
You are currently looking at **version 1.3** of this notebook. To download notebooks and datafiles, as well as get help on Jupyter notebooks in the Coursera platform, visit the [Jupyter Notebook FAQ](https://www.coursera.org/learn/python-machine-learning/resources/bANLa) (<https://www.coursera.org/learn/python-machine-learning/resources/bANLa>) course resource.

Assignment 1 - Introduction to Machine Learning

For this assignment, you will be using the Breast Cancer Wisconsin (Diagnostic) Database to create a classifier that can help diagnose patients. First, read through the description of the dataset (below).

```
In [1]: %load_ext autoreload
        %autoreload 2
        %matplotlib notebook

import sys
import numpy as np
import pandas as pd

from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
import matplotlib.pyplot as plt

# Hide warnings
import warnings
warnings.filterwarnings('ignore')

print('You\'re running python %s' % sys.version.split(' ')[0])

You're running python 3.6.2
```

```
In [2]: # Loading the dataset
cancer = load_breast_cancer()
```

```
In [3]: print(cancer.DESCR)
```

Breast Cancer Wisconsin (Diagnostic) Database

=====

Notes

Data Set Characteristics:

:Number of Instances: 569

:Number of Attributes: 30 numeric, predictive attributes and the class

:Attribute Information:

- radius (mean of distances from center to points on the perimeter)
- texture (standard deviation of gray-scale values)
- perimeter
- area
- smoothness (local variation in radius lengths)
- compactness (perimeter² / area - 1.0)
- concavity (severity of concave portions of the contour)
- concave points (number of concave portions of the contour)
- symmetry
- fractal dimension ("coastline approximation" - 1)

The mean, standard error, and "worst" or largest (mean of the three largest values) of these features were computed for each image, resulting in 30 features. For instance, field 3 is Mean Radius, field 13 is Radius SE, field 23 is Worst Radius.

- class:
 - WDBC-Malignant
 - WDBC-Benign

:Summary Statistics:

	Min	Max
radius (mean):	6.981	28.11
texture (mean):	9.71	39.28
perimeter (mean):	43.79	188.5
area (mean):	143.5	2501.0
smoothness (mean):	0.053	0.163
compactness (mean):	0.019	0.345
concavity (mean):	0.0	0.427
concave points (mean):	0.0	0.201
symmetry (mean):	0.106	0.304
fractal dimension (mean):	0.05	0.097
radius (standard error):	0.112	2.873
texture (standard error):	0.36	4.885
perimeter (standard error):	0.757	21.98
area (standard error):	6.802	542.2
smoothness (standard error):	0.002	0.031
compactness (standard error):	0.002	0.135
concavity (standard error):	0.0	0.396
concave points (standard error):	0.0	0.053
symmetry (standard error):	0.008	0.079
fractal dimension (standard error):	0.001	0.03
radius (worst):	7.93	36.04
texture (worst):	12.02	49.54
perimeter (worst):	50.41	251.2
area (worst):	185.2	4254.0
smoothness (worst):	0.071	0.223
compactness (worst):	0.027	1.058
concavity (worst):	0.0	1.252
concave points (worst):	0.0	0.291
symmetry (worst):	0.156	0.664
fractal dimension (worst):	0.055	0.208

:Missing Attribute Values: None

:Class Distribution: 212 - Malignant, 357 - Benign

:Creator: Dr. William H. Wolberg, W. Nick Street, Olvi L. Mangasarian

:Donor: Nick Street

:Date: November, 1995

This is a copy of UCI ML Breast Cancer Wisconsin (Diagnostic) datasets.
<https://goo.gl/U2Uwz2>

Features are computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. They describe characteristics of the cell nuclei present in the image.

Separating plane described above was obtained using Multisurface Method-Tree (MSM-T) [K. P. Bennett, "Decision Tree Construction Via Linear Programming." Proceedings of the 4th Midwest Artificial Intelligence and Cognitive Science Society, pp. 97-101, 1992], a classification method which uses linear programming to construct a decision tree. Relevant features were selected using an exhaustive search in the space of 1-4 features and 1-3 separating planes.

The actual linear program used to obtain the separating plane in the 3-dimensional space is that described in: [K. P. Bennett and O. L. Mangasarian: "Robust Linear Programming Discrimination of Two Linearly Inseparable Sets", Optimization Methods and Software 1, 1992, 23-34].

This database is also available through the UW CS ftp server:

```
ftp ftp.cs.wisc.edu
cd math-prog/cpo-dataset/machine-learn/WDBC/
```

References

- W.N. Street, W.H. Wolberg and O.L. Mangasarian. Nuclear feature extraction for breast tumor diagnosis. IS&T/SPIE 1993 International Symposium on Electronic Imaging: Science and Technology, volume 1905, pages 861-870, San Jose, CA, 1993.
- O.L. Mangasarian, W.N. Street and W.H. Wolberg. Breast cancer diagnosis and prognosis via linear programming. Operations Research, 43(4), pages 570-577, July-August 1995.
- W.H. Wolberg, W.N. Street, and O.L. Mangasarian. Machine learning techniques to diagnose breast cancer from fine-needle aspirates. Cancer Letters 77 (1994) 163-171.

The object returned by `load_breast_cancer()` is a scikit-learn Bunch object, which is similar to a dictionary.

```
In [4]: cancer.keys()
```

```
Out[4]: dict_keys(['data', 'target', 'target_names', 'DESCR', 'feature_names'])
```

```
In [5]: # examining the data
cancer['data'][:1]
```

```
Out[5]: array([[ 1.79900000e+01,  1.03800000e+01,  1.22800000e+02,
                  1.00100000e+03,  1.18400000e-01,  2.77600000e-01,
                  3.00100000e-01,  1.47100000e-01,  2.41900000e-01,
                  7.87100000e-02,  1.09500000e+00,  9.05300000e-01,
                  8.58900000e+00,  1.53400000e+02,  6.39900000e-03,
                  4.90400000e-02,  5.37300000e-02,  1.58700000e-02,
                  3.00300000e-02,  6.19300000e-03,  2.53800000e+01,
                  1.73300000e+01,  1.84600000e+02,  2.01900000e+03,
                  1.62200000e-01,  6.65600000e-01,  7.11900000e-01,
                  2.65400000e-01,  4.60100000e-01,  1.18900000e-01]])
```

```
In [6]: # examining column names
cancer['feature_names']
```

```
Out[6]: array(['mean radius', 'mean texture', 'mean perimeter', 'mean area',
               'mean smoothness', 'mean compactness', 'mean concavity',
               'mean concave points', 'mean symmetry', 'mean fractal dimension',
               'radius error', 'texture error', 'perimeter error', 'area error',
               'smoothness error', 'compactness error', 'concavity error',
               'concave points error', 'symmetry error', 'fractal dimension error',
               'worst radius', 'worst texture', 'worst perimeter', 'worst area',
               'worst smoothness', 'worst compactness', 'worst concavity',
               'worst concave points', 'worst symmetry', 'worst fractal dimension'],
              dtype='<U23')
```

Question 0 (Example)

How many features does the breast cancer dataset have?

This function should return an integer.

```
In [7]: # You should write your whole answer within the function provided. The autograder will call
# this function and compare the return value against the correct solution value
def answer_zero():
    # This function returns the number of features of the breast cancer dataset, which is an integer.
    # The assignment question description will tell you the general format the autograder is expecting
    return len(cancer['feature_names'])

# You can examine what your function returns by calling it in the cell. If you have questions
# about the assignment formats, check out the discussion forums for any FAQs
answer_zero()

Out[7]: 30
```

Question 1

Scikit-learn works with lists, numpy arrays, scipy-sparse matrices, and pandas DataFrames, so converting the dataset to a DataFrame is not necessary for training this model. Using a DataFrame does however help make many things easier such as munging data, so let's practice creating a classifier with a pandas DataFrame.

Convert the sklearn.dataset cancer to a DataFrame.

This function should return a (569, 31) DataFrame with

columns =

```
['mean radius', 'mean texture', 'mean perimeter', 'mean area',
 'mean smoothness', 'mean compactness', 'mean concavity',
 'mean concave points', 'mean symmetry', 'mean fractal dimension',
 'radius error', 'texture error', 'perimeter error', 'area error',
 'smoothness error', 'compactness error', 'concavity error',
 'concave points error', 'symmetry error', 'fractal dimension error',
 'worst radius', 'worst texture', 'worst perimeter', 'worst area',
 'worst smoothness', 'worst compactness', 'worst concavity',
 'worst concave points', 'worst symmetry', 'worst fractal dimension',
 'target']
```

and index =

```
RangeIndex(start=0, stop=569, step=1)
```

```
In [8]: def answer_one():  
  
    # Your code here  
  
    # features  
    cancerdf = pd.DataFrame(cancer['data'], columns=cancer['feature_names'])  
  
    # labels  
    cancerdf['target'] = cancer['target']  
  
    # index  
    cancerdf.set_index(pd.RangeIndex(start=0, stop=569, step=1))  
  
    return cancerdf  
answer_one()
```

