# Week08\_Cohort

December 10, 2021

# Week 8 Problem Set

```
In [3]: import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        import numpy as np
```

### 1.1 Cohort Sessions

504 0.10959

CS1. Reading Data: Read CSV file for Boston Housing prices.

- Task 1: Read the data set. Hint:
  - Pandas read\_csv
  - Boston's housing data set (filename: housing\_processed.csv):
  - Boston's housing data description.

```
In [4]: # Task 1
        # read CSV file, replace the None
        df = pd.read_csv("housing_processed.csv")
        ###
        ### YOUR CODE HERE
        ###
        display(df)
        CRIM
                ZN
                    INDUS
                            CHAS
                                    NOX
                                            RM
                                                  AGE
                                                          DIS
                                                               RAD
                                                                       TAX
     0.00632
                                 0.538 6.575
                                                 65.2
0
             18.0
                     2.31
                               0
                                                      4.0900
                                                                    296.0
                                                                 1
1
     0.02731
               0.0
                     7.07
                                 0.469
                                         6.421
                                                 78.9
                                                       4.9671
                                                                    242.0
2
                     7.07
     0.02729
               0.0
                               0
                                  0.469
                                         7.185
                                                 61.1
                                                       4.9671
                                                                    242.0
3
               0.0
                     2.18
                                  0.458
                                         6.998
     0.03237
                                                 45.8
                                                       6.0622
                                                                    222.0
4
     0.06905
               0.0
                     2.18
                                  0.458
                                         7.147
                                                 54.2
                                                       6.0622
                                                                    222.0
                       . . .
               . . .
                                    . . .
                                            . . .
                                                  . . .
                                                                       . . .
     0.06263
               0.0 11.93
                                  0.573 6.593
                                                       2.4786
                                                                    273.0
501
                               0
                                                 69.1
                                                                 1
     0.04527
               0.0 11.93
                               0 0.573 6.120
502
                                                 76.7
                                                       2.2875
                                                                 1 273.0
     0.06076
               0.0 11.93
                               0
                                0.573 6.976
                                                 91.0 2.1675
                                                                 1 273.0
503
               0.0 11.93
                               0 0.573 6.794 89.3 2.3889
                                                                 1 273.0
```

```
505 0.04741 0.0 11.93
                           0 0.573 6.030 80.8 2.5050 1 273.0
    PTRATIO
                  B LSTAT MEDV
0
        15.3 396.90
                      4.98 24.0
1
        17.8 396.90
                      9.14 21.6
2
        17.8 392.83
                      4.03 34.7
3
        18.7 394.63
                     2.94 33.4
4
        18.7 396.90
                     5.33 36.2
               . . .
                       . . .
                            . . .
        . . .
       21.0 391.99
                     9.67 22.4
501
502
       21.0 396.90
                     9.08 20.6
       21.0 396.90
                      5.64 23.9
503
        21.0 393.45
                      6.48 22.0
504
505
        21.0 396.90
                     7.88 11.9
[506 rows x 14 columns]
In [5]: assert isinstance(df, pd.DataFrame)
        assert df.shape == (506, 14)
        assert df.columns[0] == 'CRIM' and df.columns[-1] == 'MEDV'
  • Task 2: Display the number of rows and columns. Hint:
       - you can use df. shape to get the number of rows and columns
In [6]: # Task 2
        # get the shape from the data frame, replace the None
        shape = df.shape
        # use the 'shape' variable to get the row and the column
        # replace the None
        row = shape[0]
        col = shape[1]
        ###
        ### YOUR CODE HERE
        ###
        print(shape)
       print(row, col)
(506, 14)
506 14
In [7]: assert shape == (506, 14)
        assert row == 506
        assert col == 14
```

- Task 3: Display the name of all the columns. Hint:
  - you can use df.columns to get the name of all the columns
  - check the meaning of each column using the link above

- Task 4: Do the following:
  - Create a subset data set containing only the following columns: "RM", "DIS", "INDUS" for the features. Make sure it is of pd.DataFrame type.
  - Create a subset data set containing only "MEDV" for the target. Make sure it is of pd.DataFrame type.

```
R.M
               DIS INDUS
0
     6.575 4.0900
                     2.31
     6.421 4.9671
1
                     7.07
2
    7.185 4.9671
                    7.07
3
     6.998 6.0622
                     2.18
4
    7.147 6.0622
                     2.18
. .
       . . .
               . . .
                     . . .
501
    6.593 2.4786
                   11.93
502 6.120 2.2875 11.93
503 6.976 2.1675 11.93
504 6.794 2.3889 11.93
505 6.030 2.5050 11.93
[506 rows x 3 columns]
    MEDV
0
     24.0
1
     21.6
2
     34.7
3
     33.4
4
     36.2
     . . .
501 22.4
502 20.6
503 23.9
504 22.0
505 11.9
[506 rows x 1 columns]
In []:
In [11]: assert isinstance(df_feature, pd.DataFrame)
         assert isinstance(df_target, pd.DataFrame)
         assert df_feature.shape == (506, 3)
         assert df_target.shape == (506, 1)
         assert np.all(df_feature.columns == pd.Index(['RM', 'DIS', 'INDUS']))
         assert df_target.columns == pd.Index(['MEDV'])
  CS2. Data Frame Operation:
  Reference: - Indexing and Selecting Data
  Create separate and new data frame for the columns: "RM", "DIS", "INDUS", "MEDV" that
```

• Task 1: All records with weighted distances to ve Boston employment centers between 0 to 3.

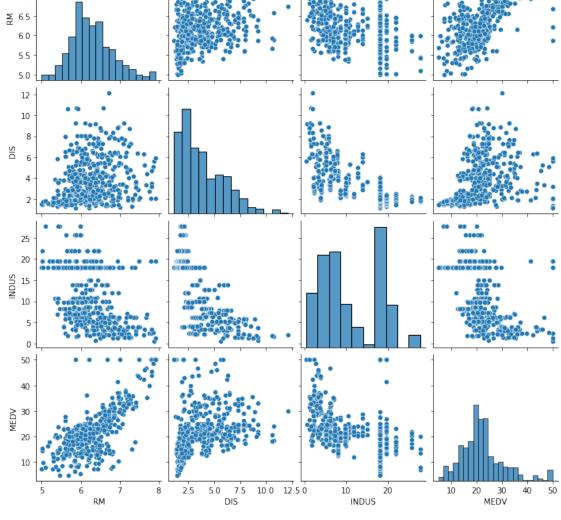
satisfies each of the following condition:

```
In [12]: # specify the columns of interest, replace the None
          columns = ["RM", "DIS", "INDUS", "MEDV"]
          # use conditions for row selector and column selector
          # replace the None
          df_1 = df[columns]
          ###
          ### YOUR CODE HERE
          ###
          myplot = sns.pairplot(data=df_1)
        8
      ₩ 6
       5
       12
       10
     SIO 6
       25
       20
     SOUN 15
10
       0
       50
       40
       30
       20
       10
                                   5.0 7.5
DIS
                                                                             30
MEDV
                               2.5
                                          10.0 12.5 0
                                                                       10
```

• Task 2: All records with average number of room between 5 to 8.

INDUS

```
In [13]: # specify the columns of interest, replace the None
         columns = ["RM", "DIS", "INDUS", "MEDV"]
         \# use conditions for row selector and column selector
         # replace the None
         df_2 = df.loc[(df['RM'] \le 8) & (df['RM'] \ge 5), columns]
         ###
         ### YOUR CODE HERE
         ###
         myplot = sns.pairplot(data=df_2)
      8.0
      7.5
      7.0
     ₹ 6.5
      6.0
      5.5
       12
       10
```



In [14]: df.loc[:15,:]

```
Out [14]:
                CRIM
                        ZN
                            INDUS CHAS
                                           NOX
                                                   RM
                                                         AGE
                                                                 DIS
                                                                      RAD
                                                                             TAX \
             0.00632
                             2.31
                                               6.575
                                                             4.0900
                                                                           296.0
        0
                     18.0
                                      0
                                        0.538
                                                        65.2
                                                                        1
                             7.07
         1
             0.02731
                       0.0
                                      0
                                        0.469
                                               6.421
                                                        78.9
                                                             4.9671
                                                                        2
                                                                           242.0
         2
             0.02729
                       0.0
                             7.07
                                      0
                                         0.469
                                               7.185
                                                        61.1
                                                              4.9671
                                                                        2
                                                                           242.0
             0.03237
                             2.18
                                         0.458
                                               6.998
                                                              6.0622
                                                                           222.0
         3
                       0.0
                                                        45.8
                                                                        3
         4
             0.06905
                             2.18
                                        0.458
                                               7.147
                                                        54.2
                                                              6.0622
                                                                           222.0
                       0.0
                                                                        3
         5
             0.02985
                       0.0
                             2.18
                                        0.458
                                               6.430
                                                        58.7
                                                              6.0622
                                                                        3
                                                                           222.0
        6
             0.08829
                      12.5
                             7.87
                                         0.524 6.012
                                                        66.6
                                                              5.5605
                                                                        5
                                                                           311.0
        7
             0.14455
                      12.5
                             7.87
                                        0.524 6.172
                                                        96.1 5.9505
                                                                           311.0
                                      0
                                                                        5
        8
             0.21124
                     12.5
                             7.87
                                      0 0.524 5.631
                                                       100.0
                                                              6.0821
                                                                        5
                                                                           311.0
             0.17004
                     12.5
                             7.87
                                      0 0.524 6.004
                                                        85.9
        9
                                                              6.5921
                                                                        5
                                                                           311.0
            0.22489
                      12.5
                             7.87
                                      0 0.524 6.377
                                                        94.3
                                                              6.3467
                                                                        5
                                                                           311.0
         10
            0.11747
                                        0.524 6.009
                      12.5
                             7.87
                                                        82.9
                                                              6.2267
                                                                           311.0
         11
                                                                        5
            0.09378
                             7.87
                                      0 0.524 5.889
                                                        39.0 5.4509
                                                                           311.0
         12
                      12.5
                                                                        5
                                        0.538 5.949
                                                                           307.0
        13
            0.62976
                      0.0
                             8.14
                                                        61.8 4.7075
                                                                        4
         14
            0.63796
                      0.0
                             8.14
                                      0 0.538 6.096
                                                        84.5 4.4619
                                                                        4 307.0
         15
            0.62739
                      0.0
                             8.14
                                      0 0.538 5.834
                                                        56.5 4.4986
                                                                           307.0
                             LSTAT MEDV
            PTRATIO
                           В
        0
                15.3
                     396.90
                               4.98
                                    24.0
        1
                17.8
                      396.90
                               9.14 21.6
        2
                17.8 392.83
                               4.03 34.7
         3
                18.7
                      394.63
                               2.94 33.4
         4
                18.7
                      396.90
                               5.33 36.2
        5
                18.7
                     394.12
                               5.21 28.7
         6
                15.2
                     395.60
                              12.43 22.9
        7
                15.2
                     396.90
                              19.15 27.1
        8
                15.2
                     386.63
                              29.93
                                    16.5
                15.2
        9
                     386.71
                              17.10 18.9
         10
                15.2 392.52
                              20.45 15.0
         11
                15.2 396.90
                              13.27
                                    18.9
         12
                15.2 390.50
                              15.71 21.7
         13
                21.0 396.90
                               8.26 20.4
         14
                21.0 380.02
                              10.26
                                    18.2
                21.0 395.62
                               8.47 19.9
         15
  • Task 3: The first 15 records in the table.
In [15]: # specify the columns of interest, replace the None
         columns = ["RM", "DIS", "INDUS", "MEDV"]
         # use conditions for row selector and column selector
         # replace the None
        df_3 = df.iloc[:15,:]
         ###
```

