*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) 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 [15]:

```
import numpy as np
import pandas as pd
from sklearn.datasets import load_breast_cancer

cancer = load_breast_cancer()

print(cancer.DESCR) # Print the data set description
```

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 (perimeter^2 / 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. Manga
sarian

:Donor: Nick Street

:Date: November, 1995

This is a copy of UCI ML Breast Cancer Wisconsin (Diagnostic) datase
ts.
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 Sympos
ium 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 d

```
iagnosis and
     prognosis via linear programming. Operations Research, 43(4), p
ages 570-577,
     July-August 1995.
   - W.H. Wolberg, W.N. Street, and O.L. Mangasarian. Machine learni
ng techniques
     to diagnose breast cancer from fine-needle aspirates. Cancer Le
tters 77 (1994)
     163-171.
```

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

In [16]:

```
cancer['data']
```

Out[16]:

```
array([[  1.79900000e+01,   1.03800000e+01,   1.22800000e+02, ...,
          2.65400000e-01,   4.60100000e-01,   1.18900000e-01],
       [  2.05700000e+01,   1.77700000e+01,   1.32900000e+02, ...,
          1.86000000e-01,   2.75000000e-01,   8.90200000e-02],
       [  1.96900000e+01,   2.12500000e+01,   1.30000000e+02, ...,
          2.43000000e-01,   3.61300000e-01,   8.75800000e-02],
       ...,
       [  1.66000000e+01,   2.80800000e+01,   1.08300000e+02, ...,
          1.41800000e-01,   2.21800000e-01,   7.82000000e-02],
       [  2.06000000e+01,   2.93300000e+01,   1.40100000e+02, ...,
          2.65000000e-01,   4.08700000e-01,   1.24000000e-01],
       [  7.76000000e+00,   2.45400000e+01,   4.79200000e+01, ...,
          0.00000000e+00,   2.87100000e-01,   7.03900000e-02]])
```

Question 0 (Example)

How many features does the breast cancer dataset have?

This function should return an integer.

In [17]:

```
# You should write your whole answer within the function provided. The autograde
r 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 a
utograder is expecting
    return len(cancer['feature_names'])

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

Out[17]:

```
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 [19]:

```
def answer_one():

    # Your code here
    cancer = load_breast_cancer()
    X = pd.DataFrame(data = cancer['data'],
                     columns = cancer['feature_names'])
    y = pd.DataFrame(data = cancer['target'],
                   columns = ['target'])
    df = pd.merge(X, y, how = 'inner', left_index = True, right_index = True)
    return df # Return your answer


answer_one()
```

Out[19]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concav points
0	17.990	10.38	122.80	1001.0	0.11840	0.27760	0.300100	0.14710
1	20.570	17.77	132.90	1326.0	0.08474	0.07864	0.086900	0.07017
2	19.690	21.25	130.00	1203.0	0.10960	0.15990	0.197400	0.12790
3	11.420	20.38	77.58	386.1	0.14250	0.28390	0.241400	0.10520
4	20.290	14.34	135.10	1297.0	0.10030	0.13280	0.198000	0.10430
5	12.450	15.70	82.57	477.1	0.12780	0.17000	0.157800	0.08089
6	18.250	19.98	119.60	1040.0	0.09463	0.10900	0.112700	0.07400
7	13.710	20.83	90.20	577.9	0.11890	0.16450	0.093660	0.05985
8	13.000	21.82	87.50	519.8	0.12730	0.19320	0.185900	0.09353
9	12.460	24.04	83.97	475.9	0.11860	0.23960	0.227300	0.08543
10	16.020	23.24	102.70	797.8	0.08206	0.06669	0.032990	0.03323
11	15.780	17.89	103.60	781.0	0.09710	0.12920	0.099540	0.06606
12	19.170	24.80	132.40	1123.0	0.09740	0.24580	0.206500	0.11180
13	15.850	23.95	103.70	782.7	0.08401	0.10020	0.099380	0.05364
14	13.730	22.61	93.60	578.3	0.11310	0.22930	0.212800	0.08025
15	14.540	27.54	96.73	658.8	0.11390	0.15950	0.163900	0.07364
16	14.680	20.13	94.74	684.5	0.09867	0.07200	0.073950	0.05259
17	16.130	20.68	108.10	798.8	0.11700	0.20220	0.172200	0.10280
18	19.810	22.15	130.00	1260.0	0.09831	0.10270	0.147900	0.09498
19	13.540	14.36	87.46	566.3	0.09779	0.08129	0.066640	0.04781
20	13.080	15.71	85.63	520.0	0.10750	0.12700	0.045680	0.03110
21	9.504	12.44	60.34	273.9	0.10240	0.06492	0.029560	0.02076
22	15.340	14.26	102.50	704.4	0.10730	0.21350	0.207700	0.09756
23	21.160	23.04	137.20	1404.0	0.09428	0.10220	0.109700	0.08632
24	16.650	21.38	110.00	904.6	0.11210	0.14570	0.152500	0.09170
25	17.140	16.40	116.00	912.7	0.11860	0.22760	0.222900	0.14010
26	14.580	21.53	97.41	644.8	0.10540	0.18680	0.142500	0.08783
27	18.610	20.25	122.10	1094.0	0.09440	0.10660	0.149000	0.07731
28	15.300	25.27	102.40	732.4	0.10820	0.16970	0.168300	0.08751
29	17.570	15.05	115.00	955.1	0.09847	0.11570	0.098750	0.07953
...	...	...	...	...	...	...	...	...
539	7.691	25.44	48.34	170.4	0.08668	0.11990	0.092520	0.01364