Out[8]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst texture	worst perimeter	worst area	worst smoothne
0	17.990	10.38	122.80	1001.0	0.11840	0.27760	0.300100	0.147100	0.2419	0.07871	...	17.33	184.60	2019.0	0.16220
1	20.570	17.77	132.90	1326.0	0.08474	0.07864	0.086900	0.070170	0.1812	0.05667	...	23.41	158.80	1956.0	0.12380
2	19.690	21.25	130.00	1203.0	0.10960	0.15990	0.197400	0.127900	0.2069	0.05999	...	25.53	152.50	1709.0	0.14440
3	11.420	20.38	77.58	386.1	0.14250	0.28390	0.241400	0.105200	0.2597	0.09744	...	26.50	98.87	567.7	0.20980
4	20.290	14.34	135.10	1297.0	0.10030	0.13280	0.198000	0.104300	0.1809	0.05883	...	16.67	152.20	1575.0	0.13740
5	12.450	15.70	82.57	477.1	0.12780	0.17000	0.157800	0.080890	0.2087	0.07613	...	23.75	103.40	741.6	0.17910
6	18.250	19.98	119.60	1040.0	0.09463	0.10900	0.112700	0.074000	0.1794	0.05742	...	27.66	153.20	1606.0	0.14420
7	13.710	20.83	90.20	577.9	0.11890	0.16450	0.093660	0.059850	0.2196	0.07451	...	28.14	110.60	897.0	0.16540
8	13.000	21.82	87.50	519.8	0.12730	0.19320	0.185900	0.093530	0.2350	0.07389	...	30.73	106.20	739.3	0.17030
9	12.460	24.04	83.97	475.9	0.11860	0.23960	0.227300	0.085430	0.2030	0.08243	...	40.68	97.65	711.4	0.18530
10	16.020	23.24	102.70	797.8	0.08206	0.06669	0.032990	0.033230	0.1528	0.05697	...	33.88	123.80	1150.0	0.11810
11	15.780	17.89	103.60	781.0	0.09710	0.12920	0.099540	0.066060	0.1842	0.06082	...	27.28	136.50	1299.0	0.13960
12	19.170	24.80	132.40	1123.0	0.09740	0.24580	0.206500	0.111800	0.2397	0.07800	...	29.94	151.70	1332.0	0.10370
13	15.850	23.95	103.70	782.7	0.08401	0.10020	0.099380	0.053640	0.1847	0.05338	...	27.66	112.00	876.5	0.11310
14	13.730	22.61	93.60	578.3	0.11310	0.22930	0.212800	0.080250	0.2069	0.07682	...	32.01	108.80	697.7	0.16510
15	14.540	27.54	96.73	658.8	0.11390	0.15950	0.163900	0.073640	0.2303	0.07077	...	37.13	124.10	943.2	0.16780
16	14.680	20.13	94.74	684.5	0.09867	0.07200	0.073950	0.052590	0.1586	0.05922	...	30.88	123.40	1138.0	0.14640
17	16.130	20.68	108.10	798.8	0.11700	0.20220	0.172200	0.102800	0.2164	0.07356	...	31.48	136.80	1315.0	0.17890
18	19.810	22.15	130.00	1260.0	0.09831	0.10270	0.147900	0.094980	0.1582	0.05395	...	30.88	186.80	2398.0	0.15120
19	13.540	14.36	87.46	566.3	0.09779	0.08129	0.066640	0.047810	0.1885	0.05766	...	19.26	99.70	711.2	0.14400
20	13.080	15.71	85.63	520.0	0.10750	0.12700	0.045680	0.031100	0.1967	0.06811	...	20.49	96.09	630.5	0.13120
21	9.504	12.44	60.34	273.9	0.10240	0.06492	0.029560	0.020760	0.1815	0.06905	...	15.66	65.13	314.9	0.13240
22	15.340	14.26	102.50	704.4	0.10730	0.21350	0.207700	0.097560	0.2521	0.07032	...	19.08	125.10	980.9	0.13900
23	21.160	23.04	137.20	1404.0	0.09428	0.10220	0.109700	0.086320	0.1769	0.05278	...	35.59	188.00	2615.0	0.14010
24	16.650	21.38	110.00	904.6	0.11210	0.14570	0.152500	0.091700	0.1995	0.06330	...	31.56	177.00	2215.0	0.18050
25	17.140	16.40	116.00	912.7	0.11860	0.22760	0.222900	0.140100	0.3040	0.07413	...	21.40	152.40	1461.0	0.15450
26	14.580	21.53	97.41	644.8	0.10540	0.18680	0.142500	0.087830	0.2252	0.06924	...	33.21	122.40	896.9	0.15250
27	18.610	20.25	122.10	1094.0	0.09440	0.10660	0.149000	0.077310	0.1697	0.05699	...	27.26	139.90	1403.0	0.13380
28	15.300	25.27	102.40	732.4	0.10820	0.16970	0.168300	0.087510	0.1926	0.06540	...	36.71	149.30	1269.0	0.16410
29	17.570	15.05	115.00	955.1	0.09847	0.11570	0.098750	0.079530	0.1739	0.06149	...	19.52	134.90	1227.0	0.12550
...
539	7.691	25.44	48.34	170.4	0.08668	0.11990	0.092520	0.013640	0.2037	0.07751	...	31.89	54.49	223.6	0.15960
540	11.540	14.44	74.65	402.9	0.09984	0.11200	0.067370	0.025940	0.1818	0.06782	...	19.68	78.78	457.8	0.13450
541	14.470	24.99	95.81	656.4	0.08837	0.12300	0.100900	0.038900	0.1872	0.06341	...	31.73	113.50	808.9	0.13400
542	14.740	25.42	94.70	668.6	0.08275	0.07214	0.041050	0.030270	0.1840	0.05680	...	32.29	107.40	826.4	0.10600
543	13.210	28.06	84.88	538.4	0.08671	0.06877	0.029870	0.032750	0.1628	0.05781	...	37.17	92.48	629.6	0.10720
544	13.870	20.70	89.77	584.8	0.09578	0.10180	0.036880	0.023690	0.1620	0.06688	...	24.75	99.17	688.6	0.12640
545	13.620	23.23	87.19	573.2	0.09246	0.06747	0.029740	0.024430	0.1664	0.05801	...	29.09	97.58	729.8	0.12160
546	10.320	16.35	65.31	324.9	0.09434	0.04994	0.010120	0.005495	0.1885	0.06201	...	21.77	71.12	384.9	0.12850
547	10.260	16.58	65.85	320.8	0.08877	0.08066	0.043580	0.024380	0.1669	0.06714	...	22.04	71.08	357.4	0.14610
548	9.683	19.34	61.05	285.7	0.08491	0.05030	0.023370	0.009615	0.1580	0.06235	...	25.59	69.10	364.2	0.11990
549	10.820	24.21	68.89	361.6	0.08192	0.06602	0.015480	0.008160	0.1976	0.06328	...	31.45	83.90	505.6	0.12040
550	10.860	21.48	68.51	360.5	0.07431	0.04227	0.000000	0.000000	0.1661	0.05948	...	24.77	74.08	412.3	0.10010
551	11.130	22.44	71.49	378.4	0.09566	0.08194	0.048240	0.022570	0.2030	0.06552	...	28.26	77.80	436.6	0.10870
552	12.770	29.43	81.35	507.9	0.08276	0.04234	0.019970	0.014990	0.1539	0.05637	...	36.00	88.10	594.7	0.12340
553	9.333	21.94	59.01	264.0	0.09240	0.05605	0.039960	0.012820	0.1692	0.06576	...	25.05	62.86	295.8	0.11030
554	12.880	28.92	82.50	514.3	0.08123	0.05824	0.061950	0.023430	0.1566	0.05708	...	35.74	88.84	595.7	0.12270

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst texture	worst perimeter	worst area	worst smoothne
555	10.290	27.61	65.67	321.4	0.09030	0.07658	0.059990	0.027380	0.1593	0.06127	...	34.91	69.57	357.6	0.13840
556	10.160	19.59	64.73	311.7	0.10030	0.07504	0.005025	0.011160	0.1791	0.06331	...	22.88	67.88	347.3	0.12650
557	9.423	27.88	59.26	271.3	0.08123	0.04971	0.000000	0.000000	0.1742	0.06059	...	34.24	66.50	330.6	0.10730
558	14.590	22.68	96.39	657.1	0.08473	0.13300	0.102900	0.037360	0.1454	0.06147	...	27.27	105.90	733.5	0.10260
559	11.510	23.93	74.52	403.5	0.09261	0.10210	0.111200	0.041050	0.1388	0.06570	...	37.16	82.28	474.2	0.12980
560	14.050	27.15	91.38	600.4	0.09929	0.11260	0.044620	0.043040	0.1537	0.06171	...	33.17	100.20	706.7	0.12410
561	11.200	29.37	70.67	386.0	0.07449	0.03558	0.000000	0.000000	0.1060	0.05502	...	38.30	75.19	439.6	0.09267
562	15.220	30.62	103.40	716.9	0.10480	0.20870	0.255000	0.094290	0.2128	0.07152	...	42.79	128.70	915.0	0.14170
563	20.920	25.09	143.00	1347.0	0.10990	0.22360	0.317400	0.147400	0.2149	0.06879	...	29.41	179.10	1819.0	0.14070
564	21.560	22.39	142.00	1479.0	0.11100	0.11590	0.243900	0.138900	0.1726	0.05623	...	26.40	166.10	2027.0	0.14100
565	20.130	28.25	131.20	1261.0	0.09780	0.10340	0.144000	0.097910	0.1752	0.05533	...	38.25	155.00	1731.0	0.11660
566	16.600	28.08	108.30	858.1	0.08455	0.10230	0.092510	0.053020	0.1590	0.05648	...	34.12	126.70	1124.0	0.11390
567	20.600	29.33	140.10	1265.0	0.11780	0.27700	0.351400	0.152000	0.2397	0.07016	...	39.42	184.60	1821.0	0.16500
568	7.760	24.54	47.92	181.0	0.05263	0.04362	0.000000	0.000000	0.1587	0.05884	...	30.37	59.16	268.6	0.08996

569 rows × 31 columns

Question 2

What is the class distribution? (i.e. how many instances of malignant (encoded 0) and how many benign (encoded 1)?)