### YOUR CODE HERE

###

### display(df\_3)

```
INDUS
                                                  AGE
                                                                       TAX \
       CRIM
                           CHAS
                                   NOX
                                            RM
                                                          DIS
                                                               RAD
0
    0.00632
             18.0
                     2.31
                              0
                                 0.538
                                        6.575
                                                 65.2
                                                       4.0900
                                                                     296.0
                                                                  1
1
    0.02731
              0.0
                    7.07
                                 0.469
                                        6.421
                                                 78.9
                                                       4.9671
                                                                  2
                                                                     242.0
                    7.07
2
    0.02729
              0.0
                                 0.469
                                        7.185
                                                 61.1
                                                       4.9671
                                                                  2
                                                                     242.0
3
    0.03237
              0.0
                    2.18
                                 0.458
                                        6.998
                                                       6.0622
                                                                     222.0
                                                 45.8
                                                                  3
                              0
4
    0.06905
              0.0
                    2.18
                                 0.458
                                        7.147
                                                 54.2
                                                       6.0622
                                                                     222.0
                                                                  3
    0.02985
                                 0.458
                                        6.430
                                                                     222.0
5
              0.0
                    2.18
                                                 58.7
                                                       6.0622
                                                                  3
6
    0.08829
             12.5
                    7.87
                                 0.524
                                        6.012
                                                 66.6
                                                       5.5605
                                                                     311.0
7
                    7.87
                              0 0.524
                                        6.172
                                                 96.1
                                                                     311.0
    0.14455
             12.5
                                                       5.9505
8
    0.21124
             12.5
                    7.87
                                 0.524
                                        5.631
                                                100.0
                                                       6.0821
                                                                  5
                                                                     311.0
    0.17004
                    7.87
                              0 0.524
9
             12.5
                                        6.004
                                                 85.9
                                                       6.5921
                                                                  5
                                                                     311.0
10 0.22489
             12.5
                    7.87
                              0 0.524
                                        6.377
                                                 94.3
                                                       6.3467
                                                                  5
                                                                     311.0
   0.11747
             12.5
                    7.87
                              0 0.524
                                        6.009
                                                 82.9
                                                       6.2267
                                                                  5
                                                                     311.0
11
12 0.09378
             12.5
                    7.87
                              0 0.524
                                        5.889
                                                       5.4509
                                                                     311.0
                                                 39.0
                              0 0.538
13 0.62976
              0.0
                    8.14
                                        5.949
                                                 61.8
                                                       4.7075
                                                                     307.0
14 0.63796
              0.0
                    8.14
                              0 0.538
                                        6.096
                                                 84.5 4.4619
                                                                  4 307.0
                     LSTAT
                             MEDV
    PTRATIO
                  В
0
       15.3
             396.90
                       4.98
                             24.0
1
       17.8
             396.90
                       9.14
                             21.6
2
       17.8
             392.83
                       4.03
                             34.7
3
       18.7
             394.63
                       2.94
                             33.4
                       5.33
4
       18.7
             396.90
                             36.2
5
                       5.21
       18.7
             394.12
                             28.7
6
       15.2
             395.60
                      12.43
                             22.9
7
       15.2
             396.90
                      19.15
                             27.1
8
       15.2
             386.63
                      29.93
                             16.5
9
                      17.10
       15.2
             386.71
                             18.9
10
       15.2
             392.52
                      20.45
                             15.0
       15.2
             396.90
11
                      13.27
                             18.9
       15.2
             390.50
12
                      15.71
                             21.7
13
       21.0
             396.90
                       8.26
                             20.4
       21.0
             380.02 10.26
14
                             18.2
```

#### • Task 4: The last 15 records in the table.

```
###
         ### YOUR CODE HERE
         ###
         display(df_4)
        CRIM
                    INDUS
                           CHAS
                                    NOX
                                             RM
                                                  AGE
                                                           DIS
                                                                RAD
                                                                        TAX \
                ZN
     0.10574
                    27.74
                                                 98.8
                                                                     711.0
491
               0.0
                                  0.609
                                         5.983
                                                        1.8681
                                                                  4
                               0
492
     0.11132
                    27.74
                                  0.609
                                          5.983
                                                 83.5
                                                        2.1099
                                                                      711.0
               0.0
     0.17331
                                                                      391.0
493
               0.0
                     9.69
                                  0.585
                                          5.707
                                                 54.0
                                                        2.3817
                                                                   6
494
     0.27957
               0.0
                     9.69
                                  0.585
                                          5.926
                                                 42.6
                                                        2.3817
                                                                      391.0
                                                                      391.0
495
     0.17899
              0.0
                     9.69
                                  0.585
                                          5.670
                                                 28.8
                                                        2.7986
                                                                  6
496
     0.28960
              0.0
                     9.69
                                  0.585
                                          5.390
                                                 72.9
                                                        2.7986
                                                                  6
                                                                      391.0
497
     0.26838
              0.0
                     9.69
                                  0.585
                                          5.794
                                                 70.6
                                                        2.8927
                                                                  6
                                                                     391.0
     0.23912
                     9.69
                                  0.585
                                          6.019
                                                 65.3
                                                                     391.0
498
              0.0
                               0
                                                        2.4091
                                                                  6
499
     0.17783
              0.0
                     9.69
                                  0.585
                                          5.569
                                                 73.5
                                                        2.3999
                                                                   6
                                                                     391.0
     0.22438
                     9.69
                                          6.027
                                                                     391.0
500
              0.0
                                  0.585
                                                 79.7
                                                        2.4982
501
     0.06263
              0.0
                    11.93
                                  0.573
                                          6.593
                                                 69.1
                                                        2.4786
                                                                     273.0
502
     0.04527
              0.0
                    11.93
                                  0.573
                                          6.120
                                                 76.7
                                                        2.2875
                                                                   1
                                                                      273.0
503
     0.06076
              0.0
                    11.93
                                  0.573
                                          6.976
                                                 91.0
                                                        2.1675
                                                                     273.0
                                                                   1
     0.10959
                    11.93
                                  0.573
                                          6.794
                                                 89.3
                                                                     273.0
504
              0.0
                               0
                                                        2.3889
                                                                   1
505
     0.04741
              0.0
                    11.93
                                  0.573
                                         6.030
                                                 80.8
                                                        2.5050
                                                                   1
                                                                      273.0
     PTRATIO
                    В
                       LSTAT
                               MEDV
               390.11
                       18.07
491
        20.1
                               13.6
492
        20.1
               396.90
                       13.35
                               20.1
                       12.01
493
        19.2
               396.90
                               21.8
494
        19.2
               396.90
                       13.59
                               24.5
495
        19.2
               393.29
                       17.60
                               23.1
496
        19.2
               396.90
                       21.14
                               19.7
497
        19.2
              396.90
                       14.10
                               18.3
498
        19.2
               396.90
                       12.92
                               21.2
499
        19.2
               395.77
                       15.10
                               17.5
500
        19.2
               396.90
                       14.33
                               16.8
501
        21.0
               391.99
                        9.67
                               22.4
        21.0
               396.90
                        9.08
502
                               20.6
503
        21.0
               396.90
                        5.64
                               23.9
                        6.48
                               22.0
504
        21.0
              393.45
505
        21.0
               396.90
                        7.88
                               11.9
   • Task 5: All records with even index numbers, i.e. index 0, 2, 4, ...
In [17]: # specify the columns of interest, replace the None
         columns = ["RM", "DIS", "INDUS", "MEDV"]
```

# use conditions for row selector and column selector

# replace the None

```
df_5 = df.loc[df.index%2==0,:]
          # or df.loc[::2,columns]
          ###
          ### YOUR CODE HERE
          ###
          display(df_5)
        CRIM
                 ZN
                      INDUS
                              CHAS
                                       NOX
                                                RM
                                                      AGE
                                                                DIS
                                                                     RAD
                                                                             TAX
                                                                                 \
     0.00632
                                    0.538
                                                      65.2
                                                                           296.0
0
               18.0
                       2.31
                                 0
                                            6.575
                                                            4.0900
                                                                       1
2
     0.02729
                0.0
                       7.07
                                 0
                                    0.469
                                            7.185
                                                      61.1
                                                            4.9671
                                                                       2
                                                                           242.0
4
     0.06905
                0.0
                                                      54.2
                                                                       3
                       2.18
                                 0
                                    0.458
                                            7.147
                                                            6.0622
                                                                           222.0
6
     0.08829
               12.5
                                    0.524
                                            6.012
                                                                       5
                       7.87
                                 0
                                                      66.6
                                                            5.5605
                                                                           311.0
8
     0.21124
               12.5
                       7.87
                                 0
                                    0.524
                                            5.631
                                                    100.0
                                                            6.0821
                                                                       5
                                                                           311.0
          . . .
                . . .
                         . . .
                                       . . .
                                               . . .
                                                       . . .
                                                                . . .
                                                                             . . .
. .
                               . . .
                                                                     . . .
496
     0.28960
                0.0
                       9.69
                                 0
                                    0.585
                                            5.390
                                                      72.9
                                                            2.7986
                                                                       6
                                                                           391.0
498
     0.23912
                0.0
                       9.69
                                 0
                                    0.585
                                            6.019
                                                      65.3
                                                            2.4091
                                                                       6
                                                                           391.0
     0.22438
500
                0.0
                       9.69
                                 0
                                    0.585
                                            6.027
                                                      79.7
                                                            2.4982
                                                                       6
                                                                           391.0
     0.04527
                0.0
                                 0
                                    0.573
                                            6.120
502
                      11.93
                                                      76.7
                                                            2.2875
                                                                       1
                                                                           273.0
504
     0.10959
                0.0
                      11.93
                                 0
                                    0.573
                                            6.794
                                                      89.3
                                                           2.3889
                                                                           273.0
                                                                       1
     PTRATIO
                     В
                        LSTAT
                                MEDV
               396.90
                         4.98
0
         15.3
                                24.0
2
         17.8
               392.83
                         4.03
                                34.7
                         5.33
4
         18.7
               396.90
                                36.2
6
         15.2
               395.60
                        12.43
                                22.9
8
         15.2
               386.63
                        29.93
                                16.5
. .
          . . .
                   . . .
                           . . .
496
         19.2
               396.90
                        21.14
                                19.7
                        12.92
498
         19.2
               396.90
                                21.2
500
         19.2
               396.90
                        14.33
                                16.8
502
         21.0
               396.90
                         9.08
                                20.6
504
         21.0
               393.45
                         6.48 22.0
```

