Lab Project 1: Breast Cancer Classification

March 23, 2022

1 UE19EC353: Machine Learning · Jan - May 2022 · Lab Project 1

Given the features and the target, build a Machine Learning Classification model that can classify from a given set of features, if the cancer is Benign or Malignant. You can use any classification algorithm.

```
[1]: import pandas as pd import numpy as np[2]: import matplotlib.pyplot as plt import seaborn as sns
```

C:\Users\venka\Anaconda3\lib\site-packages\statsmodels\tools_testing.py:19:
FutureWarning: pandas.util.testing is deprecated. Use the functions in the public API at pandas.testing instead.
 import pandas.util.testing as tm

```
[3]: df=pd.read_csv('C:

→\Users\\venka\\Desktop\\TAMachineLearning\\Project_Assignments\\Solutions\\data.

→csv')

#https://www.kaggle.com/uciml/breast-cancer-wisconsin-data -> get data from here
```

[4]: df.head()

[4]:	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	١
0	842302	M	17.99	10.38	122.80	1001.0	
1	842517	M	20.57	17.77	132.90	1326.0	
2	84300903	M	19.69	21.25	130.00	1203.0	
3	84348301	М	11.42	20.38	77.58	386.1	
4	84358402	M	20.29	14.34	135.10	1297.0	
						\	

	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	\
0	0.11840	0.27760	0.3001	0.14710	
1	0.08474	0.07864	0.0869	0.07017	
2	0.10960	0.15990	0.1974	0.12790	
3	0.14250	0.28390	0.2414	0.10520	
4	0.10030	0.13280	0.1980	0.10430	