This function should return a Series named target of length 2 with integer values and index = ['malignant', 'benign']

```
In [9]: def answer_two():

        cancerdf = answer_one()

        return cancerdf['target'].apply(lambda x: 'malignant' if(x==0) else 'benign').value_counts()

answer_two()
```

Out[9]: benign 357
malignant 212
Name: target, dtype: int64

Question 3

Split the DataFrame into x (the data) and y (the labels).

This function should return a tuple of length 2: (X, y), where

- X, a pandas DataFrame, has shape (569, 30)
- y, a pandas Series, has shape (569,).


```
In [10]: def answer_three():
        cancerdf = answer_one()

        # Your code here

        X = cancerdf.drop('target', axis=1)
        y = cancerdf['target']

        return X, y
answer_three()
```

```

Out[10]: (      mean radius  mean texture  mean perimeter  mean area  mean smoothness  \
0          17.990         10.38         122.80        1001.0         0.11840
1          20.570         17.77         132.90        1326.0         0.08474
2          19.690         21.25         130.00        1203.0         0.10960
3          11.420         20.38         77.58         386.1         0.14250
4          20.290         14.34         135.10        1297.0         0.10030
5          12.450         15.70         82.57         477.1         0.12780
6          18.250         19.98         119.60        1040.0         0.09463
7          13.710         20.83         90.20         577.9         0.11890
8          13.000         21.82         87.50         519.8         0.12730
9          12.460         24.04         83.97         475.9         0.11860
10         16.020         23.24         102.70         797.8         0.08206
11         15.780         17.89         103.60         781.0         0.09710
12         19.170         24.80         132.40        1123.0         0.09740
13         15.850         23.95         103.70         782.7         0.08401
14         13.730         22.61         93.60         578.3         0.11310
15         14.540         27.54         96.73         658.8         0.11390
16         14.680         20.13         94.74         684.5         0.09867
17         16.130         20.68         108.10         798.8         0.11700
18         19.810         22.15         130.00        1260.0         0.09831
19         13.540         14.36         87.46         566.3         0.09779
20         13.080         15.71         85.63         520.0         0.10750
21          9.504         12.44         60.34         273.9         0.10240
22         15.340         14.26         102.50         704.4         0.10730
23         21.160         23.04         137.20        1404.0         0.09428
24         16.650         21.38         110.00         904.6         0.11210
25         17.140         16.40         116.00         912.7         0.11860
26         14.580         21.53         97.41         644.8         0.10540
27         18.610         20.25         122.10        1094.0         0.09440
28         15.300         25.27         102.40         732.4         0.10820
29         17.570         15.05         115.00         955.1         0.09847
...         ...         ...         ...         ...         ...
539         7.691         25.44         48.34         170.4         0.08668
540        11.540         14.44         74.65         402.9         0.09984
541        14.470         24.99         95.81         656.4         0.08837
542        14.740         25.42         94.70         668.6         0.08275
543        13.210         28.06         84.88         538.4         0.08671
544        13.870         20.70         89.77         584.8         0.09578
545        13.620         23.23         87.19         573.2         0.09246
546        10.320         16.35         65.31         324.9         0.09434
547        10.260         16.58         65.85         320.8         0.08877
548          9.683         19.34         61.05         285.7         0.08491
549        10.820         24.21         68.89         361.6         0.08192
550        10.860         21.48         68.51         360.5         0.07431
551        11.130         22.44         71.49         378.4         0.09566
552        12.770         29.43         81.35         507.9         0.08276
553          9.333         21.94         59.01         264.0         0.09240
554        12.880         28.92         82.50         514.3         0.08123
555        10.290         27.61         65.67         321.4         0.09030
556        10.160         19.59         64.73         311.7         0.10030
557          9.423         27.88         59.26         271.3         0.08123
558        14.590         22.68         96.39         657.1         0.08473
559        11.510         23.93         74.52         403.5         0.09261
560        14.050         27.15         91.38         600.4         0.09929
561        11.200         29.37         70.67         386.0         0.07449
562        15.220         30.62         103.40         716.9         0.10480
563        20.920         25.09         143.00        1347.0         0.10990
564        21.560         22.39         142.00        1479.0         0.11100
565        20.130         28.25         131.20        1261.0         0.09780
566        16.600         28.08         108.30         858.1         0.08455
567        20.600         29.33         140.10        1265.0         0.11780
568          7.760         24.54         47.92         181.0         0.05263

```

```

      mean compactness  mean concavity  mean concave points  mean symmetry  \
0          0.27760         0.300100         0.147100         0.2419
1          0.07864         0.086900         0.070170         0.1812
2          0.15990         0.197400         0.127900         0.2069
3          0.28390         0.241400         0.105200         0.2597
4          0.13280         0.198000         0.104300         0.1809
5          0.17000         0.157800         0.080890         0.2087
6          0.10900         0.112700         0.074000         0.1794
7          0.16450         0.093660         0.059850         0.2196
8          0.19320         0.185900         0.093530         0.2350
9          0.23960         0.227300         0.085430         0.2030
10         0.06669         0.032990         0.033230         0.1528
11         0.12920         0.099540         0.066060         0.1842
12         0.24580         0.206500         0.111800         0.2397
13         0.10020         0.099380         0.053640         0.1847
14         0.22930         0.212800         0.080250         0.2069
15         0.15950         0.163900         0.073640         0.2303
16         0.07200         0.073950         0.052590         0.1586
17         0.20220         0.172200         0.102800         0.2164
18         0.10270         0.147900         0.094980         0.1582
19         0.08129         0.066640         0.047810         0.1885
20         0.12700         0.045680         0.031100         0.1967

```

21	0.06492	0.029560	0.020760	0.1815
22	0.21350	0.207700	0.097560	0.2521
23	0.10220	0.109700	0.086320	0.1769
24	0.14570	0.152500	0.091700	0.1995
25	0.22760	0.222900	0.140100	0.3040
26	0.18680	0.142500	0.087830	0.2252
27	0.10660	0.149000	0.077310	0.1697
28	0.16970	0.168300	0.087510	0.1926
29	0.11570	0.098750	0.079530	0.1739
..
539	0.11990	0.092520	0.013640	0.2037
540	0.11200	0.067370	0.025940	0.1818
541	0.12300	0.100900	0.038900	0.1872
542	0.07214	0.041050	0.030270	0.1840
543	0.06877	0.029870	0.032750	0.1628
544	0.10180	0.036880	0.023690	0.1620
545	0.06747	0.029740	0.024430	0.1664
546	0.04994	0.010120	0.005495	0.1885
547	0.08066	0.043580	0.024380	0.1669
548	0.05030	0.023370	0.009615	0.1580
549	0.06602	0.015480	0.008160	0.1976
550	0.04227	0.000000	0.000000	0.1661
551	0.08194	0.048240	0.022570	0.2030
552	0.04234	0.019970	0.014990	0.1539
553	0.05605	0.039960	0.012820	0.1692
554	0.05824	0.061950	0.023430	0.1566
555	0.07658	0.059990	0.027380	0.1593
556	0.07504	0.005025	0.011160	0.1791
557	0.04971	0.000000	0.000000	0.1742
558	0.13300	0.102900	0.037360	0.1454
559	0.10210	0.111200	0.041050	0.1388
560	0.11260	0.044620	0.043040	0.1537
561	0.03558	0.000000	0.000000	0.1060
562	0.20870	0.255000	0.094290	0.2128
563	0.22360	0.317400	0.147400	0.2149
564	0.11590	0.243900	0.138900	0.1726
565	0.10340	0.144000	0.097910	0.1752
566	0.10230	0.092510	0.053020	0.1590
567	0.27700	0.351400	0.152000	0.2397
568	0.04362	0.000000	0.000000	0.1587

	mean fractal dimension	...	worst radius \
0	0.07871	...	25.380
1	0.05667	...	24.990
2	0.05999	...	23.570
3	0.09744	...	14.910
4	0.05883	...	22.540
5	0.07613	...	15.470
6	0.05742	...	22.880
7	0.07451	...	17.060
8	0.07389	...	15.490
9	0.08243	...	15.090
10	0.05697	...	19.190
11	0.06082	...	20.420
12	0.07800	...	20.960
13	0.05338	...	16.840
14	0.07682	...	15.030
15	0.07077	...	17.460
16	0.05922	...	19.070
17	0.07356	...	20.960
18	0.05395	...	27.320
19	0.05766	...	15.110
20	0.06811	...	14.500
21	0.06905	...	10.230
22	0.07032	...	18.070
23	0.05278	...	29.170
24	0.06330	...	26.460
25	0.07413	...	22.250
26	0.06924	...	17.620
27	0.05699	...	21.310
28	0.06540	...	20.270
29	0.06149	...	20.010
..
539	0.07751	...	8.678
540	0.06782	...	12.260
541	0.06341	...	16.220
542	0.05680	...	16.510
543	0.05781	...	14.370
544	0.06688	...	15.050
545	0.05801	...	15.350
546	0.06201	...	11.250
547	0.06714	...	10.830
548	0.06235	...	10.930
549	0.06328	...	13.030
550	0.05948	...	11.660