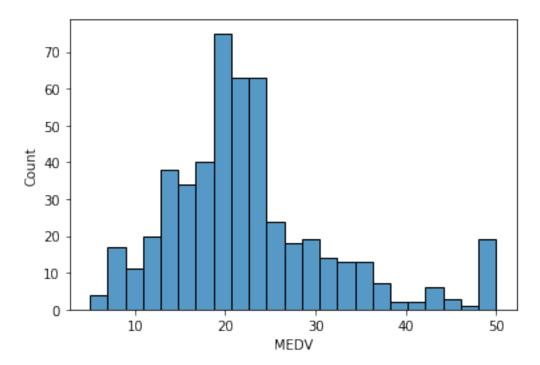
[253 rows x 14 columns]

**CS3.** *Histogram and Box plot:* Plot the histogram for the median value in \$1000 for the Boston's housing price.

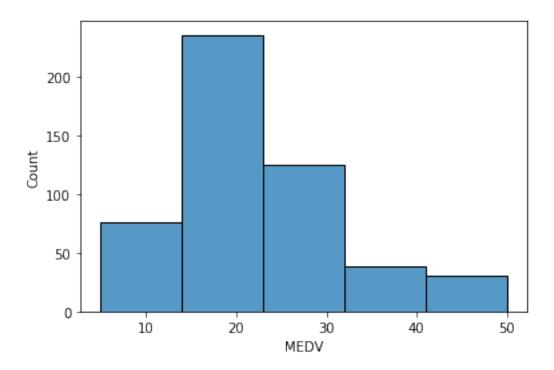
Reference: - Histogram - Box plot

• Task 1: Plot the histogram with default bin values.

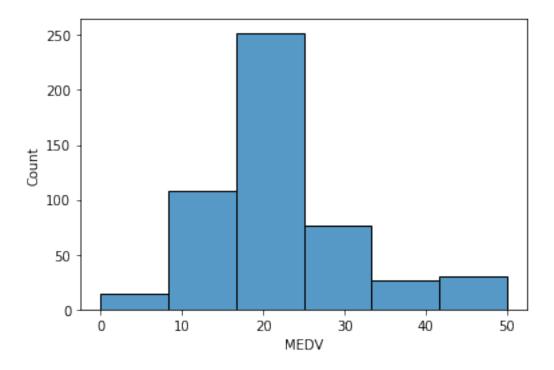
```
# set the y label, write the code below
###
### YOUR CODE HERE
###
```



# • Task 2: Plot the histogram with 5 bins only. Hint:



• Task 3: Plot the histogram with the following bin edges 0, 10, 20, 30, 40, 50.

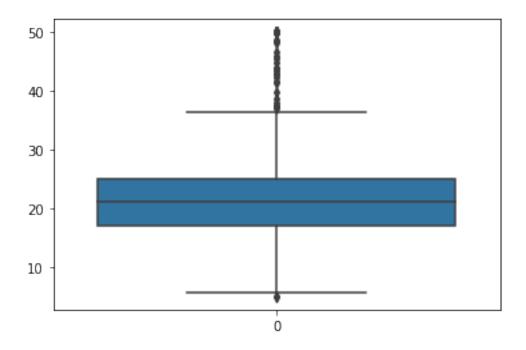


• Task 4: Plot the same data using a box plot in a horizontal manner.

```
In [21]: # plot boxplot for MEDV, replace the None
    myplot = sns.boxplot(data = df['MEDV'])

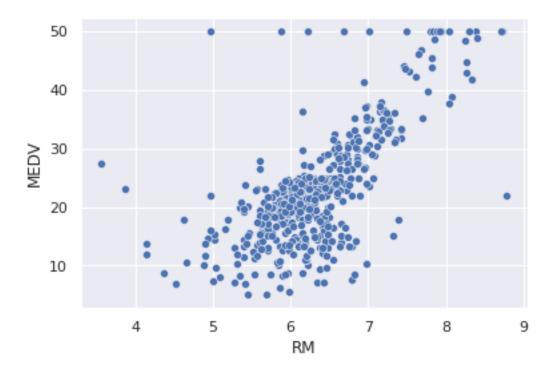
# set the x label, write the code below

###
### YOUR CODE HERE
###
```

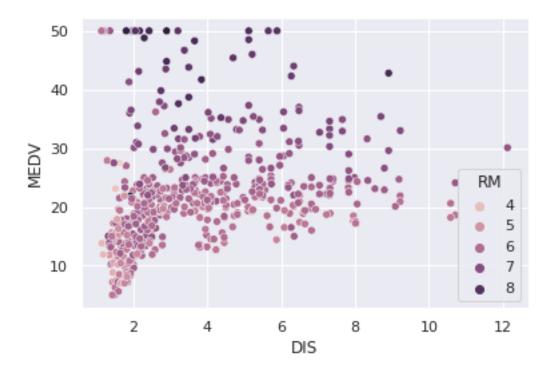


**CS4.** *Scatter plot:* Do the following plots.

- Task 1: Display scatter plot of "RM" versus "MEDV". Hint:
  - Use Seaborn default theme instead of matplotlib
  - Seaborn scatter plot
  - Use "RM" as x data
  - Use "MEDV" as y data



• Task 2: Display a scatter plot "weighted distances to ve Boston employment centers" versus "Median value of owner-occupied homes in \$1000s". Use average number of rooms per dwelling as the hue data.



• Task 3: Display a scatter plot "proportion of non-retail business acres per town" versus "Median value of owner-occupied homes in \$1000s". Use "proportion of residential land zoned for lots over 25,000 sq.ft." as the hue data.



Answer the following: - How many columns are there? - How many rows are there? - What are the names of the columns - What is the range of the median value in \$1000 when the average number of room per dwelling is 8? - What's the relationship between distance to five Boston's employment centres and the median value in \$1000? - What's the relationship between the proportion of non-retail business acres per town adn the median value in \$1000?

**CS5.** *Standardization:* Write a function that takes in data frame where all the column are the features and normalize each column according to the following formula.

$$normalized = \frac{data - \mu}{\sigma}$$

where  $\mu$  is the mean of the data and  $\sigma$  is the standard deviation of the data. **You need to normalize for each column respectively**. The function should return a new data frame.

Use the following functions from Pandas: - df.mean(axis=0): This is to calculate the mean along the index axis. - df.std(axis=0): This is to calculate the standard deviation along the index axis.

Note: Your function should be able to handle a numpy array as well as Panda's data frame. *Hint: use axis=0 argument when calculating mean and standard deviation.* 

```
display(stats)
         assert np.isclose(stats.loc["mean", "RM"], 0.0) and \
               np.isclose(stats.loc["std", "RM"], 1.0, atol=1e-3)
         assert np.isclose(stats.loc["mean", "DIS"], 0.0) and \
               np.isclose(stats.loc["std", "DIS"], 1.0, atol=1e-3)
        assert np.isclose(stats.loc["mean", "INDUS"], 0.0) and \
               np.isclose(stats.loc["std", "INDUS"], 1.0, atol=1e-3)
                              DIS
                                          INDUS
count 5.060000e+02 5.060000e+02 5.060000e+02
mean -1.148313e-14 7.161597e-16 -3.145486e-15
      1.000000e+00 1.000000e+00 1.000000e+00
std
     -3.876413e+00 -1.265817e+00 -1.556302e+00
min
25%
     -5.680681e-01 -8.048913e-01 -8.668328e-01
50%
     -1.083583e-01 -2.790473e-01 -2.108898e-01
75%
      4.822906e-01 6.617161e-01 1.014995e+00
       3.551530e+00 3.956602e+00 2.420170e+00
max
```

**CS6.** Splitting Data Randomly: Create a function to split the Data Frame randomly. The function should have the following arguments: - df\_feature: which is the data frame for the features. - df\_target: which is the data frame for the target. - random\_state: which is the seed used to split randomly. - test\_size: which is the fraction for the test data set (0 to 1), by default is set to 0.5

The output of the function is a tuple of four items: -df\_feature\_train: which is the train set for the features data frame -df\_feature\_test: which is the test set for the features data frame -df\_target\_train: which is the train set for the target data frame -df\_target\_test: which is the test set for the target data frame

```
In [ ]: df_feature_train, df_feature_test, df_target_train, df_target_test = split_data(df_feature_test)
        display(df_feature_train.describe())
        display(df_feature_test.describe())
        display(df_target_train.describe())
        display(df_target_test.describe())
        assert np.all(df_feature_train.count() == 355)
        assert np.all(df_feature_test.count() == 151)
        assert np.all(df_target_train.count() == 355)
        assert np.all(df_target_test.count() == 151)
        assert np.isclose(df_feature_train["RM"].mean(), 6.2968)
        assert np.isclose(df_feature_test["DIS"].std(), 2.2369)
        assert np.isclose(df_target_train["MEDV"].median(), 21.40)
        assert np.isclose(df_target_test["MEDV"].median(), 20.90)
In [ ]: df_feature_train.count()
In []:
```