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```
radius_worst texture_worst perimeter_worst
                                                        area_worst \
               25.38
                                17.33
                                                184.60
                                                             2019.0
0
               24.99
                               23.41
1
  . . .
                                                158.80
                                                             1956.0
2
               23.57
                               25.53
                                                152.50
                                                             1709.0
  . . .
3
               14.91
                               26.50
                                                 98.87
                                                              567.7
  . . .
               22.54
                               16.67
                                                             1575.0
                                                152.20
  . . .
   smoothness_worst
                      compactness_worst concavity_worst concave points_worst \
             0.1622
0
                                 0.6656
                                                   0.7119
                                                                           0.2654
1
             0.1238
                                 0.1866
                                                   0.2416
                                                                           0.1860
             0.1444
2
                                 0.4245
                                                   0.4504
                                                                           0.2430
3
             0.2098
                                 0.8663
                                                   0.6869
                                                                           0.2575
4
             0.1374
                                 0.2050
                                                   0.4000
                                                                           0.1625
   symmetry_worst fractal_dimension_worst
0
           0.4601
                                     0.11890
           0.2750
                                     0.08902
1
2
           0.3613
                                     0.08758
3
           0.6638
                                     0.17300
           0.2364
                                     0.07678
[5 rows x 32 columns]
```

to lowb h oz colum

[5]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 32 columns):

#	Column	Non-Null Count	Dtype
0	id	569 non-null	int64
1	diagnosis	569 non-null	object
2	radius_mean	569 non-null	float64
3	texture_mean	569 non-null	float64
4	perimeter_mean	569 non-null	float64
5	area_mean	569 non-null	float64
6	smoothness_mean	569 non-null	float64
7	compactness_mean	569 non-null	float64
8	concavity_mean	569 non-null	float64
9	concave points_mean	569 non-null	float64
10	symmetry_mean	569 non-null	float64
11	fractal_dimension_mean	569 non-null	float64
12	radius_se	569 non-null	float64
13	texture_se	569 non-null	float64
14	perimeter_se	569 non-null	float64
15	area_se	569 non-null	float64
16	smoothness_se	569 non-null	float64
17	compactness_se	569 non-null	float64

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18	concavity_se	569	non-null	float64
19	concave points_se	569	non-null	float64
20	symmetry_se	569	non-null	float64
21	fractal_dimension_se	569	non-null	float64
22	radius_worst	569	non-null	float64
23	texture_worst	569	non-null	float64
24	perimeter_worst	569	non-null	float64
25	area_worst	569	non-null	float64
26	smoothness_worst	569	non-null	float64
27	compactness_worst	569	non-null	float64
28	concavity_worst	569	non-null	float64
29	concave points_worst	569	non-null	float64
30	symmetry_worst	569	non-null	float64
31	fractal_dimension_worst	569	non-null	float64
dtyp	es: float64(30), int64(1)	, ob	ject(1)	

memory usage: 142.4+ KB

[6]	:	df.	des	crib	e()
U	•	uı.	ues	CTID	C	٠.

լօյ.	di.describe()										
[6]:		id	radiu	ıs_mean	texture	e_mean	perimete	r_mean	area_m	ean '	\
	count	5.690000e+02	569.	000000	569.0	00000	569.	000000	569.000	000	
	mean	3.037183e+07	14.	127292	19.2	289649	91.	969033	654.889	104	
	std	1.250206e+08	3.	524049	4.3	301036	24.	298981	351.914	129	
	min	8.670000e+03	6.	981000	9.7	710000	43.	790000	143.500	000	
	25%	8.692180e+05	11.	700000	16.1	L70000	75.	170000	420.300	000	