551	0.06552	...	12.020
552	0.05637	...	13.870
553	0.06576	...	9.845
554	0.05708	...	13.890
555	0.06127	...	10.840
556	0.06331	...	10.650
557	0.06059	...	10.490
558	0.06147	...	15.480
559	0.06570	...	12.480
560	0.06171	...	15.300
561	0.05502	...	11.920
562	0.07152	...	17.520
563	0.06879	...	24.290
564	0.05623	...	25.450
565	0.05533	...	23.690
566	0.05648	...	18.980
567	0.07016	...	25.740
568	0.05884	...	9.456

	worst texture	worst perimeter	worst area	worst smoothness \
0	17.33	184.60	2019.0	0.16220
1	23.41	158.80	1956.0	0.12380
2	25.53	152.50	1709.0	0.14440
3	26.50	98.87	567.7	0.20980
4	16.67	152.20	1575.0	0.13740
5	23.75	103.40	741.6	0.17910
6	27.66	153.20	1606.0	0.14420
7	28.14	110.60	897.0	0.16540
8	30.73	106.20	739.3	0.17030
9	40.68	97.65	711.4	0.18530
10	33.88	123.80	1150.0	0.11810
11	27.28	136.50	1299.0	0.13960
12	29.94	151.70	1332.0	0.10370
13	27.66	112.00	876.5	0.11310
14	32.01	108.80	697.7	0.16510
15	37.13	124.10	943.2	0.16780
16	30.88	123.40	1138.0	0.14640
17	31.48	136.80	1315.0	0.17890
18	30.88	186.80	2398.0	0.15120
19	19.26	99.70	711.2	0.14400
20	20.49	96.09	630.5	0.13120
21	15.66	65.13	314.9	0.13240
22	19.08	125.10	980.9	0.13900
23	35.59	188.00	2615.0	0.14010
24	31.56	177.00	2215.0	0.18050
25	21.40	152.40	1461.0	0.15450
26	33.21	122.40	896.9	0.15250
27	27.26	139.90	1403.0	0.13380
28	36.71	149.30	1269.0	0.16410
29	19.52	134.90	1227.0	0.12550
...
539	31.89	54.49	223.6	0.15960
540	19.68	78.78	457.8	0.13450
541	31.73	113.50	808.9	0.13400
542	32.29	107.40	826.4	0.10600
543	37.17	92.48	629.6	0.10720
544	24.75	99.17	688.6	0.12640
545	29.09	97.58	729.8	0.12160
546	21.77	71.12	384.9	0.12850
547	22.04	71.08	357.4	0.14610
548	25.59	69.10	364.2	0.11990
549	31.45	83.90	505.6	0.12040
550	24.77	74.08	412.3	0.10010
551	28.26	77.80	436.6	0.10870
552	36.00	88.10	594.7	0.12340
553	25.05	62.86	295.8	0.11030
554	35.74	88.84	595.7	0.12270
555	34.91	69.57	357.6	0.13840
556	22.88	67.88	347.3	0.12650
557	34.24	66.50	330.6	0.10730
558	27.27	105.90	733.5	0.10260
559	37.16	82.28	474.2	0.12980
560	33.17	100.20	706.7	0.12410
561	38.30	75.19	439.6	0.09267
562	42.79	128.70	915.0	0.14170
563	29.41	179.10	1819.0	0.14070
564	26.40	166.10	2027.0	0.14100
565	38.25	155.00	1731.0	0.11660
566	34.12	126.70	1124.0	0.11390
567	39.42	184.60	1821.0	0.16500
568	30.37	59.16	268.6	0.08996

	worst compactness	worst concavity	worst concave points	worst symmetry \
0	0.66560	0.71190	0.26540	0.4601
1	0.18660	0.24160	0.18600	0.2750

2	0.42450	0.45040	0.24300	0.3613
3	0.86630	0.68690	0.25750	0.6638
4	0.20500	0.40000	0.16250	0.2364
5	0.52490	0.53550	0.17410	0.3985
6	0.25760	0.37840	0.19320	0.3063
7	0.36820	0.26780	0.15560	0.3196
8	0.54010	0.53900	0.20600	0.4378
9	1.05800	1.10500	0.22100	0.4366
10	0.15510	0.14590	0.09975	0.2948
11	0.56090	0.39650	0.18100	0.3792
12	0.39030	0.36390	0.17670	0.3176
13	0.19240	0.23220	0.11190	0.2809
14	0.77250	0.69430	0.22080	0.3596
15	0.65770	0.70260	0.17120	0.4218
16	0.18710	0.29140	0.16090	0.3029
17	0.42330	0.47840	0.20730	0.3706
18	0.31500	0.53720	0.23880	0.2768
19	0.17730	0.23900	0.12880	0.2977
20	0.27760	0.18900	0.07283	0.3184
21	0.11480	0.08867	0.06227	0.2450
22	0.59540	0.63050	0.23930	0.4667
23	0.26000	0.31550	0.20090	0.2822
24	0.35780	0.46950	0.20950	0.3613
25	0.39490	0.38530	0.25500	0.4066
26	0.66430	0.55390	0.27010	0.4264
27	0.21170	0.34460	0.14900	0.2341
28	0.61100	0.63350	0.20240	0.4027
29	0.28120	0.24890	0.14560	0.2756
...
539	0.30640	0.33930	0.05000	0.2790
540	0.21180	0.17970	0.06918	0.2329
541	0.42020	0.40400	0.12050	0.3187
542	0.13760	0.16110	0.10950	0.2722
543	0.13810	0.10620	0.07958	0.2473
544	0.20370	0.13770	0.06845	0.2249
545	0.15170	0.10490	0.07174	0.2642
546	0.08842	0.04384	0.02381	0.2681
547	0.22460	0.17830	0.08333	0.2691
548	0.09546	0.09350	0.03846	0.2552
549	0.16330	0.06194	0.03264	0.3059
550	0.07348	0.00000	0.00000	0.2458
551	0.17820	0.15640	0.06413	0.3169
552	0.10640	0.08653	0.06498	0.2407
553	0.08298	0.07993	0.02564	0.2435
554	0.16200	0.24390	0.06493	0.2372
555	0.17100	0.20000	0.09127	0.2226
556	0.12000	0.01005	0.02232	0.2262
557	0.07158	0.00000	0.00000	0.2475
558	0.31710	0.36620	0.11050	0.2258
559	0.25170	0.36300	0.09653	0.2112
560	0.22640	0.13260	0.10480	0.2250
561	0.05494	0.00000	0.00000	0.1566
562	0.79170	1.17000	0.23560	0.4089
563	0.41860	0.65990	0.25420	0.2929
564	0.21130	0.41070	0.22160	0.2060
565	0.19220	0.32150	0.16280	0.2572
566	0.30940	0.34030	0.14180	0.2218
567	0.86810	0.93870	0.26500	0.4087
568	0.06444	0.00000	0.00000	0.2871

worst fractal dimension	
0	0.11890
1	0.08902
2	0.08758
3	0.17300
4	0.07678
5	0.12440
6	0.08368
7	0.11510
8	0.10720
9	0.20750
10	0.08452
11	0.10480
12	0.10230
13	0.06287
14	0.14310
15	0.13410
16	0.08216
17	0.11420
18	0.07615
19	0.07259
20	0.08183
21	0.07773
22	0.09946
23	0.07526

24	0.09564
25	0.10590
26	0.12750
27	0.07421
28	0.09876
29	0.07919
..	...
539	0.10660
540	0.08134
541	0.10230
542	0.06956
543	0.06443
544	0.08492
545	0.06953
546	0.07399
547	0.09479
548	0.07920
549	0.07626
550	0.06592
551	0.08032
552	0.06484
553	0.07393
554	0.07242
555	0.08283
556	0.06742
557	0.06969
558	0.08004
559	0.08732
560	0.08321
561	0.05905
562	0.14090
563	0.09873
564	0.07115
565	0.06637
566	0.07820
567	0.12400
568	0.07039

[569 rows x 30 columns], 0 0

1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0
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12	0
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16	0
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21	1
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23	0
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26	0
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545	1
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547	1
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551	1
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553	1
554	1

```
555    1
556    1
557    1
558    1
559    1
560    1
561    1
562    0
563    0
564    0
565    0
566    0
567    0
568    1
Name: target, dtype: int64)
```

Question 4

Using `train_test_split`, split `X` and `y` into training and test sets (`X_train`, `X_test`, `y_train`, and `y_test`).

Set the random number generator state to 0 using `random_state=0` to make sure your results match the autograder!