# Week08\_Homework

December 10, 2021

## 1 Week 8 Problem Set

### 1.1 Homeworks

```
In [4]: import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns
    import numpy as np
```

**HW1.** Breast Cancer Data: Read Breast Cancer data using Pandas library: - **Task 1:** Read the file: breast\_cancer\_data.csv: - Download the CSV file - Read Description of Data - use comma "," as field separator - use "utf-8" as encoding field

```
In [5]: # Task 1
        # Read file, replace the None
        df = pd.read_csv("breast_cancer_data.csv", sep=",", encoding="utf-8")
        ###
        ### YOUR CODE HERE
        display(df)
           id diagnosis radius_mean texture_mean perimeter_mean area_mean
0
       842302
                      Μ
                                17.99
                                               10.38
                                                               122.80
                                                                           1001.0
1
       842517
                      Μ
                                20.57
                                               17.77
                                                               132.90
                                                                          1326.0
2
     84300903
                      М
                                19.69
                                               21.25
                                                               130.00
                                                                          1203.0
3
     84348301
                       Μ
                                11.42
                                               20.38
                                                               77.58
                                                                           386.1
4
                                20.29
                                               14.34
                                                                          1297.0
     84358402
                      Μ
                                                               135.10
                                                 . . .
                                                                  . . .
                                                                              . . .
564
       926424
                       М
                                21.56
                                               22.39
                                                               142.00
                                                                          1479.0
565
       926682
                      Μ
                                20.13
                                               28.25
                                                               131.20
                                                                          1261.0
566
       926954
                      Μ
                                16.60
                                               28.08
                                                               108.30
                                                                           858.1
       927241
                                20.60
                                               29.33
                                                               140.10
                                                                          1265.0
567
                      М
568
        92751
                       В
                                 7.76
                                               24.54
                                                                47.92
                                                                           181.0
     smoothness_mean compactness_mean concavity_mean concave points_mean \
             0.11840
                                0.27760
                                                 0.30010
                                                                       0.14710
0
             0.08474
                                                                       0.07017
1
                                0.07864
                                                 0.08690
```

2	0.10960	0.15990	0.19740		0.12790
3	0.14250	0.28390	0.24140		0.10520
4	0.10030	0.13280	0.19800		0.10430
	•••				
564	0.11100	0.11590	0.24390		0.13890
565	0.09780	0.11030	0.14400		0.09791
566	0.08455	0.10230	0.09251		0.05302
567	0.11780	0.27700	0.35140		0.15200
568	0.05263	0.04362	0.00000		0.00000
					\
0		exture_worst pe		area_worst	\
0	25.380	17.33	184.60	2019.0	
1	24.990	23.41	158.80	1956.0	
2	23.570	25.53	152.50	1709.0	
3	14.910	26.50	98.87	567.7	
4	22.540	16.67	152.20	1575.0	
• •	•••	• • •	• • •	• • •	
564	25.450	26.40	166.10	2027.0	
565	23.690	38.25	155.00	1731.0	
566	18.980	34.12	126.70	1124.0	
567	25.740	39.42	184.60	1821.0	
568	9.456	30.37	59.16	268.6	
		npactness_worst	· · · · · · · · · · · · · · · · · · ·		
0	0.16220	0.66560	0.71	19	
1	0.12380	0.18660	0.24	16	
2	0.14440	0.42450	0.45	04	
3	0.20980	0.86630	0.68	69	
4	0.13740	0.20500	0.40	00	
564	0.14100	0.21130	0.41	07	
565	0.11660	0.19220	0.32	15	
566	0.11390	0.30940	0.34		
567	0.16500	0.86810	0.93		
568	0.08996	0.06444	0.00		
000	0.0000	0.00111	0.00		
	concave points_worst	symmetry_worst	fractal_dime	nsion worst	
0	0.2654	0.4601	_	0.11890	
1	0.1860	0.2750		0.08902	
2	0.2430	0.3613		0.08758	
3	0.2575			0.17300	
		0.6638			
4	0.1625	0.2364	:	0.07678	
 E <i>G</i> 4	0.0016	0.0060		0.07115	
564	0.2216	0.2060		0.07115	
565	0.1628	0.2572		0.06637	
566	0.1418	0.2218		0.07820	
567	0.2650	0.4087		0.12400	
568	0.0000	0.2871		0.07039	

```
[569 rows x 32 columns]
```

```
In [6]: assert isinstance(df, pd.DataFrame)
        assert df.shape == (569, 32)
        assert df.columns[0] == 'id' and df.columns[-1] == 'fractal_dimension_worst'
  • Task 2: Find the number of rows and columns.
In [7]: # Task 2
        # get the shape
        shape = df.shape
        # get rows and columns from shape
        row = shape[0]
        col = shape[1]
        ###
        ### YOUR CODE HERE
        ###
In [8]: assert shape == (569, 32)
        assert row == 569
        assert col == 32
  • Task 3: Find the name of all the columns.
In [9]: # Task 3
        # display the name of all the columns
        names = df.columns
        ###
        ### YOUR CODE HERE
        ###
        print(names)
Index(['id', 'diagnosis', 'radius_mean', 'texture_mean', 'perimeter_mean',
       'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_mean',
       'concave points_mean', 'symmetry_mean', 'fractal_dimension_mean',
       'radius_se', 'texture_se', 'perimeter_se', 'area_se', 'smoothness_se',
       'compactness_se', 'concavity_se', 'concave points_se', 'symmetry_se',
       'fractal_dimension_se', 'radius_worst', 'texture_worst',
       'perimeter_worst', 'area_worst', 'smoothness_worst',
       'compactness_worst', 'concavity_worst', 'concave points_worst',
```

'symmetry\_worst', 'fractal\_dimension\_worst'],

dtype='object')

```
In [10]: assert isinstance(names, pd.Index)
    assert np.all(names == pd.Index(['id', 'diagnosis', 'radius_mean', 'texture_mean', 'posterior 'poster
```

- Task 4: Create a subset data set containing only the following features:
  - 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)
  - concavity (severity of concave portions of the contour)

# Make sure the data type is pd.DataFrame.

```
In [11]: # Task 4
         # set the name of the columnbs for the subset of data
         columns = ['radius_mean','texture_mean','perimeter_mean','area_mean','smoothness_mean
         # extract the columns, replace the None
         df_features = df.loc[:,columns]
         ###
         ### YOUR CODE HERE
         ###
         df_features
Out [11]:
              radius mean
                            texture mean perimeter mean
                                                            area mean smoothness mean \
                                                                                0.11840
         0
                     17.99
                                   10.38
                                                   122.80
                                                               1001.0
         1
                    20.57
                                   17.77
                                                   132.90
                                                               1326.0
                                                                                0.08474
         2
                    19.69
                                   21.25
                                                   130.00
                                                               1203.0
                                                                                0.10960
         3
                    11.42
                                   20.38
                                                    77.58
                                                                386.1
                                                                                0.14250
         4
                     20.29
                                   14.34
                                                               1297.0
                                                   135.10
                                                                                0.10030
                    21.56
                                   22.39
                                                   142.00
                                                               1479.0
         564
                                                                                0.11100
         565
                    20.13
                                   28.25
                                                   131.20
                                                               1261.0
                                                                                0.09780
                                   28.08
         566
                     16.60
                                                   108.30
                                                                858.1
                                                                                0.08455
         567
                     20.60
                                   29.33
                                                   140.10
                                                               1265.0
                                                                                0.11780
                                                                                0.05263
         568
                     7.76
                                   24.54
                                                    47.92
                                                                181.0
```

concavity\_mean

```
0
                      0.30010
                      0.08690
         1
         2
                      0.19740
         3
                      0.24140
         4
                      0.19800
                           . . .
         564
                      0.24390
         565
                      0.14400
         566
                      0.09251
         567
                      0.35140
         568
                      0.00000
         [569 rows x 6 columns]
In [12]: assert isinstance(df_features, pd.DataFrame)
         assert df_features.columns[0] == 'radius_mean'
         assert df_features.columns[-1] == 'concavity_mean'
         assert df_features.shape == (569, 6)
   • Task 5: Create a subset data set containing only the target from the column "diagnosis".
   Make sure the data type is pd.DataFrame.
In [13]: #5.
         # extract target
```

```
df_target = df[["diagnosis"]]
         ###
         ### YOUR CODE HERE
         ###
         df_target
Out[13]:
             diagnosis
         0
         1
                     М
         2
         3
                     M
         4
                     Μ
         564
                      Μ
         565
                      Μ
         566
                      М
         567
                      Μ
         568
                      В
         [569 rows x 1 columns]
In [14]: assert isinstance(df_target, pd.DataFrame)
         assert df_target.shape == (569, 1)
         assert df_target.columns[0] == 'diagnosis'
```

- Task 6: Create a new Data Frame from the column "diagnosis", called "diagnosis\_int" which is the integer representation of the column diagnosis. Copy the column into the original data frame so that it has a copy.
  - if the value in "diagnosis" column is "M", the value in the column "diagnosis\_int" should be set to 1
  - otherwise, it should be set to 0

Hint: use .apply() method.

```
In [15]: # Task 6
    # creating diagnosis_int
    df_target["diagnosis_int"] = df_target["diagnosis"].apply(lambda x : 1 if x == "M" ele
    # or we can use this instead
    # df.loc[:,"diagnosis_int"] = 1

# copy the new column into the original data frame
    df["diagnosis_int"] = df_target["diagnosis_int"]

###
    ### YOUR CODE HERE
    ###

    display(df_target)
    display(df["diagnosis_int"])

/usr/lib/python3.7/site-packages/ipykernel_launcher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row_indexer,col_indexer] = value instead
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/ This is separate from the ipykernel package so we can avoid doing imports until

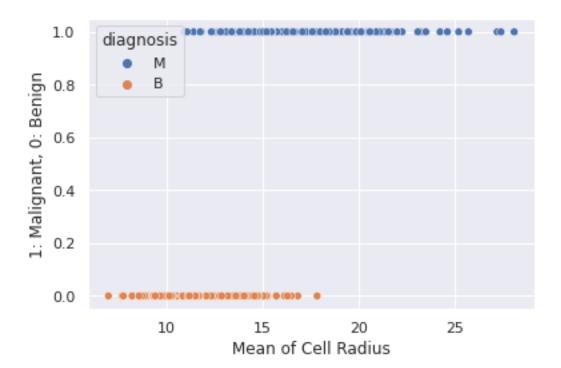
	diagnosis	diagnosis_int
0	M	1
1	M	1
2	M	1
3	M	1
4	M	1
564	M	1
565	M	1
566	M	1
567	M	1
568	В	0

[569 rows x 2 columns]

