                                         0
                                                         207.0 126.5
                                                                         80.0
                                                                                19.71
                                                    0
     4235
                          0
                                         0
                                                    0
                                                         248.0
                                                                131.0
                                                                         72.0
                                                                                22.00
```

4236		0	0	0	210.0	126.5	87.0	19.16	
4237		0	0	0	269.0	133.5	83.0	21.47	
	heartRate	glucose	${\tt TenYearCHD}$						
0	80.0	77.0	0						
1	95.0	76.0	0						
2	75.0	70.0	0						
3	65.0	103.0	1						
4	85.0	85.0	0						
•••	•••	•••	•••						
4233	66.0	86.0	1						
4234	65.0	68.0	0						
4235	84.0	86.0	0						
4236	86.0	NaN	0						
4237	80.0	107.0	0						
[4238	rows x 16	columns]							
: df.he	ad()								

[4]:	male	age	education	currentSmoker	cigsPerDay	BPMeds	prevalentStroke	\
0	1	39	4.0	0	0.0	0.0	0	
1	0	46	2.0	0	0.0	0.0	0	
2	1	48	1.0	1	20.0	0.0	0	
3	0	61	3.0	1	30.0	0.0	0	
4	0	46	3.0	1	23.0	0.0	0	

	${ t prevalentHyp}$	diabetes	totChol	sysBP	diaBP	BMI	heartRate	glucose	\
0	0	0	195.0	106.0	70.0	26.97	80.0	77.0	
1	0	0	250.0	121.0	81.0	28.73	95.0	76.0	
2	0	0	245.0	127.5	80.0	25.34	75.0	70.0	
3	1	0	225.0	150.0	95.0	28.58	65.0	103.0	
4	0	0	285.0	130.0	84.0	23.10	85.0	85.0	

#### TenYearCHD

# 1 Data Cleaning and Data Preprocessing

[5]: df.dropna(inplace=True) df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 3656 entries, 0 to 4237
Data columns (total 16 columns):

#	Column	Non-Null Count	Dtype
0	male	3656 non-null	int64
1	age	3656 non-null	int64
2	education	3656 non-null	float64
3	currentSmoker	3656 non-null	int64
4	cigsPerDay	3656 non-null	float64
5	BPMeds	3656 non-null	float64
6	${\tt prevalentStroke}$	3656 non-null	int64
7	${\tt prevalentHyp}$	3656 non-null	int64
8	diabetes	3656 non-null	int64
9	totChol	3656 non-null	float64
10	sysBP	3656 non-null	float64
11	diaBP	3656 non-null	float64
12	BMI	3656 non-null	float64
13	heartRate	3656 non-null	float64
14	glucose	3656 non-null	float64
15	TenYearCHD	3656 non-null	int64
34	47+04(0) :	+ (1 (7)	

dtypes: float64(9), int64(7)

memory usage: 485.6 KB

## [6]: df.describe()

[6]:		male	age	education	currentSmoker	cigsPerDay \	
	count	3656.000000	3656.000000	3656.000000	3656.000000	3656.000000	
	mean	0.443654	49.557440	1.979759	0.489059	9.022155	
	std	0.496883	8.561133	1.022657	0.499949	11.918869	
	min	0.000000	32.000000	1.000000	0.000000	0.000000	
	25%	0.000000	42.000000	1.000000	0.000000	0.000000	
	50%	0.000000	49.000000	2.000000	0.000000	0.000000	
	75%	1.000000	56.000000	3.000000	1.000000	20.000000	
	max	1.000000	70.000000	4.000000	1.000000	70.000000	
		BPMeds	prevalentStro	ke prevalent	tHyp diabet	es totChol	\
	count	3656.000000	3656.0000	00 3656.000	0000 3656.0000	00 3656.000000	
	mean	0.030361	0.0057	44 0.311	0.0270	79 236.873085	
	std	0.171602	0.0755	81 0.463	0.1623	35 44.096223	
	min	0.000000	0.0000	0.000	0.0000	00 113.000000	
	25%	0.000000	0.0000	0.000	0.0000	206.000000	

```
75%
                0.000000
                                  0.000000
                                                 1.000000
                                                              0.000000
                                                                          263.250000
      max
                1.000000
                                  1.000000
                                                 1.000000
                                                              1.000000
                                                                          600.000000
                                                 BMI
                                                        heartRate
                   sysBP
                                 diaBP
                                                                        glucose
                                                                   3656.000000
             3656.000000
                           3656.000000
                                        3656.000000
                                                      3656.000000
      count
                                                        75.730580