This function should return a tuple of length 4: (`X_train`, `X_test`, `y_train`, `y_test`), where

- `X_train` has shape (426, 30)
- `X_test` has shape (143, 30)
- `y_train` has shape (426,)
- `y_test` has shape (143,)

```
In [11]: def answer_four():
        X, y = answer_three()

        # Your code here
        X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 0)

        return X_train, X_test, y_train, y_test
answer_four()
```



```

Out[11]: (      mean radius  mean texture  mean perimeter  mean area  mean smoothness  \
293      11.850      17.46      75.54      432.7      0.08372
332      11.220      19.86      71.94      387.3      0.10540
565      20.130      28.25      131.20     1261.0      0.09780
278      13.590      17.84      86.24      572.3      0.07948
489      16.690      20.20      107.10      857.6      0.07497
346      12.060      18.90      76.66      445.3      0.08386
357      13.870      16.21      88.52      593.7      0.08743
355      12.560      19.07      81.92      485.8      0.08760
112      14.260      19.65      97.83      629.9      0.07837
68       9.029      17.33      58.79      250.5      0.10660
526      13.460      18.75      87.44      551.1      0.10750
206      9.876      17.27      62.92      295.4      0.10890
65      14.780      23.94      97.40      668.3      0.11720
437      14.040      15.98      89.78      611.2      0.08458
126      13.610      24.69      87.76      572.6      0.09258
429      12.720      17.67      80.98      501.3      0.07896
392      15.490      19.97      102.40      744.7      0.11600
343      19.680      21.68      129.90     1194.0      0.09797
334      12.300      19.02      77.88      464.4      0.08313
440      10.970      17.20      71.73      371.5      0.08915
441      17.270      25.42      112.40      928.8      0.08331
137      11.430      15.39      73.06      399.8      0.09639
230      17.050      19.08      113.40      895.0      0.11410
7       13.710      20.83      90.20      577.9      0.11890
408      17.990      20.66      117.80      991.7      0.10360
523      13.710      18.68      88.73      571.0      0.09916
361      13.300      21.57      85.24      546.1      0.08582
553      9.333      21.94      59.01      264.0      0.09240
478      11.490      14.59      73.99      404.9      0.10460
303      10.490      18.61      66.86      334.3      0.10680
..      ...      ...      ...      ...      ...
459      9.755      28.20      61.68      290.9      0.07984
510      11.740      14.69      76.31      426.0      0.08099
151      8.219      20.70      53.27      203.9      0.09405
244      19.400      23.50      129.10     1155.0      0.10270
543      13.210      28.06      84.88      538.4      0.08671
544      13.870      20.70      89.77      584.8      0.09578
265      20.730      31.12      135.70     1419.0      0.09469
288      11.260      19.96      73.72      394.1      0.08020
423      13.660      19.13      89.46      575.3      0.09057
147      14.950      18.77      97.84      689.5      0.08138
177      16.460      20.11      109.30      832.9      0.09831
99      14.420      19.77      94.48      642.5      0.09752
448      14.530      19.34      94.25      659.7      0.08388
431      12.400      17.68      81.47      467.8      0.10540
115      11.930      21.53      76.53      438.6      0.09768
72      17.200      24.52      114.20      929.4      0.10710
537      11.690      24.44      76.37      406.4      0.12360
174      10.660      15.15      67.49      349.6      0.08792
87      19.020      24.59      122.00     1076.0      0.09029
551      11.130      22.44      71.49      378.4      0.09566
486      14.640      16.85      94.21      666.0      0.08641
314      8.597      18.60      54.09      221.2      0.10740
396      13.510      18.89      88.10      558.1      0.10590
472      14.920      14.93      96.45      686.9      0.08098
70      18.940      21.31      123.60     1130.0      0.09009
277      18.810      19.98      120.90     1102.0      0.08923
9       12.460      24.04      83.97      475.9      0.11860
359      9.436      18.32      59.82      278.6      0.10090
192      9.720      18.22      60.73      288.1      0.06950
559      11.510      23.93      74.52      403.5      0.09261

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      mean compactness  mean concavity  mean concave points  mean symmetry  \
293      0.05642      0.026880      0.022800      0.1875
332      0.06779      0.005006      0.007583      0.1940
565      0.10340      0.144000      0.097910      0.1752
278      0.04052      0.019970      0.012380      0.1573
489      0.07112      0.036490      0.023070      0.1846
346      0.05794      0.007510      0.008488      0.1555
357      0.05492      0.015020      0.020880      0.1424
355      0.10380      0.103000      0.043910      0.1533
112      0.22330      0.300300      0.077980      0.1704
68      0.14130      0.313000      0.043750      0.2111
526      0.11380      0.042010      0.031520      0.1723
206      0.07232      0.017560      0.019520      0.1934
65      0.14790      0.126700      0.090290      0.1953
437      0.05895      0.035340      0.029440      0.1714
126      0.07862      0.052850      0.030850      0.1761
429      0.04522      0.014020      0.018350      0.1459
392      0.15620      0.189100      0.091130      0.1929
343      0.13390      0.186300      0.110300      0.2082
334      0.04202      0.007756      0.008535      0.1539
440      0.11130      0.094570      0.036130      0.1489
441      0.11090      0.120400      0.057360      0.1467

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137	0.06889	0.035030	0.028750	0.1734
230	0.15720	0.191000	0.109000	0.2131
7	0.16450	0.093660	0.059850	0.2196
408	0.13040	0.120100	0.088240	0.1992
523	0.10700	0.053850	0.037830	0.1714
361	0.06373	0.033440	0.024240	0.1815
553	0.05605	0.039960	0.012820	0.1692
478	0.08228	0.053080	0.019690	0.1779
303	0.06678	0.022970	0.017800	0.1482
..
459	0.04626	0.015410	0.010430	0.1621
510	0.09661	0.067260	0.026390	0.1499
151	0.13050	0.132100	0.021680	0.2222
244	0.15580	0.204900	0.088860	0.1978
543	0.06877	0.029870	0.032750	0.1628
544	0.10180	0.036880	0.023690	0.1620
265	0.11430	0.136700	0.086460	0.1769
288	0.11810	0.092740	0.055880	0.2595
423	0.11470	0.096570	0.048120	0.1848
147	0.11670	0.090500	0.035620	0.1744
177	0.15560	0.179300	0.088660	0.1794
99	0.11410	0.093880	0.058390	0.1879
448	0.07800	0.088170	0.029250	0.1473
431	0.13160	0.077410	0.027990	0.1811
115	0.07849	0.033280	0.020080	0.1688
72	0.18300	0.169200	0.079440	0.1927
537	0.15520	0.045150	0.045310	0.2131
174	0.04302	0.000000	0.000000	0.1928
87	0.12060	0.146800	0.082710	0.1953
551	0.08194	0.048240	0.022570	0.2030
486	0.06698	0.051920	0.027910	0.1409
314	0.05847	0.000000	0.000000	0.2163
396	0.11470	0.085800	0.053810	0.1806
472	0.08549	0.055390	0.032210	0.1687
70	0.10290	0.108000	0.079510	0.1582
277	0.05884	0.080200	0.058430	0.1550
9	0.23960	0.227300	0.085430	0.2030
359	0.05956	0.027100	0.014060	0.1506
192	0.02344	0.000000	0.000000	0.1653
559	0.10210	0.111200	0.041050	0.1388

	mean fractal dimension	...	worst radius \
293	0.05715	...	13.060
332	0.06028	...	11.980
565	0.05533	...	23.690
278	0.05520	...	15.500
489	0.05325	...	19.180
346	0.06048	...	13.640
357	0.05883	...	15.110
355	0.06184	...	13.370
112	0.07769	...	15.300
68	0.08046	...	10.310
526	0.06317	...	15.350
206	0.06285	...	10.420
65	0.06654	...	17.310
437	0.05898	...	15.660
126	0.06130	...	16.890
429	0.05544	...	13.820
392	0.06744	...	21.200
343	0.05715	...	22.750
334	0.05945	...	13.350
440	0.06640	...	12.360
441	0.05407	...	20.380
137	0.05865	...	12.320
230	0.06325	...	19.590
7	0.07451	...	17.060
408	0.06069	...	21.080
523	0.06843	...	15.110
361	0.05696	...	14.200
553	0.06576	...	9.845
478	0.06574	...	12.400
303	0.06600	...	11.060
..
459	0.05952	...	10.670
510	0.06758	...	12.450
151	0.08261	...	9.092
244	0.06000	...	21.650
543	0.05781	...	14.370
544	0.06688	...	15.050
265	0.05674	...	32.490
288	0.06233	...	11.860
423	0.06181	...	15.140
147	0.06493	...	16.250
177	0.06323	...	17.790
99	0.06390	...	16.330

448	0.05746	...	16.300
431	0.07102	...	12.880
115	0.06194	...	13.670
72	0.06487	...	23.320
537	0.07405	...	12.980
174	0.05975	...	11.540