```
1
                       1
2
                       1
3
                       1
4
                       1
564
                      1
565
566
                       1
567
                       1
568
Name: diagnosis_int, Length: 569, dtype: int64
In [16]: assert isinstance(df_target, pd.DataFrame) and isinstance(df, pd.DataFrame)
                              assert df_target.shape == (569, 2)
                             assert np.all(df_target.columns == ["diagnosis", "diagnosis_int"])
                              assert "diagnosis_int" in df.columns
         • Task 7: Use scatter plot to see the relationship between "radius_mean" and "diagnosis_int".
                       - Use the "diagnosis" column as the hue for the scatter plot.
                       - Label the x axis as "Mean of Cell Radius"
                      - Label the y axis as "1: Malignant, 0: Benign"
In [17]: # Task 7
                              # set the default theme to use Seaborn
                             sns.set()
                              # display using scatter plot
                             myplot = sns.scatterplot(data = df, x = "radius_mean",y= "diagnosis_int",hue = "dia
                             myplot.set(xlabel="Mean of Cell Radius", ylabel = "1: Malignant, 0: Benign")
Out[17]: [Text(0.5, 0, 'Mean of Cell Radius'), Text(0, 0.5, '1: Malignant, 0: Benign')]
```

0

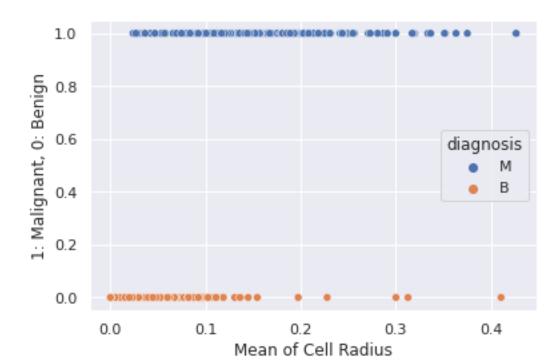
1



```
In [18]: df["radius_mean"]
Out[18]: 0
                 17.99
                 20.57
         1
         2
                 19.69
         3
                 11.42
                 20.29
                 . . .
                 21.56
         564
         565
                 20.13
         566
                 16.60
                 20.60
         567
         568
                  7.76
         Name: radius_mean, Length: 569, dtype: float64
```

- Task 8: Use scatter plot to see the relationship between "concavity\_mean" and "diagnosis\_int".
  - Use the "diagnosis" column as the hue for the scatter plot.
  - Label the x axis as "Mean of Cell Concavity"
  - Label the y axis as "1: Malignant, 0: Benign"

```
# display using scatter plot
myplot = sns.scatterplot(data = df, x = "concavity_mean",y= "diagnosis_int",hue = df[
myplot.set(xlabel="Mean of Cell Radius", ylabel = "1: Malignant, 0: Benign")
Out[19]: [Text(0.5, 0, 'Mean of Cell Radius'), Text(0, 0.5, '1: Malignant, 0: Benign')]
```



**HW2.** Count Plot: Create a function to count how many records are diagnosed as Malignant and Benign. The function should return a tuple: (n\_malignant, n\_benign), where n\_malignant is the number of records diagnosed as Malignant cell and n\_benign is the number of records diagnosed as Benign.

Use Count plot to verify the answer.

Reference: - Count Plot

```
In [21]: result = count_cell(df_target["diagnosis"])
         assert result == (212, 357)
In [22]: result
Out [22]: (212, 357)
In [23]: # write the code to plot the count of the two classes
         myplot = sns.countplot(x="diagnosis",data = df)
         ###
         ### YOUR CODE HERE
         ###
           350
           300
           250
       count
           200
           150
           100
            50
             0
                                                             В
                               М
```

**HW3.** *Normalization:* Create a function that takes in Data Frame as the input and returns the normalized Data Frame as the output. **Each column** is normalized separately using **min-max normalization**. The function should return a new data frame instead of modifying the input data frame.

diagnosis

$$normalized = \frac{data - min}{max - min}$$

Use the following functions from Pandas or Numpy: -df.copy(): This is to create a new copy of the data frame. -df.min(axis=0): This is to get the minimum along the index axis. -df.max(axis=0): This is to get the maximum along the index axis.

Note: Your function should be able to handle a numpy array as well as Panda's data frame.

```
In [1]: def normalize_minmax(dfin):
            dfout = (dfin - dfin.min(axis=0))/(dfin.max(axis=0)-dfin.min(axis=0))
            return dfout
In [2]: data_norm = normalize_minmax(df_features.to_numpy())
        assert data_norm[:,0].max() == 1.0 and \
               data_norm[:,0].min() == 0 and \
               np.isclose(data_norm[:,0].mean(), 0.338222)
        assert data norm[:,1].max() == 1.0 and \
               data_norm[:,1].min() == 0 and\
               np.isclose(data norm[:,1].mean(), 0.323965)
        NameError
                                                   Traceback (most recent call last)
        <ipython-input-2-c65c2397dfc5> in <module>
    ---> 1 data_norm = normalize_minmax(df_features.to_numpy())
          2 assert data_norm[:,0].max() == 1.0 and \setminus
                   data norm[:,0].min() == 0 and \
                   np.isclose(data_norm[:,0].mean(), 0.338222)
          5 assert data_norm[:,1].max() == 1.0 and \
        NameError: name 'df_features' is not defined
In [26]: data_norm = normalize_minmax(df_features)
         stats = data_norm.describe()
         display(stats)
         assert stats.loc["max", "radius_mean"] == 1.0 and \
                stats.loc["min", "radius_mean"] == 0 and \
                np.isclose(stats.loc["mean", "radius_mean"], 0.338222)
         assert stats.loc["max", "texture_mean"] == 1.0 and \
                stats.loc["min", "texture_mean"] == 0 and\
                np.isclose(stats.loc["mean", "texture_mean"], 0.323965)
       radius_mean
                    texture_mean perimeter_mean
                                                    area_mean
                                                               smoothness_mean
        569.000000
                      569.000000
                                      569.000000
                                                                    569.000000
count
                                                   569.000000
          0.338222
                        0.323965
                                        0.332935
                                                     0.216920
                                                                      0.394785
mean
                                        0.167915
                                                     0.149274
std
          0.166787
                        0.145453
                                                                      0.126967
min
          0.000000
                        0.000000
                                        0.000000
                                                     0.000000
                                                                      0.000000
25%
          0.223342
                                        0.216847
                                                     0.117413
                        0.218465
                                                                      0.304595
50%
          0.302381
                        0.308759
                                        0.293345
                                                     0.172895
                                                                      0.390358
75%
          0.416442
                        0.408860
                                        0.416765
                                                     0.271135
                                                                      0.475490
          1.000000
                        1.000000
                                        1.000000
                                                     1.000000
                                                                      1.000000
max
```

```
concavity_mean
           569.000000
count
             0.208058
mean
std
             0.186785
             0.000000
min
25%
             0.069260
50%
             0.144189
75%
             0.306232
max
             1.000000
In [27]: data_norm = normalize_minmax(df_features.to_numpy())
         assert data_norm[:,0].max() == 1.0 and \
                data norm[:,0].min() == 0 and 
                np.isclose(data_norm[:,0].mean(), 0.338222)
         assert data norm[:,1].max() == 1.0 and \
                data_norm[:,1].min() == 0 and\
                np.isclose(data_norm[:,1].mean(), 0.323965)
```

**HW4.** Splitting the Data: Use the function to split the breast cancer data set into a training data set and a testing data set. Use random\_state=100 and test\_size=0.3 and the normalized features data set from the previous exercise.