	50%	9.060240e+05	13.	370000	18.8	340000	86.	240000	551.100	000	
	75%	8.813129e+06	15.	780000	21.8	300000	104.	100000	782.700	000	
	max	9.113205e+08	28.	110000	39.2	280000	188.	500000	2501.000	000	
		smoothness_mea	an co	mpactne	ss_mean	conca	vity_mean	conca	ve points	_mean	\
	count	569.0000	00	569	.000000	5	69.000000)	569.0	00000	
	mean	0.09636	60	0	.104341		0.088799)	0.0	48919	
	std	0.0140	64	0	.052813		0.079720)	0.0	38803	
	min	0.0526	30	0	.019380		0.000000)	0.0	00000	
	25%	0.0863	70	0	.064920		0.029560)	0.0	20310	
	50%	0.0958	70	0	.092630		0.061540)	0.0	33500	
	75%	0.10530	00	0	.130400		0.130700)	0.0	74000	
	max	0.16340	00	0	.345400		0.426800)	0.2	01200	
		symmetry_mean			_worst			-	er_worst	\	
	count	569.000000		569.	000000	569	.000000	56	9.000000		
	mean	0.181162		16.	269190	25	.677223	10	7.261213		
	std	0.027414		4.	833242	6	. 146258	3	3.602542		
	min	0.106000		7.	930000	12	.020000	5	0.410000		
	25%	0.161900		13.	010000	21	.080000	8	4.110000		
	50%	0.179200		14.	970000	25	.410000	9	7.660000		
	75%	0.195700		18.	790000	29	.720000	12	5.400000		
	max	0.304000		36.	040000	49	.540000	25	1.200000		

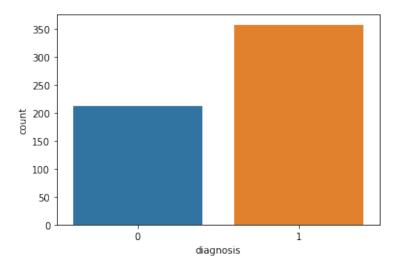
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	area_wo	IDO DINOCOIIII	ess_worst	compactness_wo	rst concavity_wors	st '
coun	t 569.000	000 5	69.000000	569.000	569.0000	00
mean	880.583	128	0.132369	0.254	265 0.27218	38
std	569.356	993	0.022832	0.157	336 0.20862	24
min	185.200	000	0.071170	0.027	290 0.00000	00
25%	515.300	000	0.116600	0.147	200 0.11450	00
50%	686.500	000	0.131300	0.211	900 0.22670	00
75%	1084.000	000	0.146000	0.339	0.38290	00
max	4254.000	000	0.222600	1.058	1.25200	00
	concave	points_worst	symmetry_	worst fractal	_dimension_worst	
coun	t	569.000000	569.0	00000	569.000000	
mean		0.114606	0.2	90076	0.083946	
std		0.065732	0.0	61867	0.018061	
min		0.000000	0.1	56500	0.055040	
25%		0.064930	0.2	50400	0.071460	
50%		0.099930	0.2	82200	0.080040	
75%		0.161400	0.3	17900	0.092080	
nax		0.291000		63800	0.207500	
lf [' <i>→n</i> ≀		=pd.get_dumm	ies(df[' <mark>di</mark> a	ngnosis']) #Con	nvert string to labo	eled
lf [' <i>⇔n</i> ≀	diagnosis'] umbers					eled
lf[' <i>⊶nı</i>	diagnosis'] umbers	diagnosis r	adius_mean	texture_mean	perimeter_mean \	eled
lf[' <i>⇔ni</i> lf	diagnosis'] umbers id 842302	diagnosis r 0	adius_mean 17.99	texture_mean 10.38	perimeter_mean \ 122.80	elea
df [' <i>→nu</i> df	diagnosis'] umbers id 842302 842517	diagnosis r 0 0	adius_mean 17.99 20.57	texture_mean 10.38 17.77	perimeter_mean \	eled
lf ['	diagnosis'] umbers id 842302 842517 84300903	diagnosis r 0 0	adius_mean 17.99 20.57 19.69	texture_mean 10.38 17.77 21.25	perimeter_mean \	eled
df[' →n: df 1 2 3	diagnosis'] umbers id 842302 842517	diagnosis r 0 0	adius_mean 17.99 20.57	texture_mean 10.38 17.77	perimeter_mean \	eled
lf ['	id 842302 842517 84300903 84348301 84358402	diagnosis r 0 0 0 0 0	adius_mean 17.99 20.57 19.69 11.42 20.29	texture_mean 10.38 17.77 21.25 20.38 14.34	perimeter_mean \	eled
df [' → ni df 0 1 2 3 4	id 842302 842517 84300903 84348301 84358402 926424	diagnosis r 0 0 0 0 0	adius_mean 17.99 20.57 19.69 11.42 20.29 	texture_mean 10.38 17.77 21.25 20.38 14.34 22.39	perimeter_mean \ 122.80 132.90 130.00 77.58 135.10 142.00	eled
off['\ →nv iff	id 842302 842517 84300903 84348301 84358402 926424 926682	diagnosis r 0 0 0 0 0 0	adius_mean 17.99 20.57 19.69 11.42 20.29 21.56 20.13	texture_mean 10.38 17.77 21.25 20.38 14.34 22.39 28.25	perimeter_mean \	eleá
### ##################################	id 842302 842517 84300903 84348301 84358402 926424 926682 926954	diagnosis r 0 0 0 0 0 0 0 0	adius_mean 17.99 20.57 19.69 11.42 20.29 21.56 20.13 16.60	texture_mean 10.38 17.77 21.25 20.38 14.34 22.39 28.25 28.08	perimeter_mean \ 122.80 132.90 130.00 77.58 135.10 142.00 131.20 108.30	eleá
f['	id 842302 842517 84300903 84348301 84358402 926424 926682 926954 927241	diagnosis r 0 0 0 0 0 0 0 0 0	adius_mean 17.99 20.57 19.69 11.42 20.29 21.56 20.13 16.60 20.60	texture_mean 10.38 17.77 21.25 20.38 14.34 22.39 28.25 28.08 29.33	perimeter_mean \ 122.80 132.90 130.00 77.58 135.10 142.00 131.20 108.30 140.10	eled
if [''	id 842302 842517 84300903 84348301 84358402 926424 926682 926954	diagnosis r 0 0 0 0 0 0 0 0	adius_mean 17.99 20.57 19.69 11.42 20.29 21.56 20.13 16.60	texture_mean 10.38 17.77 21.25 20.38 14.34 22.39 28.25 28.08	perimeter_mean \ 122.80 132.90 130.00 77.58 135.10 142.00 131.20 108.30	eleá
