unxx8hr4k

August 1, 2023

```
[7]: 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
[8]: from google.colab import drive
     drive.mount('/content/drive')
    Drive already mounted at /content/drive; to attempt to forcibly remount, call
    drive.mount("/content/drive", force_remount=True).
[9]: df=pd.read_csv("/content/drive/MyDrive/mydatasets/C4_framingham.csv")
     df
[9]:
                      education currentSmoker
                                                  cigsPerDay
                                                              BPMeds
           male
                 age
                  39
                             4.0
     0
              1
                                                         0.0
                                                                  0.0
                                               0
     1
                             2.0
                                               0
                                                         0.0
                                                                  0.0
              0
                  46
     2
                             1.0
                                                        20.0
              1
                  48
                                               1
                                                                 0.0
                             3.0
     3
              0
                  61
                                               1
                                                        30.0
                                                                 0.0
     4
                             3.0
                                                        23.0
                                                                 0.0
                  46
                                               1
     4233
                  50
                             1.0
                                                         1.0
                                                                 0.0
              1
                                               1
     4234
                  51
                             3.0
                                               1
                                                        43.0
                                                                 0.0
     4235
                             2.0
                                                        20.0
                                                                 NaN
                  48
                                               1
     4236
                             1.0
                                                        15.0
              0
                  44
                                                                 0.0
     4237
                  52
                             2.0
                                                         0.0
                                                                 0.0
                                               0
           prevalentStroke
                            prevalentHyp
                                           diabetes
                                                     totChol
                                                              sysBP
                                                                       diaBP
                                                                                BMI
     0
                                                   0
                                                        195.0
                                                              106.0
                                                                        70.0
                                                                              26.97
                          0
                                        0
     1
                          0
                                                   0
                                                        250.0 121.0
                                                                        81.0
                                                                              28.73
                                        0
     2
                          0
                                        0
                                                   0
                                                        245.0 127.5
                                                                        80.0
                                                                              25.34
     3
                                                                              28.58
                          0
                                        1
                                                   0
                                                        225.0 150.0
                                                                        95.0
     4
                          0
                                        0
                                                   0
                                                        285.0
                                                              130.0
                                                                        84.0
                                                                              23.10
     4233
                          0
                                                   0
                                                        313.0 179.0
                                                                        92.0
                                                                              25.97
                                        1
     4234
                          0
                                        0
                                                   0
                                                        207.0 126.5
                                                                        80.0 19.71
```

4235 4236 4237		0 0 0	0 0 0	0 0 0	248.0 210.0 269.0	131.0 126.5 133.5	72.0 87.0 83.0	22.00 19.16 21.47
	heartRate	glucose	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]

[10]: df.head()

[10]:		${\tt male}$	age	education	С	urrentSmo	ker	cigsPe	rDay	BPMe	ds prevale	ntStroke	\
	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	
		preva	lentH	yp diabete	es	totChol	sysBl	P dia	ιBΡ	BMI	${\tt heartRate}$	glucose	\
	0			0	0	195.0	106.0	0 70	0.0	26.97	80.0	77.0	
	1			0	0	250.0	121.0	0 81	.0	28.73	95.0	76.0	
	2			0	0	245.0	127.	5 80	0.0	25.34	75.0	70.0	
	3			1	0	225.0	150.0	0 95	5.0	28.58	65.0	103.0	

285.0 130.0

84.0 23.10

85.0

85.0

${\tt TenYearCHD}$

1 Data Cleaning and Data Preprocessing

```
[11]: 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
	67 .04(0) .	. 0 4 (7)	

 ${\tt dtypes:\ float64(9),\ int64(7)}$

memory usage: 485.6 KB

[12]: df.describe()

E : 07	_		_			
[12]:	male	age	education o	currentSmoker	cigsPerDay \setminus	
coun	t 3656.000000	3656.000000 3	8656.000000	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	prevalentStrok	e prevalentH	Hyp diabete	es totChol	. \
coun	t 3656.000000	3656.00000	00 3656.0000	3656.0000	00 3656.000000	
mean	0.030361	0.00574	4 0.3115	0.0270	79 236.873085	
std	0.171602	0.07558	0.4631	0.1623	35 44.096223	
min	0.000000	0.00000	0.0000	0.0000	00 113.000000	
25%	0.000000	0.00000	0.0000	0.0000	206.000000	

```
50%
                0.000000
                                  0.000000
                                                 0.000000
                                                              0.000000
                                                                          234.000000
      75%
                0.000000
                                  0.000000
                                                 1.000000
                                                              0.000000
                                                                          263.250000
      max
                1.000000
                                  1.000000
                                                 1.000000
                                                              1.000000
                                                                          600.000000
                                 diaBP
                                                 BMI
                                                        heartRate
                   sysBP
                                                                        glucose
                                                                   3656.000000
             3656.000000
                           3656.000000
                                        3656.000000
                                                      3656.000000
      count
                                                        75.730580
              132.368025
                                                                      81.856127
      mean
                             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%
              117.000000
                             75.000000
                                          23.080000
                                                        68.000000
                                                                      71.000000
      50%
              128.000000
                             82.000000
                                          25.380000
                                                        75.000000
                                                                      78.000000
      75%
              144.000000
                             90.000000
                                          28.040000
                                                        82.000000
                                                                      87.000000
      max
              295.000000
                            142.500000
                                          56.800000
                                                       143.000000
                                                                    394.000000
              TenYearCHD
             3656.000000
      count
      mean
                0.152352
      std
                0.359411
      min
                0.000000
      25%
                0.000000
      50%
                0.000000
      75%
                0.000000
      max
                1.000000
[13]: df.columns
[13]: Index(['male', 'age', 'education', 'currentSmoker', 'cigsPerDay', 'BPMeds',
             'prevalentStroke', 'prevalentHyp', 'diabetes', 'totChol', 'sysBP',
             'diaBP', 'BMI', 'heartRate', 'glucose', 'TenYearCHD'],
            dtype='object')
[14]: feature_matrix = df.iloc[:,0:15]
      target_vector = df.iloc[:,-1]
[15]: fs = StandardScaler().fit transform(feature matrix)
      logr = LogisticRegression()
      logr.fit(fs,target_vector)
[15]: LogisticRegression()
[16]: observation=[[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15]]
      prediction = logr.predict(observation)
      print(prediction)
     [1]
[17]: logr.classes
```

```
[17]: array([0, 1])
[18]: logr.predict_proba(observation)
[18]: array([[2.21478351e-04, 9.99778522e-01]])
```