```
In [31]: def split_data(df_feature, df_target, random_state=None, test_size=0.5):
             np.random.seed(random state)
             N = df_feature.shape[0]
             print(N)
             sample = int(test_size*N)
             train_idx = np.random.choice(N, N-sample,replace=False)
             df_feature_train = df_feature.iloc[train_idx]
             df_target_train = df_target.iloc[train_idx]
             test_idx = [idx for idx in range(N) if idx not in train_idx]
             print(len(test_idx))
             df_feature_test = df_feature.iloc[test_idx]
             df_target_test = df_target.iloc[test_idx]
             return df_feature_train, df_feature_test, df_target_train, df_target_test
In [35]: # call normalize_minmax() to normalize df_features
         data_norm = data_norm = normalize_minmax(df_features)
         ###
         ### YOUR CODE HERE
```

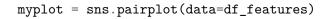
```
###
         # call split_data() with seed of 100 and test size of 30%
         datasets_tupple = split_data(data_norm, df_target, 100, 0.3)
         ###
         ### YOUR CODE HERE
         ###
569
170
In [36]: df_features_train = datasets_tupple[0]
         df_features_test = datasets_tupple[1]
         df_target_train = datasets_tupple[2]
         df_target_test = datasets_tupple[3]
         display(df_features_train.describe())
         display(df_features_test.describe())
         display(df_target_train.describe())
         display(df_target_test.describe())
       radius mean
                     texture_mean
                                   perimeter_mean
                                                      area mean
                                                                 smoothness mean
        399.000000
                       399.000000
                                        399.000000
                                                     399.000000
                                                                       399.000000
count
          0.333567
                         0.324109
                                          0.328153
                                                       0.212882
                                                                         0.388423
mean
                                                                         0.124730
std
          0.163565
                         0.146559
                                          0.164450
                                                       0.145811
min
          0.000000
                         0.00000
                                          0.000000
                                                       0.000000
                                                                         0.089194
25%
          0.219319
                         0.225059
                                          0.213358
                                                       0.114125
                                                                         0.299675
                                                                         0.379706
50%
          0.294335
                         0.308083
                                          0.289545
                                                       0.167508
75%
          0.406503
                         0.405140
                                          0.408127
                                                       0.258494
                                                                         0.467365
                                                       1.000000
                                                                         0.811321
          0.967343
                         1.000000
                                          0.988943
max
       concavity_mean
count
           399.000000
              0.205096
mean
              0.187089
std
min
              0.000000
25%
              0.065628
50%
              0.138051
75%
              0.288308
max
              0.999063
       radius_mean
                     texture_mean
                                   perimeter_mean
                                                      area_mean
                                                                 smoothness_mean
        170.000000
                       170.000000
                                        170.000000
                                                     170.000000
                                                                       170.000000
count
mean
          0.349148
                         0.323627
                                          0.344158
                                                       0.226399
                                                                         0.409716
          0.174122
                         0.143249
                                          0.175766
                                                                         0.131232
std
                                                       0.157139
          0.036869
                         0.022658
                                          0.028540
                                                                         0.00000
                                                       0.015907
min
```

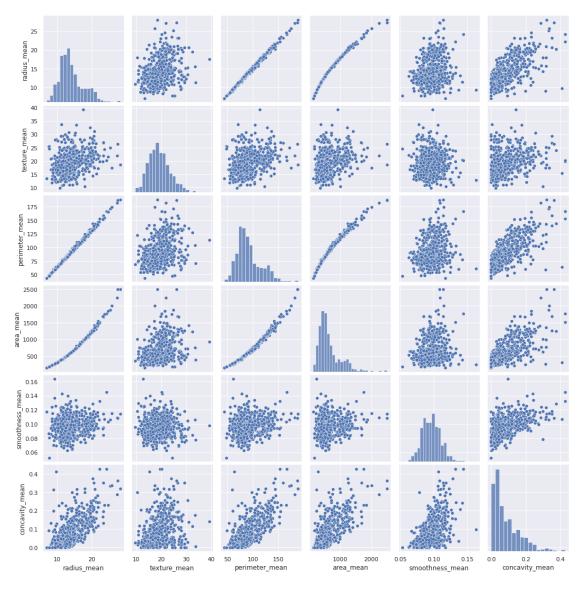
```
25%
          0.238251
                         0.206713
                                          0.232292
                                                      0.127126
                                                                        0.312336
50%
          0.317526
                         0.310112
                                          0.306060
                                                      0.183351
                                                                        0.406157
          0.437385
                                                      0.283372
                                                                        0.487000
75%
                         0.411989
                                          0.445443
          1.000000
                         0.815015
                                          1.000000
                                                      0.999152
                                                                        1.000000
max
       concavity_mean
           170.000000
count
mean
             0.215012
std
             0.186435
             0.000000
min
25%
             0.080325
50%
             0.155155
75%
             0.315194
             1.000000
max
       diagnosis_int
          399.000000
count
mean
            0.353383
std
            0.478621
            0.00000
min
25%
            0.000000
50%
            0.00000
75%
            1.000000
            1.000000
max
       diagnosis_int
          170.000000
count
            0.417647
mean
std
            0.494628
min
            0.00000
25%
            0.00000
50%
            0.00000
75%
            1.000000
            1.000000
max
In [ ]: assert isinstance(df_features_train, pd.DataFrame)
        assert isinstance(df_features_test, pd.DataFrame)
        assert isinstance(df target train, pd.DataFrame)
        assert isinstance(df_target_test, pd.DataFrame)
        assert df features train.shape == (399, 6)
        assert df_features_test.shape == (170, 6)
        assert df_target_train.shape == (399, 2)
        assert df_target_test.shape == (170, 2)
```

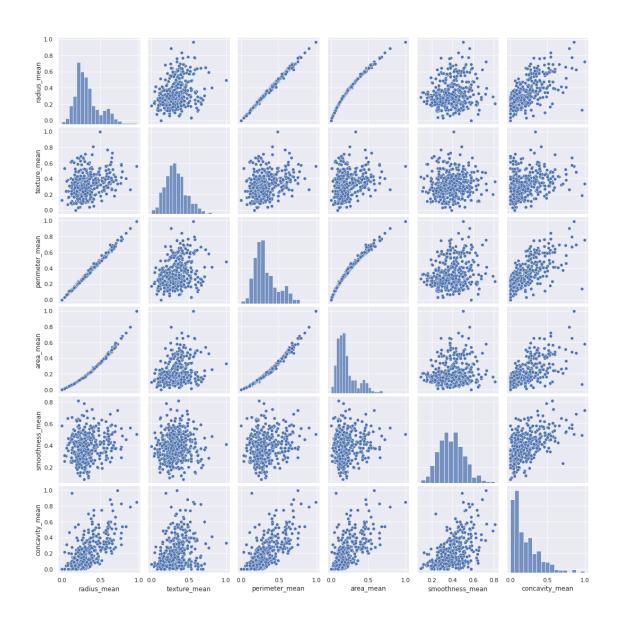
```
assert np.isclose(df_features_train.mean().mean(), 0.29844) assert np.isclose(df_features_test.mean().mean(), 0.311966) assert np.isclose(df_target_train.mean().mean(), 0.358396) assert np.isclose(df_target_test.mean().mean(), 0.40588)
```

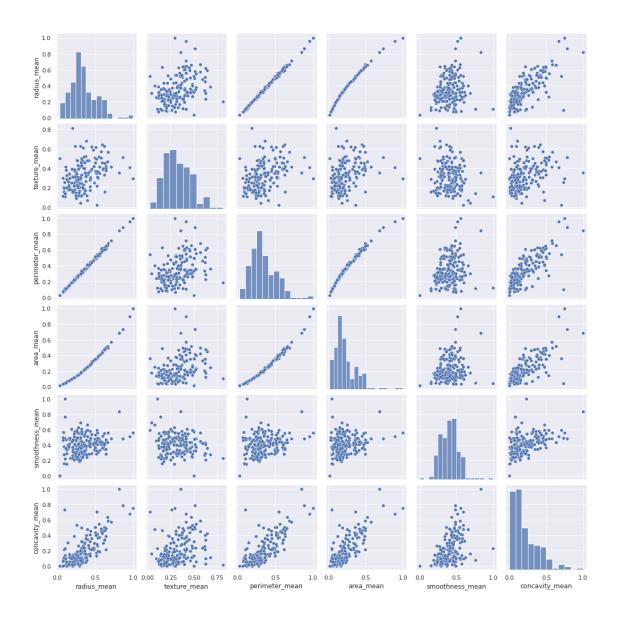
**HW5.** *Pair Plot:* Use pair plot to find out the relationship between different columns in df\_features. Ensure that similar relationship exists in both the training and the test datasets.

In [37]: # write your code below to plot for  $df_f$ eatures









In []:

## Week09\_Cohort

December 10, 2021

### 1 Week 9 Problem Set

#### 1.1 Cohort Session

```
In [54]: import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns
```

**CS0.** *Plot:* Read data for Boston Housing Prices and write a function get\_features\_targets() to get the columns for the features and the targets from the input argument data frame. The function should take in Pandas' dataframe and two lists. The first list is for the feature names and the other list is for the target names.

We will use the following columns for our test cases: - x data: RM column - use z normalization (standardization) - y data: MEDV column

Make sure you return a new data frame for both the features and the targets.

We will normalize the feature using z normalization. Plot the data using scatter plot.

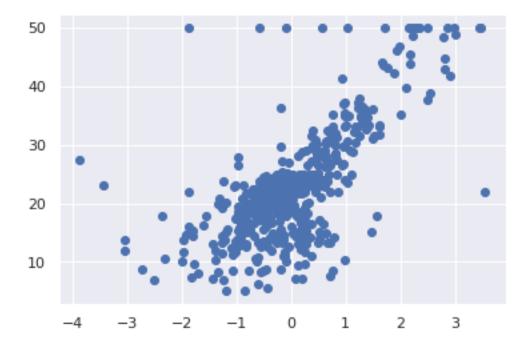
```
In [55]: def normalize_z(dfin):
             dfout = (dfin - dfin.mean(axis=0))/dfin.std(axis=0)
             return dfout
In [56]: def get_features_targets(df, feature_names, target_names):
             df_feature = df[feature_names]
             df_target = df[target_names]
             return df_feature, df_target
In [57]: df = pd.read_csv("housing_processed.csv")
         df_feature, df_target = get_features_targets(df,["RM"],["MEDV"])
         df_feature = normalize_z(df_feature)
         assert isinstance(df_feature, pd.DataFrame)
         assert isinstance(df_target, pd.DataFrame)
         assert np.isclose(df_feature.mean(), 0.0)
         assert np.isclose(df_feature.std(), 1.0)
         assert np.isclose(df_target.mean(), 22.532806)
         assert np.isclose(df target.std(), 9.1971)
```

```
In [58]: ###

### AUTOGRADER TEST - DO NOT REMOVE

###
```

Out[59]: <matplotlib.collections.PathCollection at 0x7f32aa631690>



**CS1.** *Cost Function:* Write a function compute\_cost() to compute the cost function of a linear regression model. The function should take in two 2-D numpy arrays. The first one is the matrix of the linear equation and the second one is the actual target value.

Recall that:

$$J(\hat{\beta}_0, \hat{\beta}_1) = \frac{1}{2m} \sum_{i=1}^{m} (\hat{y}(x^i) - y^i)^2$$

where

$$\hat{y}(x^i) = \hat{\beta}_0 + \hat{\beta}_1 x^i$$

The function should receive a numpy array, so we will need to convert to numpy array and change the shape. To do this, we will create two other functions: - prepare\_feature(df): which takes in a data frame for the feature. The function should convert the data frame to a numpy array and change it into a column vector. The function should also add a column of constant 1s in the first column. - prepare\_target(df): which takes in a data frame for the target. The function should simply convert the data frame to a numpy array and change it into column vectors. The function should be able to handle if the data frame has more than one column.

You can use the following methods in your code: -df.to\_numpy(): which is to convert a Pandas data frame to Numpy array. -np.reshape(row, col): which is to reshape the numpy array to a particular shape. -np.concatenate((array1, array2), axis): which is to join a sequence of arrays along an existing axis. -np.matmul(array1, array2): which is to do matrix multiplication on two Numpy arrays.