df [' → nn df 0 1 2 3 4 564 565 566 567	id 842302 842517 84300903 84348301 84358402 926424 926682 926954 927241 92751 area_mean	diagnosis r 0 0 0 0 0 0 0 0 1 smoothness_	adius_mean 17.99 20.57 19.69 11.42 20.29 21.56 20.13 16.60 20.60 7.76 mean compa	texture_mean 10.38 17.77 21.25 20.38 14.34 22.39 28.25 28.08 29.33 24.54	perimeter_mean \ 122.80 132.90 130.00 77.58 135.10 142.00 131.20 108.30 140.10 47.92	eled
df [' → nn df 0 1 2 3 4 564 565 566 567	id 842302 842517 84300903 84348301 84358402 926424 926682 926954 927241 92751 area_mean 1001.0	diagnosis r 0 0 0 0 0 0 0 0 1 smoothness_ 0.1	adius_mean 17.99 20.57 19.69 11.42 20.29 21.56 20.13 16.60 20.60 7.76 mean compa 1840	texture_mean 10.38 17.77 21.25 20.38 14.34 22.39 28.25 28.08 29.33 24.54 .ctness_mean 0.27760	perimeter_mean \	eled
of df 0 1 2 3 4 564 565 566 567 568	id 842302 842517 84300903 84348301 84358402 926424 926682 926954 927241 92751 area_mean 1001.0 1326.0	diagnosis r 0 0 0 0 0 0 0 0 1 smoothness_ 0.1	adius_mean 17.99 20.57 19.69 11.42 20.29 21.56 20.13 16.60 20.60 7.76 mean compa 1840 8474	texture_mean	perimeter_mean \	eled
df [' → nv df 0 1 2 3 4 564 565 566 567 568	id 842302 842517 84300903 84348301 84358402 926424 926682 926954 927241 92751 area_mean 1001.0 1326.0 1203.0	diagnosis r 0 0 0 0 0 0 0 0 0 1 smoothness_ 0.1 0.0 0.1	adius_mean 17.99 20.57 19.69 11.42 20.29 21.56 20.13 16.60 20.60 7.76 mean compa 1840 8474 0960	texture_mean 10.38 17.77 21.25 20.38 14.34 22.39 28.25 28.08 29.33 24.54 .ctness_mean 0.27760 0.07864 0.15990	perimeter_mean \	eled
df ['	id 842302 842517 84300903 84348301 84358402 926424 926682 926954 927241 92751 area_mean 1001.0 1326.0 1203.0 386.1	diagnosis r 0 0 0 0 0 0 0 0 0 1 smoothness_ 0.1 0.0 0.1	adius_mean 17.99 20.57 19.69 11.42 20.29 21.56 20.13 16.60 20.60 7.76 mean compa 1840 8474 0960 4250	texture_mean	perimeter_mean \	eleá
11 (1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	id 842302 842517 84300903 84348301 84358402 926424 926682 926954 927241 92751 area_mean 1001.0 1326.0 1203.0	diagnosis r 0 0 0 0 0 0 0 0 0 1 smoothness_ 0.1 0.0 0.1	adius_mean 17.99 20.57 19.69 11.42 20.29 21.56 20.13 16.60 20.60 7.76 mean compa 1840 8474 0960	texture_mean 10.38 17.77 21.25 20.38 14.34 22.39 28.25 28.08 29.33 24.54 .ctness_mean 0.27760 0.07864 0.15990	perimeter_mean \	eled

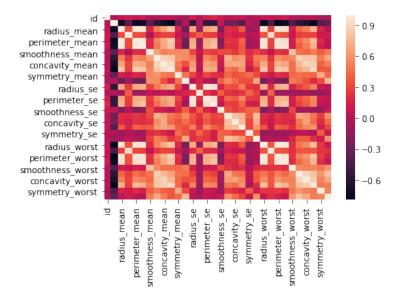
E <i>G</i> /	1470 0	0	11100	0	11590	0	04300	
564 565	1479.0 1261.0		11100 09780		10340		0.24390 0.14400	
566	858.1		08455		10230		0.09251	
							0.35140	
567	1265.0		11780 05263		27700			
568	181.0	0.	05265	0.	04362	U	.00000	
	concave poi		rad	ius_worst	texture	_worst	perimeter_worst	: \
0		0.14710		25.380		17.33	184.60)
1		0.07017		24.990		23.41	158.80)
2		0.12790		23.570		25.53	152.50)
3		0.10520		14.910		26.50	98.87	7
4		0.10430		22.540		16.67	152.20)
• •		• • •	• • •			• • •	• • •	
564		0.13890		25.450		26.40	166.10	
565		0.09791		23.690		38.25	155.00)
566		0.05302		18.980		34.12	126.70)
567		0.15200		25.740		39.42	184.60)
568		0.00000		9.456		30.37	59.16	3
_	area_worst	smoothnes		compactne		conca	vity_worst \	
0	2019.0		0.16220		0.66560		0.7119	
1	1956.0		0.12380		0.18660		0.2416	
2	1709.0		0.14440		0.42450		0.4504	
3	567.7		0.20980		0.86630		0.6869	
4	1575.0		0.13740		0.20500		0.4000	
 564	2027.0		0.14100		0.21130		0.4107	
565	1731.0		0.11660		0.19220		0.3215	
566	1124.0		0.11390		0.30940		0.3403	
567	1821.0		0.16500		0.86810		0.9387	
568	268.6		0.08996		0.06444		0.0000	
	concave poi	nts_worst	symmetr	y_worst f	ractal_d:	imensio	n_worst	
0		0.2654		0.4601			0.11890	
1		0.1860		0.2750			0.08902	
2		0.2430		0.3613			0.08758	
3		0.2575		0.6638			0.17300	
4		0.1625		0.2364			0.07678	
564		0.2216		0.2060			0.07115	
565		0.1628		0.2572			0.06637	
566		0.1418		0.2218			0.07820	
567		0.2650		0.4087			0.12400	
568		0.0000		0.2871			0.07039	

[569 rows x 32 columns]

- [9]: # See number of cases of Malignant and Benign
 sns.countplot(x=df['diagnosis'],data=df)
- [9]: <matplotlib.axes._subplots.AxesSubplot at 0x260cbed1b38>



- [10]: sns.heatmap(df.corr()) # Correlation Map
- [10]: <matplotlib.axes._subplots.AxesSubplot at 0x260cdf858d0>



- [11]: X=df.drop('diagnosis',axis=1).values # Everything except the 'Diagnosis' column_□

 →makes up the Features
- [12]: y=df['diagnosis'].values # The target is the 'Diagnosis' Column

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0.9736842105263158

[23]:	from sklearn.metrics import classification_report
[24]:	<pre>print(classification_report(y_test,predictions))</pre>

	precision	recall	f1-score	support
	_			
0	1.00	0.93	0.96	42
1	0.96	1.00	0.98	72
accuracy			0.97	114
macro avg	0.98	0.96	0.97	114
weighted avg	0.97	0.97	0.97	114

2 Contact for Doubts:

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