87	0.05629	...	24.560
551	0.06552	...	12.020
486	0.05355	...	16.460
314	0.07359	...	8.952
396	0.06079	...	14.800
472	0.05669	...	17.180
70	0.05461	...	24.860
277	0.04996	...	19.960
9	0.08243	...	15.090
359	0.06959	...	12.020
192	0.06447	...	9.968
559	0.06570	...	12.480

	worst texture	worst perimeter	worst area	worst smoothness \
293	25.75	84.35	517.8	0.13690
332	25.78	76.91	436.1	0.14240
565	38.25	155.00	1731.0	0.11660
278	26.10	98.91	739.1	0.10500
489	26.56	127.30	1084.0	0.10090
346	27.06	86.54	562.6	0.12890
357	25.58	96.74	694.4	0.11530
355	22.43	89.02	547.4	0.10960
112	23.73	107.00	709.0	0.08949
68	22.65	65.50	324.7	0.14820
526	25.16	101.90	719.8	0.16240
206	23.22	67.08	331.6	0.14150
65	33.39	114.60	925.1	0.16480
437	21.58	101.20	750.0	0.11950
126	35.64	113.20	848.7	0.14710
429	20.96	88.87	586.8	0.10680
392	29.41	142.10	1359.0	0.16810
343	34.66	157.60	1540.0	0.12180
334	28.46	84.53	544.3	0.12220
440	26.87	90.14	476.4	0.13910
441	35.46	132.80	1284.0	0.14360
137	22.02	79.93	462.0	0.11900
230	24.89	133.50	1189.0	0.17030
7	28.14	110.60	897.0	0.16540
408	25.41	138.10	1349.0	0.14820
523	25.63	99.43	701.9	0.14250
361	29.20	92.94	621.2	0.11400
553	25.05	62.86	295.8	0.11030
478	21.90	82.04	467.6	0.13520
303	24.54	70.76	375.4	0.14130
..
459	36.92	68.03	349.9	0.11100
510	17.60	81.25	473.8	0.10730
151	29.72	58.08	249.8	0.16300
244	30.53	144.90	1417.0	0.14630
543	37.17	92.48	629.6	0.10720
544	24.75	99.17	688.6	0.12640
265	47.16	214.00	3432.0	0.14010
288	22.33	78.27	437.6	0.10280
423	25.50	101.40	708.8	0.11470
147	25.47	107.10	809.7	0.09970
177	28.45	123.50	981.2	0.14150
99	30.86	109.50	826.4	0.14310
448	28.39	108.10	830.5	0.10890
431	22.91	89.61	515.8	0.14500
115	26.15	87.54	583.0	0.15000
72	33.82	151.60	1681.0	0.15850
537	32.19	86.12	487.7	0.17680
174	19.20	73.20	408.3	0.10760
87	30.41	152.90	1623.0	0.12490
551	28.26	77.80	436.6	0.10870
486	25.44	106.00	831.0	0.11420
314	22.44	56.65	240.1	0.13470
396	27.20	97.33	675.2	0.14280
472	18.22	112.00	906.6	0.10650
70	26.58	165.90	1866.0	0.11930
277	24.30	129.00	1236.0	0.12430
9	40.68	97.65	711.4	0.18530
359	25.02	75.79	439.6	0.13330
192	20.83	62.25	303.8	0.07117
559	37.16	82.28	474.2	0.12980

	worst compactness	worst concavity	worst concave points	worst symmetry \
293	0.17580	0.13160	0.09140	0.3101
332	0.09669	0.01335	0.02022	0.3292

565	0.19220	0.32150	0.16280	0.2572
278	0.07622	0.10600	0.05185	0.2335
489	0.29200	0.24770	0.08737	0.4677
346	0.13520	0.04506	0.05093	0.2880
357	0.10080	0.05285	0.05556	0.2362
355	0.20020	0.23880	0.09265	0.2121
112	0.41930	0.67830	0.15050	0.2398
68	0.43650	1.25200	0.17500	0.4228
526	0.31240	0.26540	0.14270	0.3518
206	0.12470	0.06213	0.05588	0.2989
65	0.34160	0.30240	0.16140	0.3321
437	0.12520	0.11170	0.07453	0.2725
126	0.28840	0.37960	0.13290	0.3470
429	0.09605	0.03469	0.03612	0.2165
392	0.39130	0.55530	0.21210	0.3187
343	0.34580	0.47340	0.22550	0.4045
334	0.09052	0.03619	0.03983	0.2554
440	0.40820	0.47790	0.15550	0.2540
441	0.41220	0.50360	0.17390	0.2500
137	0.16480	0.13990	0.08476	0.2676
230	0.39340	0.50180	0.25430	0.3109
7	0.36820	0.26780	0.15560	0.3196
408	0.37350	0.33010	0.19740	0.3060
523	0.25660	0.19350	0.12840	0.2849
361	0.16670	0.12120	0.05614	0.2637
553	0.08298	0.07993	0.02564	0.2435
478	0.20100	0.25960	0.07431	0.2941
303	0.10440	0.08423	0.06528	0.2213
..
459	0.11090	0.07190	0.04866	0.2321
510	0.27930	0.26900	0.10560	0.2604
151	0.43100	0.53810	0.07879	0.3322
244	0.29680	0.34580	0.15640	0.2920
543	0.13810	0.10620	0.07958	0.2473
544	0.20370	0.13770	0.06845	0.2249
265	0.26440	0.34420	0.16590	0.2868
288	0.18430	0.15460	0.09314	0.2955
423	0.31670	0.36600	0.14070	0.2744
147	0.25210	0.25000	0.08405	0.2852
177	0.46670	0.58620	0.20350	0.3054
99	0.30260	0.31940	0.15650	0.2718
448	0.26490	0.37790	0.09594	0.2471
431	0.26290	0.24030	0.07370	0.2556
115	0.23990	0.15030	0.07247	0.2438
72	0.73940	0.65660	0.18990	0.3313
537	0.32510	0.13950	0.13080	0.2803
174	0.06791	0.00000	0.00000	0.2710
87	0.32060	0.57550	0.19560	0.3956
551	0.17820	0.15640	0.06413	0.3169
486	0.20700	0.24370	0.07828	0.2455
314	0.07767	0.00000	0.00000	0.3142
396	0.25700	0.34380	0.14530	0.2666
472	0.27910	0.31510	0.11470	0.2688
70	0.23360	0.26870	0.17890	0.2551
277	0.11600	0.22100	0.12940	0.2567
9	1.05800	1.10500	0.22100	0.4366
359	0.10490	0.11440	0.05052	0.2454
192	0.02729	0.00000	0.00000	0.1909
559	0.25170	0.36300	0.09653	0.2112

worst fractal dimension

293	0.07007
332	0.06522
565	0.06637
278	0.06263
489	0.07623
346	0.08083
357	0.07113
355	0.07188
112	0.10820
68	0.11750
526	0.08665
206	0.07380
65	0.08911
437	0.07234
126	0.07900
429	0.06025
392	0.10190
343	0.07918
334	0.07207
440	0.09532
441	0.07944
137	0.06765
230	0.09061
7	0.11510

408	0.08503
523	0.09031
361	0.06658
553	0.07393
478	0.09180
303	0.07842
..	...
459	0.07211
510	0.09879
151	0.14860
244	0.07614
543	0.06443
544	0.08492
265	0.08218
288	0.07009
423	0.08839
147	0.09218
177	0.09519
99	0.09353
448	0.07463
431	0.09359
115	0.08541
72	0.13390
537	0.09970
174	0.06164
87	0.09288
551	0.08032
486	0.06596
314	0.08116
396	0.07686
472	0.08273
70	0.06589
277	0.05737
9	0.20750
359	0.08136
192	0.06559
559	0.08732

[426 rows x 30 columns],

	mean radius	mean texture	mean perimeter	mean area	mean smoothness \
512	13.400	20.52	88.64	556.7	0.11060
457	13.210	25.25	84.10	537.9	0.08791
439	14.020	15.66	89.59	606.5	0.07966
298	14.260	18.17	91.22	633.1	0.06576
37	13.030	18.42	82.61	523.8	0.08983
515	11.340	18.61	72.76	391.2	0.10490
382	12.050	22.72	78.75	447.8	0.06935
310	11.700	19.11	74.33	418.7	0.08814
538	7.729	25.49	47.98	178.8	0.08098
345	10.260	14.71	66.20	321.6	0.09882
421	14.690	13.98	98.22	656.1	0.10310
90	14.620	24.02	94.57	662.7	0.08974
412	9.397	21.68	59.75	268.8	0.07969
157	16.840	19.46	108.40	880.2	0.07445
89	14.640	15.24	95.77	651.9	0.11320
172	15.460	11.89	102.50	736.9	0.12570
318	9.042	18.90	60.07	244.5	0.09968
233	20.510	27.81	134.40	1319.0	0.09159
389	19.550	23.21	128.90	1174.0	0.10100
250	20.940	23.56	138.90	1364.0	0.10070
31	11.840	18.70	77.93	440.6	0.11090
283	16.240	18.77	108.80	805.1	0.10660
482	13.470	14.06	87.32	546.3	0.10710
211	11.840	18.94	75.51	428.0	0.08871
372	21.370	15.10	141.30	1386.0	0.10010
401	11.930	10.91	76.14	442.7	0.08872
159	10.900	12.96	68.69	366.8	0.07515
14	13.730	22.61	93.60	578.3	0.11310
364	13.400	16.95	85.48	552.4	0.07937
337	18.770	21.43	122.90	1092.0	0.09116
..
500	15.040	16.74	98.73	689.4	0.09883
338	10.050	17.53	64.41	310.8	0.10070
427	10.800	21.98	68.79	359.9	0.08801
406	16.140	14.86	104.30	800.0	0.09495
96	12.180	17.84	77.79	451.1	0.10450
490	12.250	22.44	78.18	466.5	0.08192
384	13.280	13.72	85.79	541.8	0.08363
281	11.740	14.02	74.24	427.3	0.07813
325	12.670	17.30	81.25	489.9	0.10280
190	14.220	23.12	94.37	609.9	0.10750
380	11.270	12.96	73.16	386.3	0.12370
366	20.200	26.83	133.70	1234.0	0.09905
469	11.620	18.18	76.38	408.8	0.11750
225	14.340	13.47	92.51	641.2	0.09906

271	11.290	13.04	72.23	388.0	0.09834
547	10.260	16.58	65.85	320.8	0.08877
550	10.860	21.48	68.51	360.5	0.07431
492	18.010	20.56	118.40	1007.0	0.10010
185	10.080	15.11	63.76	317.5	0.09267
306	13.200	15.82	84.07	537.3	0.08511
208	13.110	22.54	87.02	529.4	0.10020
242	11.300	18.19	73.93	389.4	0.09592
313	11.540	10.72	73.73	409.1	0.08597
542	14.740	25.42	94.70	668.6	0.08275
514	15.050	19.07	97.26	701.9	0.09215
236	23.210	26.97	153.50	1670.0	0.09509
113	10.510	20.19	68.64	334.2	0.11220
527	12.340	12.27	78.94	468.5	0.09003
76	13.530	10.94	87.91	559.2	0.12910
162	19.590	18.15	130.70	1214.0	0.11200

	mean compactness	mean concavity	mean concave points	mean symmetry \
512	0.14690	0.144500	0.081720	0.2116
457	0.05205	0.027720	0.020680	0.1619
439	0.05581	0.020870	0.026520	0.1589
298	0.05220	0.024750	0.013740	0.1635
37	0.03766	0.025620	0.029230	0.1467
515	0.08499	0.043020	0.025940	0.1927
382	0.10730	0.079430	0.029780	0.1203
310	0.05253	0.015830	0.011480	0.1936
538	0.04878	0.000000	0.000000	0.1870
345	0.09159	0.035810	0.020370	0.1633
421	0.18360	0.145000	0.063000	0.2086
90	0.08606	0.031020	0.029570	0.1685
412	0.06053	0.037350	0.005128	0.1274
157	0.07223	0.051500	0.027710	0.1844
89	0.13390	0.099660	0.070640	0.2116
172	0.15550	0.203200	0.109700	0.1966
318	0.19720	0.197500	0.049080	0.2330
233	0.10740	0.155400	0.083400	0.1448
389	0.13180	0.185600	0.102100	0.1989
250	0.16060	0.271200	0.131000	0.2205
31	0.15160	0.121800	0.051820	0.2301