```
In [60]: def compute_cost(X, y, beta):
             m = X.shape[0]
             y_pred = np.matmul(X,beta)
             error = y_pred - y
             # Matrix multiplcation does both sum and square
             J = (1/(2*m))*np.matmul(error.T,error)
             return J[0][0] # Extract a scalar value from the 1 x 1 matrix
In [61]: def prepare_feature(df_feature):
            n = df_feature.shape[0]
             ones = np.ones(n).reshape(n,1)
             return np.concatenate((ones,df_feature.to_numpy()),axis = 1)
         # # df_feature is a 506 rows x 1 columns dataframe that gives the average number of r
         # # Column of constants 1 is on the left
         # # Column on the right is the feature data
         # # This function is to get the hypothesis matrix which is an 506 x 2 matrix
         # def prepare_feature(df_feature):
         #
               cols = len(df_target.columns)
               feature = df_feature.to_numpy().reshape(-1, cols)
              ones = np.ones((feature.shape[0],1))
               X = np.concatenate((ones, feature), axis=1)
               X = np.concatenate((np.ones((feature.shape[0], 1)), feature), axis=1)
         # #
               return X
In [62]: # def prepare_target(df_feature):
               return df_feature.to_numpy()
         # Converts a dataframe to a numpy array
         # One shape dimension can be -1. In this case, the value is inferred from the length
         def prepare_target(df_target):
             cols = len(df_target.columns)
             target = df_target.to_numpy().reshape(-1, cols)
             return target
In [63]: X = prepare_feature(df_feature)
         target = prepare_target(df_target)
         assert isinstance(X, np.ndarray)
         assert isinstance(target, np.ndarray)
```

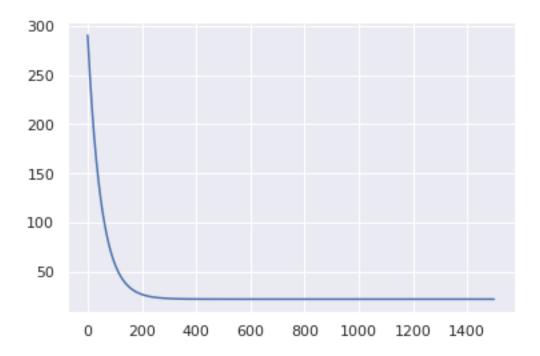
```
assert X.shape == (506, 2)
         assert target.shape == (506, 1)
In [64]: ###
         ### AUTOGRADER TEST - DO NOT REMOVE
         ###
In [65]: # print(X)
         beta = np.zeros((2,1))
         J = compute_cost(X, target, beta)
         print(J)
         assert np.isclose(J, 296.0735)
         beta = np.ones((2,1))
         J = compute_cost(X, target, beta)
         print(J)
         assert np.isclose(J, 268.157)
         beta = np.array([-1, 2]).reshape((2,1))
         J = compute_cost(X, target, beta)
         print(J)
         assert np.isclose(J, 308.337)
296.07345849802374
268.1570051486897
308.33699448710274
In [66]: ###
         ### AUTOGRADER TEST - DO NOT REMOVE
         ###
In [67]: bx = beta.transpose()
In [68]: bx.shape
Out[68]: (1, 2)
```

CS2. Gradient Descent: Write a function called gradient\_descent() that takes in these parameters: - X: is a 2-D numpy array for the features - y: is a vector array for the target - beta: is a column vector for the initial guess of the parameters - alpha: is the learning rate - num\_iters: is the number of iteration to perform

The function should return two numpy arrays: - beta: is coefficient at the end of the iteration - J\_storage: is the array that stores the cost value at each iteration

You can use some of the following functions: -np.matmul(array1, array2): which is to do matrix multiplication on two Numpy arrays. -compute\_cost(): which the function you created in the previous problem set to compute the cost.

```
In [69]: # 1. guess beta
         # 2. Decide direction
         # 3. updadte beta
         def gradient_descent(X, y, beta, alpha, num_iters):
             m = X.shape[0]
             J_storage = np.zeros(num_iters)
             for i in range(num_iters):
                 yp = np.matmul(X,beta)
                 error = yp - y
                 beta = beta - (alpha/m) * np.matmul(X.T,error)
                   beta = beta - (alpha/m)*np.matmul(X.T,np.matmul(X,beta)-y)
         #
                 cost = compute_cost(X,y,beta)
                   print(cost)
         #
                 J_storage[i] = cost
                   print(J_storage[i])
             return beta, J_storage
In [70]: iterations = 1500
         alpha = 0.01
         beta = np.zeros((2,1))
         beta, J_storage = gradient_descent(X, target, beta, alpha, iterations)
         print(beta)
         assert np.isclose(beta[0], 22.5328)
         assert np.isclose(beta[1], 6.3953)
[[22.53279993]
 [ 6.39529594]]
In [71]: ###
         ### AUTOGRADER TEST - DO NOT REMOVE
         ###
In [72]: plt.plot(J_storage)
Out[72]: [<matplotlib.lines.Line2D at 0x7f32aa5b5310>]
```



CS3. Predict: Write two functions predict() and predict\_norm() that calculate the straight line equation given the features and its coefficient. - predict(): this function should standardize the feature using z normalization, change it to a Numpy array, and add a column of constant 1s. You should use prepare\_feature() for this purpose. Lastly, this function should also call predict\_norm() to get the predicted y values. - predict\_norm(): this function should calculate the straight line equation after standardization and adding of column for constant 1.

You can use some of the following functions: -np.matmul(array1, array2): which is to do matrix multiplication on two Numpy arrays. -normalize\_z(df): which is to do z normalization on the data frame.

```
pred = predict(df_feature, beta)

assert isinstance(pred, np.ndarray)
assert pred.shape == (506, 1)
assert np.isclose(pred.mean(), 22.5328)
assert np.isclose(pred.std(), 6.38897)

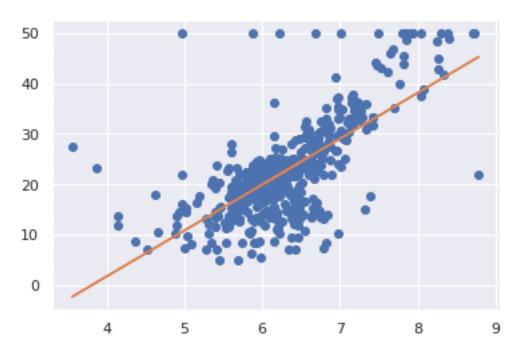
In [76]: df_feature, buf = get_features_targets(df, ["RM"], [])
beta = [[22.53279993], [6.39529594]] # from previous result
df_feature.shape

Out[76]: (506, 1)

In [77]: ###
### AUTOGRADER TEST - DO NOT REMOVE
###

In [78]: plt.plot(df_feature["RM"],target,'o')
plt.plot(df_feature["RM"],pred,'-')

Out[78]: [<matplotlib.lines.Line2D at 0x7f32aa53b710>]
```

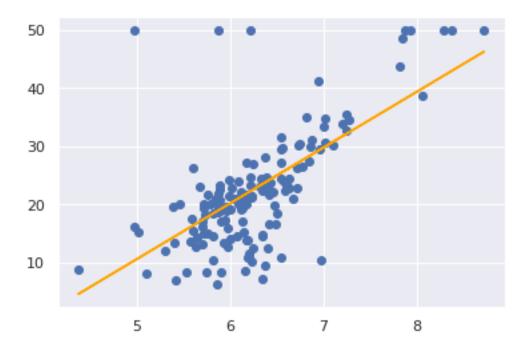


CS4. Splitting data: Do the following tasks: - Read RM as the feature and MEDV as the target from the data frame. - Use Week 9's function split\_data() to split the data into train and test using random\_state=100 and test\_size=0.3. - Normalize and prepare the features and the target. - Use the training data set and call gradient\_descent() to obtain the theta. - Use the test data set to get the predicted values.

You need to replace the None in the code below with other a function call or any other Python expressions.

```
In [97]: # def split_data(df_feature, df_target, random_state=None, test_size=0.5):
               np.random.seed(random_state)
               N = df_feature.shape[0]
         #
         #
               sample = int(test\_size*N)
         #
               train_idx = np.random.choice(N, N-sample, replace=False)
         #
               df\_feature\_train = df\_feature.iloc[train\_idx]
               df_target_train = df_target.iloc[train_idx]
               test_idx = [idx for idx in range(N) if idx not in train_idx]
         #
         #
               df_feature_test = df_feature.iloc[test_idx]
               df_target_test = df_target.iloc[test_idx]
               return df_feature_train, df_feature_test, df_target_train, df_target_test
         def split_data(df_feature, df_target, random_state=None, test_size=0.5):
             np.random.seed(random_state)
             TestSize = int(test_size*len(df_feature))
             testchoice = np.random.choice(len(df_feature), size = TestSize, replace = False)
               print(TestSize)
               print(testchoice)
             remainder = []
             for i in df_feature.index:
                 if i not in testchoice:
                     remainder.append(i)
               print(remainder)
             trainchoice = np.random.choice(remainder, size = len(remainder),replace = False)
               print(list(trainchoice))
             df_feature_train = df_feature.iloc[trainchoice]
             df_target_train = df_target.iloc[trainchoice]
             df_feature_test = df_feature.iloc[testchoice]
             df_target_test = df_target.iloc[testchoice]
             return df_feature_train, df_feature_test, df_target_train, df_target_test
In [98]: # get features and targets from data frame
         df_feature, df_target = get_features_targets(df,["RM"],["MEDV"])
         # split the data into training and test data sets
         df_feature_train, df_feature_test, df_target_train, df_target_test = split_data(df_feature_test)
         # normalize the feature using z normalization
```

```
df_feature_train_z = normalize_z(df_feature_train)
         X = prepare_feature(df_feature_train_z) # concatenating for the y intercept
         target = prepare_target(df_target_train)
         iterations = 1500
         alpha = 0.01
         beta = np.zeros((2,1)) #[0,0]
         # call the gradient_descent function
         beta, J_storage = gradient_descent(X, target, beta, alpha, iterations)
         # call the predict method to get the predicted values
         df_feature_test_z = normalize_z(df_feature_test)
         pred = predict(df_feature_test_z,beta)
         print(beta)
         ###
         ### YOUR CODE HERE
         ###
[[22.66816258]
 [ 6.27808747]]
In [99]: J_storage
Out[99]: array([290.6613454 , 285.26808904, 279.98213717, ..., 19.58945173,
                 19.58945173, 19.58945173])
In [100]: assert isinstance(pred, np.ndarray)
          assert pred.shape == (151, 1)
          assert np.isclose(pred.mean(), 22.66816)
          assert np.isclose(pred.std(), 6.257265)
In [101]: ###
          ### AUTOGRADER TEST - DO NOT REMOVE
          ###
In [102]: plt.scatter(df_feature_test, df_target_test)
          plt.plot(df_feature_test, pred, color="orange")
Out[102]: [<matplotlib.lines.Line2D at 0x7f32aa4c7d10>]
```



**CS5.** *R2 Coefficient of Determination:* Write a function to calculate the coefficient of determination as given by the following equations.

$$r^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

where

$$SS_{res} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

where  $y_i$  is the actual target value and  $\hat{y}_i$  is the predicted target value.

$$SS_{tot} = \sum_{i=1}^{n} (y_i - \overline{y})^2$$

where

$$\overline{y} = \frac{1}{n} \sum_{i=1}^{n} y_i$$

and n is the number of target values.

You can use the following functions in your code: -np.mean(array): which is to get the mean of the array. You can also call it using array.mean(). -np.sum(array): which is to sum the array along a default axis. You can specify which axis to perform the summation.

In [104]: np.sum(y)

Out[104]: 6