                                                                      81.856127
      mean
              132.368025
                             82.912062
                                          25.784185
      std
               22.092444
                             11.974825
                                            4.065913
                                                        11.982952
                                                                      23.910128
      min
               83.500000
                             48.000000
                                          15.540000
                                                        44.000000
                                                                      40.000000
      25%
                             75.000000
                                          23.080000
                                                        68.000000
                                                                      71.000000
              117.000000
      50%
              128.000000
                             82.000000
                                          25.380000
                                                        75.000000
                                                                      78.000000
      75%
              144.000000
                             90.000000
                                          28.040000
                                                        82.000000
                                                                      87.000000
              295.000000
      max
                            142.500000
                                          56.800000
                                                       143.000000
                                                                     394.000000
              TenYearCHD
             3656.000000
      count
                0.152352
      mean
      std
                0.359411
      min
                0.000000
      25%
                0.000000
      50%
                0.000000
      75%
                0.000000
      max
                1.000000
 [7]: df.columns
 [7]: Index(['male', 'age', 'education', 'currentSmoker', 'cigsPerDay', 'BPMeds',
             'prevalentStroke', 'prevalentHyp', 'diabetes', 'totChol', 'sysBP',
             'diaBP', 'BMI', 'heartRate', 'glucose', 'TenYearCHD'],
            dtype='object')
 [8]: feature_matrix = df.iloc[:,0:15]
      target_vector = df.iloc[:,-1]
 [9]: fs = StandardScaler().fit transform(feature matrix)
      logr = LogisticRegression()
      logr.fit(fs,target_vector)
 [9]: LogisticRegression()
[10]: observation=[[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15]]
      prediction = logr.predict(observation)
      print(prediction)
     [1]
[11]: logr.classes
```

50%

0.000000

0.000000

0.000000

0.000000

234.000000

```
[11]: array([0, 1])
[12]: logr.predict_proba(observation)
[12]: array([[2.21478351e-04, 9.99778522e-01]])
     Random Forest
[18]: x = df.iloc[:,0:15]
      y = df.iloc[:,-1]
[19]: from sklearn.model selection import train test split
      x_train,x_test,y_train,y_test=train_test_split(x,y,train_size=0.70)
[20]: from sklearn.ensemble import RandomForestClassifier
      rfc = RandomForestClassifier()
      rfc.fit(x_train,y_train)
[20]: RandomForestClassifier()
[21]: parameters = {'max_depth': [1,2,3,4,5], 'min_samples_leaf': [5,10,15,20,25],
                    'n_estimators': [10,20,30,40,50]
[22]: from sklearn.model selection import GridSearchCV
      grid_search = __
       GridSearchCV(estimator=rfc,param_grid=parameters,cv=2,scoring="accuracy")
      grid_search.fit(x_train,y_train)
[22]: GridSearchCV(cv=2, estimator=RandomForestClassifier(),
                   param_grid={'max_depth': [1, 2, 3, 4, 5],
                               'min_samples_leaf': [5, 10, 15, 20, 25],
                               'n_estimators': [10, 20, 30, 40, 50]},
                   scoring='accuracy')
[23]: grid_search.best_score_
[23]: 0.8499410550234558
[24]: rfc_best = grid_search.best_estimator_
[25]: from sklearn.tree import plot_tree
      plt.figure(figsize=(89,40))
      plot_tree(rfc_best.estimators_[5], feature_names=x.columns, class_names=['Yes',_

¬'No'], filled=True)
```

```
1637 \text{ nvalue} = [2167, 392] \text{ nclass} = \text{Yes'},
           Text(0.5267857142857143, 0.75, 'prevalentHyp <= 0.5 \neq 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.25 = 0.