283	0.18020	0.194800	0.090520	0.1876
482	0.11550	0.057860	0.052660	0.1779
211	0.06900	0.026690	0.013930	0.1533
372	0.15150	0.193200	0.125500	0.1973
401	0.05242	0.026060	0.017960	0.1601
159	0.03718	0.003090	0.006588	0.1442
14	0.22930	0.212800	0.080250	0.2069
364	0.05696	0.021810	0.014730	0.1650
337	0.14020	0.106000	0.060900	0.1953
..
500	0.13640	0.077210	0.061420	0.1668
338	0.07326	0.025110	0.017750	0.1890
427	0.05743	0.036140	0.014040	0.2016
406	0.08501	0.055000	0.045280	0.1735
96	0.07057	0.024900	0.029410	0.1900
490	0.05200	0.017140	0.012610	0.1544
384	0.08575	0.050770	0.028640	0.1617
281	0.04340	0.022450	0.027630	0.2101
325	0.07664	0.031930	0.021070	0.1707
190	0.24130	0.198100	0.066180	0.2384
380	0.11110	0.079000	0.055500	0.2018
366	0.16690	0.164100	0.126500	0.1875
469	0.14830	0.102000	0.055640	0.1957
225	0.07624	0.057240	0.046030	0.2075
271	0.07608	0.032650	0.027550	0.1769
547	0.08066	0.043580	0.024380	0.1669
550	0.04227	0.000000	0.000000	0.1661
492	0.12890	0.117000	0.077620	0.2116
185	0.04695	0.001597	0.002404	0.1703
306	0.05251	0.001461	0.003261	0.1632
208	0.14830	0.087050	0.051020	0.1850
242	0.13250	0.154800	0.028540	0.2054
313	0.05969	0.013670	0.008907	0.1833
542	0.07214	0.041050	0.030270	0.1840
514	0.08597	0.074860	0.043350	0.1561
236	0.16820	0.195000	0.123700	0.1909
113	0.13030	0.064760	0.030680	0.1922
527	0.06307	0.029580	0.026470	0.1689
76	0.10470	0.068770	0.065560	0.2403
162	0.16660	0.250800	0.128600	0.2027

	mean fractal dimension	...	worst radius \
512	0.07325	...	16.410
457	0.05584	...	14.350
439	0.05586	...	14.910
298	0.05586	...	16.220

37	0.05863	...	13.300
515	0.06211	...	12.470
382	0.06659	...	12.570
310	0.06128	...	12.610
538	0.07285	...	9.077
345	0.07005	...	10.880
421	0.07406	...	16.460
90	0.05866	...	16.110
412	0.06724	...	9.965
157	0.05268	...	18.220
89	0.06346	...	16.340
172	0.07069	...	18.790
318	0.08743	...	10.060
233	0.05592	...	24.470
389	0.05884	...	20.820
250	0.05898	...	25.580
31	0.07799	...	16.820
283	0.06684	...	18.550
482	0.06639	...	14.830
211	0.06057	...	13.300
372	0.06183	...	22.690
401	0.05541	...	13.800
159	0.05743	...	12.360
14	0.07682	...	15.030
364	0.05701	...	14.730
337	0.06083	...	24.540
..
500	0.06869	...	16.760
338	0.06331	...	11.160
427	0.05977	...	12.760
406	0.05875	...	17.710
96	0.06635	...	12.830
490	0.05976	...	14.170
384	0.05594	...	14.240
281	0.06113	...	13.310
325	0.05984	...	13.710
190	0.07542	...	15.740
380	0.06914	...	12.840
366	0.06020	...	24.190
469	0.07255	...	13.360
225	0.05448	...	16.770
271	0.06270	...	12.320
547	0.06714	...	10.830
550	0.05948	...	11.660
492	0.06077	...	21.530
185	0.06048	...	11.870
306	0.05894	...	14.410
208	0.07310	...	14.550
242	0.07669	...	12.580
313	0.06100	...	12.340
542	0.05680	...	16.510
514	0.05915	...	17.580
236	0.06309	...	31.010
113	0.07782	...	11.160
527	0.05808	...	13.610
76	0.06641	...	14.080
162	0.06082	...	26.730

	worst texture	worst perimeter	worst area	worst smoothness \
512	29.66	113.30	844.4	0.15740
457	34.23	91.29	632.9	0.12890
439	19.31	96.53	688.9	0.10340
298	25.26	105.80	819.7	0.09445
37	22.81	84.46	545.9	0.09701
515	23.03	79.15	478.6	0.14830
382	28.71	87.36	488.4	0.08799
310	26.55	80.92	483.1	0.12230
538	30.92	57.17	248.0	0.12560
345	19.48	70.89	357.1	0.13600
421	18.34	114.10	809.2	0.13120
90	29.11	102.90	803.7	0.11150
412	27.99	66.61	301.0	0.10860
157	28.07	120.30	1032.0	0.08774
89	18.24	109.40	803.6	0.12770
172	17.04	125.00	1102.0	0.15310
318	23.40	68.62	297.1	0.12210
233	37.38	162.70	1872.0	0.12230
389	30.44	142.00	1313.0	0.12510
250	27.00	165.30	2010.0	0.12110
31	28.12	119.40	888.7	0.16370
283	25.09	126.90	1031.0	0.13650
482	18.32	94.94	660.2	0.13930
211	24.99	85.22	546.3	0.12800
372	21.84	152.10	1535.0	0.11920
401	20.14	87.64	589.5	0.13740

159	18.20	78.07	470.0	0.11710
14	32.01	108.80	697.7	0.16510
364	21.70	93.76	663.5	0.12130
337	34.37	161.10	1873.0	0.14980
..
500	20.43	109.70	856.9	0.11350
338	26.84	71.98	384.0	0.14020
427	32.04	83.69	489.5	0.13030
406	19.58	115.90	947.9	0.12060
96	20.92	82.14	495.2	0.11400
490	31.99	92.74	622.9	0.12560
384	17.37	96.59	623.7	0.11660
281	18.26	84.70	533.7	0.10360
325	21.10	88.70	574.4	0.13840
190	37.18	106.40	762.4	0.15330
380	20.53	84.93	476.1	0.16100
366	33.81	160.00	1671.0	0.12780
469	25.40	88.14	528.1	0.17800
225	16.90	110.40	873.2	0.12970
271	16.18	78.27	457.5	0.13580
547	22.04	71.08	357.4	0.14610
550	24.77	74.08	412.3	0.10010
492	26.06	143.40	1426.0	0.13090
185	21.18	75.39	437.0	0.15210
306	20.45	92.00	636.9	0.11280
208	29.16	99.48	639.3	0.13490
242	27.96	87.16	472.9	0.13470
313	12.87	81.23	467.8	0.10920
542	32.29	107.40	826.4	0.10600
514	28.06	113.80	967.0	0.12460
236	34.51	206.00	2944.0	0.14810
113	22.75	72.62	374.4	0.13000
527	19.27	87.22	564.9	0.12920
76	12.49	91.36	605.5	0.14510
162	26.39	174.90	2232.0	0.14380

	worst compactness	worst concavity	worst concave points	worst symmetry \
512	0.38560	0.51060	0.20510	0.3585
457	0.10630	0.13900	0.06005	0.2444
439	0.10170	0.06260	0.08216	0.2136
298	0.21670	0.15650	0.07530	0.2636
37	0.04619	0.04833	0.05013	0.1987
515	0.15740	0.16240	0.08542	0.3060
382	0.32140	0.29120	0.10920	0.2191
310	0.10870	0.07915	0.05741	0.3487
538	0.08340	0.00000	0.00000	0.3058
345	0.16360	0.07162	0.04074	0.2434
421	0.36350	0.32190	0.11080	0.2827
90	0.17660	0.09189	0.06946	0.2522
412	0.18870	0.18680	0.02564	0.2376
157	0.17100	0.18820	0.08436	0.2527
89	0.30890	0.26040	0.13970	0.3151
172	0.35830	0.58300	0.18270	0.3216
318	0.37480	0.46090	0.11450	0.3135
233	0.27610	0.41460	0.15630	0.2437
389	0.24140	0.38290	0.18250	0.2576
250	0.31720	0.69910	0.21050	0.3126
31	0.57750	0.69560	0.15460	0.4761
283	0.47060	0.50260	0.17320	0.2770
482	0.24990	0.18480	0.13350	0.3227
211	0.18800	0.14710	0.06913	0.2535
372	0.28400	0.40240	0.19660	0.2730
401	0.15750	0.15140	0.06876	0.2460
159	0.08294	0.01854	0.03953	0.2738
14	0.77250	0.69430	0.22080	0.3596
364	0.16760	0.13640	0.06987	0.2741
337	0.48270	0.46340	0.20480	0.3679
..
500	0.21760	0.18560	0.10180	0.2177
338	0.14020	0.10550	0.06499	0.2894
427	0.16960	0.19270	0.07485	0.2965
406	0.17220	0.23100	0.11290	0.2778
96	0.09358	0.04980	0.05882	0.2227
490	0.18040	0.12300	0.06335	0.3100
384	0.26850	0.28660	0.09173	0.2736
281	0.08500	0.06735	0.08290	0.3101
325	0.12120	0.10200	0.05602	0.2688
190	0.93270	0.84880	0.17720	0.5166
380	0.24290	0.22470	0.13180	0.3343
366	0.34160	0.37030	0.21520	0.3271
469	0.28780	0.31860	0.14160	0.2660
225	0.15250	0.16320	0.10870	0.3062
271	0.15070	0.12750	0.08750	0.2733
547	0.22460	0.17830	0.08333	0.2691
550	0.07348	0.00000	0.00000	0.2458

492	0.23270	0.25440	0.14890	0.3251
185	0.10190	0.00692	0.01042	0.2933
306	0.13460	0.01120	0.02500	0.2651
208	0.44020	0.31620	0.11260	0.4128
242	0.48480	0.74360	0.12180	0.3308
313	0.16260	0.08324	0.04715	0.3390
542	0.13760	0.16110	0.10950	0.2722
514	0.21010	0.28660	0.11200	0.2282
236	0.41260	0.58200	0.25930	0.3103
113	0.20490	0.12950	0.06136	0.2383
527	0.20740	0.17910	0.10700	0.3110
76	0.13790	0.08539	0.07407	0.2710
162	0.38460	0.68100	0.22470	0.3643

worst fractal dimension	
512	0.11090
457	0.06788
439	0.06710
298	0.07676
37	0.06169
515	0.06783
382	0.09349
310	0.06958
538	0.09938
345	0.08488
421	0.09208
90	0.07246
412	0.09206
157	0.05972
89	0.08473
172	0.10100
318	0.10550
233	0.08328
389	0.07602
250	0.07849
31	0.14020
283	0.10630
482	0.09326
211	0.07993
372	0.08666
401	0.07262
159	0.07685
14	0.14310
364	0.07582
337	0.09870
..	...
500	0.08549
338	0.07664
427	0.07662
406	0.07012
96	0.07376
490	0.08203
384	0.07320
281	0.06688
325	0.06888
190	0.14460
380	0.09215
366	0.07632
469	0.09270
225	0.06072
271	0.08022
547	0.09479
550	0.06592
492	0.07625
185	0.07697
306	0.08385
208	0.10760
242	0.12970
313	0.07434
542	0.06956
514	0.06954
236	0.08677
113	0.09026
527	0.07592
76	0.07191
162	0.09223

[143 rows x 30 columns],	
293	1
332	1
565	0
278	1
489	0
346	1
357	1

355	1
112	1
68	1
526	1
206	1
65	0
437	1
126	0
429	1
392	0
343	0
334	1
440	1
441	0
137	1
230	0
7	0
408	0
523	1
361	1
553	1
478	1
303	1
	..
459	1
510	1
151	1
244	0
543	1
544	1
265	0
288	1
423	1
147	1
177	0
99	0
448	1
431	1
115	1
72	0
537	1
174	1
87	0
551	1
486	1
314	1
396	1
472	1
70	0
277	0
9	0
359	1
192	1
559	1
Name: target, dtype: int64,	
512	0
457	1
439	1
298	1
37	1
515	1
382	1
310	1
538	1
345	1
421	1
90	1
412	1
157	1
89	1
172	0
318	1
233	0
389	0
250	0
31	0
283	0
482	1
211	1
372	0
401	1
159	1
14	0
364	1
337	0