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concav points
540	11.540	14.44	74.65	402.9	0.09984	0.11200	0.067370	0.02594
541	14.470	24.99	95.81	656.4	0.08837	0.12300	0.100900	0.03890
542	14.740	25.42	94.70	668.6	0.08275	0.07214	0.041050	0.03027
543	13.210	28.06	84.88	538.4	0.08671	0.06877	0.029870	0.03275
544	13.870	20.70	89.77	584.8	0.09578	0.10180	0.036880	0.02369
545	13.620	23.23	87.19	573.2	0.09246	0.06747	0.029740	0.02443
546	10.320	16.35	65.31	324.9	0.09434	0.04994	0.010120	0.00549
547	10.260	16.58	65.85	320.8	0.08877	0.08066	0.043580	0.02438
548	9.683	19.34	61.05	285.7	0.08491	0.05030	0.023370	0.00961
549	10.820	24.21	68.89	361.6	0.08192	0.06602	0.015480	0.00816
550	10.860	21.48	68.51	360.5	0.07431	0.04227	0.000000	0.00000
551	11.130	22.44	71.49	378.4	0.09566	0.08194	0.048240	0.02257
552	12.770	29.43	81.35	507.9	0.08276	0.04234	0.019970	0.01499
553	9.333	21.94	59.01	264.0	0.09240	0.05605	0.039960	0.01282
554	12.880	28.92	82.50	514.3	0.08123	0.05824	0.061950	0.02343
555	10.290	27.61	65.67	321.4	0.09030	0.07658	0.059990	0.02738
556	10.160	19.59	64.73	311.7	0.10030	0.07504	0.005025	0.01116
557	9.423	27.88	59.26	271.3	0.08123	0.04971	0.000000	0.00000
558	14.590	22.68	96.39	657.1	0.08473	0.13300	0.102900	0.03736
559	11.510	23.93	74.52	403.5	0.09261	0.10210	0.111200	0.04105
560	14.050	27.15	91.38	600.4	0.09929	0.11260	0.044620	0.04304
561	11.200	29.37	70.67	386.0	0.07449	0.03558	0.000000	0.00000
562	15.220	30.62	103.40	716.9	0.10480	0.20870	0.255000	0.09429
563	20.920	25.09	143.00	1347.0	0.10990	0.22360	0.317400	0.14740
564	21.560	22.39	142.00	1479.0	0.11100	0.11590	0.243900	0.13890
565	20.130	28.25	131.20	1261.0	0.09780	0.10340	0.144000	0.09791
566	16.600	28.08	108.30	858.1	0.08455	0.10230	0.092510	0.05302
567	20.600	29.33	140.10	1265.0	0.11780	0.27700	0.351400	0.15200
568	7.760	24.54	47.92	181.0	0.05263	0.04362	0.000000	0.00000

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 [24]:

```
def answer_two():
    cancerdf = answer_one()

    # Your code here
    malignant = len(cancerdf[cancerdf['target'] == 0])
    benign = len(cancerdf[cancerdf['target'] == 1])

    class_dist = pd.Series(data = {'malignant': malignant, 'benign': benign}, in
dex = ['malignant', 'benign'])
    return class_dist# Return your answer


answer_two()
```

Out[24]:

```
malignant    212
benign       357
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 [26]:

```
def answer_three():
    cancerdf = answer_one()
    # Your code here
    X = cancerdf.drop('target', axis = 1)
    y = cancerdf['target']

    return X, y
#answer_three()
```

Out[26]:

```
(     mean radius  mean texture  mean perimeter  mean area  mean smo
othness  \
 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 sy
mmetry  \
 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  wors
t 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
11     0
12     0
13     0
14     0
15     0
16     0
17     0
18     0
19     1
20     1
21     1
22     0
23     0
24     0
25     0
26     0
27     0
28     0
29     0
      ..
539    1
540    1
541    1
542    1
543    1
544    1
545    1
546    1
547    1
548    1
549    1
```

```
550    1
551    1
552    1
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 [35]:

```python
from sklearn.model_selection import train_test_split

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) # from 01-03:k-NN classification lecture
    return X_train, X_test, y_train, y_test
#result = answer_four()
#for i in range (4):
    #print(result[i].shape)
```

```
(426, 30)
(143, 30)
(426,)
(143,)
```

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 [61]:

```
from sklearn.neighbors import KNeighborsClassifier

def answer_five():
    X_train, X_test, y_train, y_test = answer_four()

    # Your code here
    knn = KNeighborsClassifier(n_neighbors = 1)
    return knn.fit(X_train, y_train)# Return your answer
#answer_five()
```

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 precict method of KNeighborsClassifier).

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

In [41]:

```
def answer_six():
    cancerdf = answer_one()
    means = cancerdf.mean()[:-1].values.reshape(1, -1)

    # Your code here
    knn = answer_five()
    return knn.predict(means) # Return your answer
#answer_six()
```

Out[41]:

```
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 [60]:

```
def answer_seven():
    X_train, X_test, y_train, y_test = answer_four()
    knn = answer_five()

    # Your code here
    result = [int(knn.predict(x.values.reshape(1,30))) for idx, x in X_test.iter
rows()]
    return np.array(result) # Return your answer
#answer_seven()
```

Out[60]:

```
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, 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, 1, 1, 0, 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 [43]:

```
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) # Return your answer
answer_eight()
```

Out[43]:

```
0.916083916083916 04
```

Optional plot

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

In [62]:

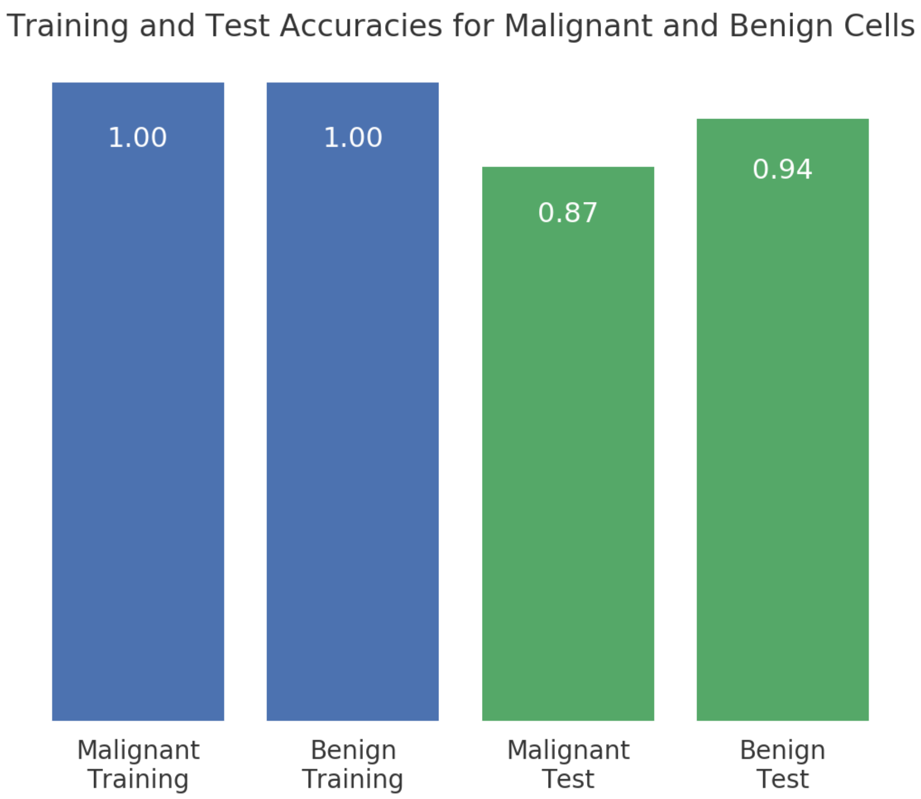
```
def accuracy_plot():
    import matplotlib.pyplot as plt

    %matplotlib notebook

    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_tr
ain_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=['#4c72b0','#4c72b0','#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:.{1}f}'.
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', alp
ha=0.8)
```

Uncomment the plotting function to see the visualization.

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

In [63]:

```
accuracy_plot()
```



In [ ]:

```

```