         1616 \text{ nvalue} = [2157, 370] \text{ nclass} = \text{Yes'}),
           Text(0.2857142857142857, 0.5833333333333334, 'age <= 48.5\ngini =
         0.186 \times = 1110 \times = [1545, 179] \times = Yes'),
           0.113\nsamples = 660\nvalue = [955, 61]\nclass = Yes'),
           Text(0.07142857142857142, 0.25, 'glucose <= 91.5 \ngini = 0.071 \nsamples =
         356\nvalue = [521, 20]\nclass = Yes'),
           Text(0.03571428571428571, 0.083333333333333333, 'gini = 0.052\nsamples =
         323\nvalue = [473, 13]\nclass = Yes'),
           Text(0.10714285714285714, 0.08333333333333333, 'gini = 0.222\nsamples =
         33\nvalue = [48, 7]\nclass = Yes'),
           Text(0.21428571428571427, 0.25, 'heartRate <= 90.5\ngini = 0.158\nsamples =</pre>
         304\nvalue = [434, 41]\nclass = Yes'),
           Text(0.17857142857142858, 0.08333333333333333, 'gini = 0.168\nsamples =
         284\nvalue = [403, 41]\nclass = Yes'),
           0]\nclass = Yes'),
           Text(0.42857142857142855, 0.416666666666667, 'cigsPerDay <= 2.5\ngini =
         0.278\nsamples = 450\nvalue = [590, 118]\nclass = Yes'),
           Text(0.35714285714285715, 0.25, 'sysBP <= 145.5 \ngini = 0.2 \nsamples =
         260\nvalue = [369, 47]\nclass = Yes'),
           Text(0.32142857142857145, 0.083333333333333333, 'gini = 0.183 \nsamples =
         245\nvalue = [352, 40]\nclass = Yes'),
           Text(0.39285714285714285, 0.08333333333333333, 'gini = 0.413\nsamples =
         15\nvalue = [17, 7]\nclass = Yes'),
           Text(0.5, 0.25, 'glucose \le 63.5 \mid = 0.368 \mid = 190 \mid = [221, ]
         71]\nclass = Yes'),
           Text(0.4642857142857143, 0.08333333333333333, 'gini = 0.0\nsamples = 19\nvalue
         = [28, 0] \setminus nclass = Yes'),
           Text(0.5357142857142857, 0.083333333333333333, 'gini = 0.393\nsamples =
         171\nvalue = [193, 71]\nclass = Yes'),
           Text(0.7678571428571429, 0.5833333333333334, 'age <= 54.5\ngini =
         0.363\nsamples = 506\nvalue = [612, 191]\nclass = Yes'),
           0.259\nsamples = 269\nvalue = [360, 65]\nclass = Yes'),
           Text(0.6428571428571429, 0.25, 'male <= 0.5 \ngini = 0.222 \nsamples = 250 \nvalue
         = [343, 50] \nclass = Yes'),
           Text(0.6071428571428571, 0.083333333333333333, 'gini = 0.123\nsamples =
         123\nvalue = [184, 13]\nclass = Yes'),
           Text(0.6785714285714286, 0.08333333333333333, 'gini = 0.306 \nsamples =
         127\nvalue = [159, 37]\nclass = Yes'),
           Text(0.7142857142857143, 0.25, 'gini = 0.498 \nsamples = 19 \nvalue = [17, ]
         15]\nclass = Yes'),
           Text(0.8571428571428571, 0.4166666666666667, 'glucose <= 69.5\ngini =
```

 $0.444\nsamples = 237\nvalue = [252, 126]\nclass = Yes'),$ 

 $Text(0.7857142857142857, 0.25, 'heartRate <= 75.5 \ngini = 0.124 \nsamples = 28 \nvalue = [42, 3] \nclass = Yes'),$ 

 $Text(0.8214285714285714, 0.083333333333333333, 'gini = 0.091\nsamples = 12\nvalue = [20, 1]\nclass = Yes'),$ 

 $Text(0.9285714285714286, 0.25, 'totChol <= 318.5 \ngini = 0.466 \nsamples = 209 \nvalue = [210, 123] \nclass = Yes'),$ 

 $Text(0.9642857142857143, 0.083333333333333333, 'gini = 0.475\nsamples = 18\nvalue = [12, 19]\nclass = No'),$ 

 $Text(0.5982142857142857, 0.75, 'gini = 0.43\nsamples = 21\nvalue = [10, 22]\nclass = No')]$ 