```

..
500 1
338 1
427 1
406 1
96 1
490 1
384 1
281 1
325 1
190 0
380 1
366 0
469 1
225 1
271 1
547 1
550 1
492 0
185 1
306 1
208 1
242 1
313 1
542 1
514 0
236 0
113 1
527 1
76 1
162 0
Name: target, dtype: int64)

```

Question 5

Using KNeighborsClassifier, fit a k-nearest neighbors (knn) classifier with X_train, y_train and using one nearest neighbor (n_neighbors = 1).

This function should return a sklearn.neighbors.classification.KNeighborsClassifier.

```

In [18]: def answer_five():
          X_train, X_test, y_train, y_test = answer_four()

          # Your code here

          knn = KNeighborsClassifier(n_neighbors=1).fit(X_train, y_train)

          return knn

answer_five()

```

```

Out[18]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                             metric_params=None, n_jobs=1, n_neighbors=1, p=2,
                             weights='uniform')

```

Question 6

Using your knn classifier, predict the class label using the mean value for each feature.

Hint: You can use cancerdf.mean()[:-1].values.reshape(1, -1) which gets the mean value for each feature, ignores the target column, and reshapes the data from 1 dimension to 2 (necessary for the predict method of KNeighborsClassifier).

This function should return a numpy array either array([0.]) or array([1.])

```

In [13]: def answer_six():
          cancerdf = answer_one()
          means = cancerdf.mean()[:-1].values.reshape(1, -1)
          knn = answer_five()

          # Your code here

          return knn.predict(means)

answer_six()

```

```

Out[13]: array([1])

```

Question 7

Using your knn classifier, predict the class labels for the test set X_test.

This function should return a numpy array with shape (143,) and values either 0.0 or 1.0.

```
In [14]: def answer_seven():
         X_train, X_test, y_train, y_test = answer_four()
         knn = answer_five()

         # Your code here

         return knn.predict(X_test)

answer_seven()
```

```
Out[14]: array([1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1,
               1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0,
               1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0,
               1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0,
               1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1,
               1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0,
               0, 1, 1, 1, 0])
```

Question 8

Find the score (mean accuracy) of your knn classifier using X_test and y_test.

This function should return a float between 0 and 1

```
In [15]: def answer_eight():
         X_train, X_test, y_train, y_test = answer_four()
         knn = answer_five()

         # Your code here

         return knn.score(X_test, y_test)

answer_eight()
```

```
Out[15]: 0.91608391608391604
```

Optional plot

Try using the plotting function below to visualize the differet prediction scores between training and test sets, as well as malignant and benign cells.

```
In [16]: def accuracy_plot():

    X_train, X_test, y_train, y_test = answer_four()

    # Find the training and testing accuracies by target value (i.e. malignant, benign)
    mal_train_X = X_train[y_train==0]
    mal_train_y = y_train[y_train==0]
    ben_train_X = X_train[y_train==1]
    ben_train_y = y_train[y_train==1]

    mal_test_X = X_test[y_test==0]
    mal_test_y = y_test[y_test==0]
    ben_test_X = X_test[y_test==1]
    ben_test_y = y_test[y_test==1]

    knn = answer_five()

    scores = [knn.score(mal_train_X, mal_train_y), knn.score(ben_train_X, ben_train_y),
              knn.score(mal_test_X, mal_test_y), knn.score(ben_test_X, ben_test_y)]

    plt.figure()

    # Plot the scores as a bar chart
    bars = plt.bar(np.arange(4), scores, color=['#EF4566', '#EF4566', '#55a868', '#55a868'])

    # directly label the score onto the bars
    for bar in bars:
        height = bar.get_height()
        plt.gca().text(bar.get_x() + bar.get_width()/2, height*.90, '{0:.1f}'.format(height, 2),
                        ha='center', color='w', fontsize=11)

    # remove all the ticks (both axes), and tick labels on the Y axis
    plt.tick_params(top='off', bottom='off', left='off', right='off', labelleft='off', labelbottom='on')

    # remove the frame of the chart
    for spine in plt.gca().spines.values():
        spine.set_visible(False)

    plt.xticks([0,1,2,3], ['Malignant\nTraining', 'Benign\nTraining', 'Malignant\nTest', 'Benign\nTest'], alpha=0.8);
    plt.title('Training and Test Accuracies for Malignant and Benign Cells', alpha=0.8)
```

Uncomment the plotting function to see the visualization.

Comment out the plotting function when submitting your notebook for grading.

```
In [17]: accuracy_plot()
```

Training and Test Accuracies for Malignant and Benign Cells