```
In [105]: np.sum(np.square(y))
Out[105]: 14
In [106]: np.matmul(y.T,y)
Out[106]: 14
In [111]: def r2_score(y, ypred):
              rss = np.sum((ypred - y) ** 2)
              tss = np.sum((y-y.mean()) ** 2)
              r2 = 1 - (rss / tss)
              return r2
In [112]: target = prepare_target(df_target_test)
          r2 = r2_score(target, pred)
          assert np.isclose(r2, 0.45398)
        IndexError
                                                   Traceback (most recent call last)
        <ipython-input-112-7601a9c51c7e> in <module>
          1 target = prepare_target(df_target_test)
    ----> 2 r2 = r2_score(target, pred)
          3 assert np.isclose(r2, 0.45398)
        <ipython-input-111-341873669eea> in r2_score(y, ypred)
                y_mean = np.mean(y)
                ss_res = np.matmul((y-ypred).T,(y-ypred))[0][0]
          3
    ---> 4
              ss_total = np.sum(np.matmul((y-y_mean).T,(y-y_mean)))[0][0]
                return 1 - (ss_res/ss_total)
        IndexError: invalid index to scalar variable.
  CS6. Mean Squared Error: Create a function to calculate the MSE as given below.
```

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y^i - \hat{y}^i)^2$$

```
return mse
In [110]: mse = mean_squared_error(target, pred)
          assert np.isclose(mse, 53.6375)
   CS8. Optional: Redo the above tasks using Sci-kit learn libraries. You will need to use the
following: - LinearRegression - train_test_split - r2_score - mean_squared_error
In [ ]: from sklearn.linear_model import LinearRegression
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import r2_score, mean_squared_error
In []: # Read the CSV and extract the features
        df = None
        df_feature, df_target = None, None
        # normalize
        df_feature = None
        ###
        ### YOUR CODE HERE
        ###
In []: # Split the data into training and test data set using scikit-learn function
        df_feature_train, df_feature_test, df_target_train, df_target_test = None, None,
        # Instantiate LinearRegression() object
        model = None
        # Call the fit() method
        pass
        ###
        ### YOUR CODE HERE
        ###
        print(model.coef_, model.intercept_)
        assert np.isclose(model.coef_,[6.05090511])
        assert np.isclose(model.intercept_, 22.52999668)
In []: # Call the predict() method
        pred = None
        ###
        ### YOUR CODE HERE
        ###
        print(type(pred), pred.mean(), pred.std())
```

mse = np.matmul(error.T,error)/n

# Week09\_Homework

December 10, 2021

### 1 Week 9 Problem Set

### 1.1 Homeworks

```
In [41]: import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns
```

**HW0.** Copy and paste some of the functions from you cohort sessions and previous exercises that you will need in this homework. See below template and the list here: - normalize\_z() - get\_features\_targets() - prepare\_feature() - prepare\_target() - predict() - predict\_norm() - split\_data() - r2\_score() - mean\_squared\_error()

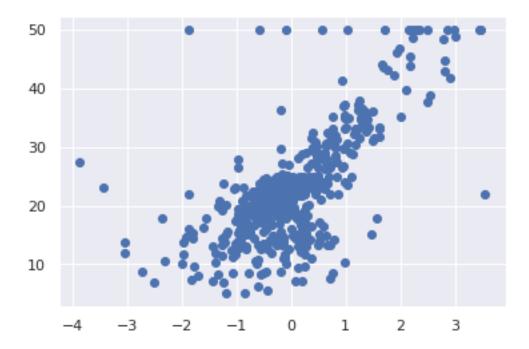
Then do the following: - Read the CSV file housing\_processed.csv and extract the following columns: - x data: RM, DIS, and INDUS columns - y data: MEDV column - Normalize the features using z normalization. - Plot the data using scatter plot. Use the following columns:

```
def predict(df_feature, beta):
    df_feature = normalize_z(df_feature)
    X = prepare_feature(df_feature)
    return predict_norm(X, beta)
def predict_norm(X, beta):
    return np.matmul(X,beta)
def split_data(df_feature, df_target, random_state=None, test_size=0.5):
    np.random.seed(random_state)
    TestSize = int(test_size*len(df_feature))
    testchoice = np.random.choice(len(df_feature), size = TestSize, replace = False)
    remainder = []
    for i in df_feature.index:
        if i not in testchoice:
            remainder.append(i)
    trainchoice = np.random.choice(remainder, size = len(remainder),replace = False)
    df_feature_train = df_feature.iloc[trainchoice]
    df_target_train = df_target.iloc[trainchoice]
    df_feature_test = df_feature.iloc[testchoice]
    df_target_test = df_target.iloc[testchoice]
    return df_feature_train, df_feature_test, df_target_train, df_target_test
def r2_score(y, ypred):
      y_{mean} = np.mean(y)
#
     ss_res = np.matmul((y-ypred).T,(y-ypred))[0][0]
     ss\_total = np.sum(np.matmul((y-y\_mean).T,(y-y\_mean)))[0][0]
     return 1 - (ss_res/ss_total)
    rss = np.sum((ypred - y) ** 2)
    tss = np.sum((y-y.mean()) ** 2)
    r2 = 1 - (rss / tss)
    return r2
def mean_squared_error(target, pred):
    n = target.shape[0]
    error = target-pred
    mse = np.matmul(error.T,error)/n
    return mse
```

```
In [43]: # Read the CSV file
         df = pd.read_csv('housing_processed.csv')
         # Extract the features and the targets
         df features, df target = get features targets(df,["RM", "DIS","INDUS"],["MEDV"])
         # Normalize using z normalization
         df features = normalize z(df features)
In [44]: ###
         ### AUTOGRADER TEST - DO NOT REMOVE
         ###
In [45]: display(df_features.describe())
         display(df_target.describe())
         assert np.isclose(df_features['RM'].mean(), 0)
         assert np.isclose(df features['DIS'].mean(), 0)
         assert np.isclose(df features['INDUS'].mean(), 0)
         assert np.isclose(df_features['RM'].std(), 1)
         assert np.isclose(df_features['DIS'].std(), 1)
         assert np.isclose(df_features['INDUS'].std(), 1)
         assert np.isclose(df_target['MEDV'].mean(), 22.532806)
         assert np.isclose(df_target['MEDV'].std(), 9.197104)
         assert np.isclose(df_features['RM'].median(), -0.1083583)
         assert np.isclose(df_features['DIS'].median(), -0.2790473)
         assert np.isclose(df_features['INDUS'].median(), -0.2108898)
                 RM
                              DIS
                                          INDUS
count 5.060000e+02 5.060000e+02 5.060000e+02
mean -9.478584e-17 -1.404235e-16 3.089316e-16
       1.000000e+00 1.000000e+00 1.000000e+00
std
     -3.876413e+00 -1.265817e+00 -1.556302e+00
min
25%
      -5.680681e-01 -8.048913e-01 -8.668328e-01
50%
     -1.083583e-01 -2.790473e-01 -2.108898e-01
75%
      4.822906e-01 6.617161e-01 1.014995e+00
max
      3.551530e+00 3.956602e+00 2.420170e+00
             MEDV
     506.000000
count
        22.532806
mean
std
        9.197104
        5.000000
min
25%
       17.025000
50%
       21.200000
75%
        25.000000
```

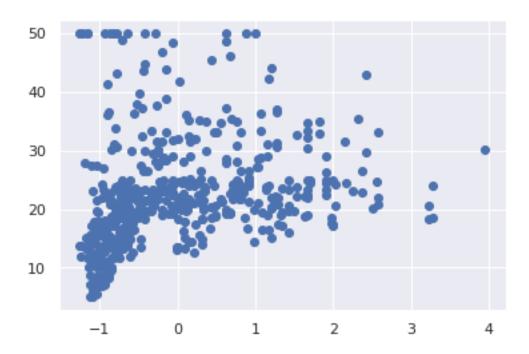
max 50.000000

Out[47]: <matplotlib.collections.PathCollection at 0x7fb728001610>



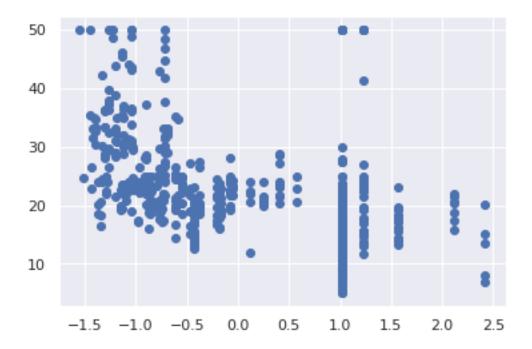
In [48]: plt.scatter(df\_features["DIS"], df\_target)

Out[48]: <matplotlib.collections.PathCollection at 0x7fb727f7da10>



In [49]: plt.scatter(df\_features["INDUS"], df\_target)

Out[49]: <matplotlib.collections.PathCollection at 0x7fb727ef73d0>



**HW1.** *Multiple variables cost function:* Write a function compute\_cost\_multi() to compute the cost function of a linear regression model. The function should take in two 2-D numpy arrays. The first one is the matrix of the linear equation and the second one is the actual target value.

Recall that:

$$J(\hat{\beta}_0, \hat{\beta}_1) = \frac{1}{2m} \sum_{i=1}^{m} (\hat{y}(x^i) - y^i)^2$$

where

$$\hat{y}(x) = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \ldots + \hat{\beta}_n x_n$$

The function should receive three Numpy arrays: - X: is the feature 2D Numpy array - y: is the target 2D Numpy array - beta: is the parameter 2D Numpy array

The function should return the cost which is a float.

You can use the following function in your code: -np.matmul(array1, array2)

Note that if you wrote your Cohort session's compute\_cost() using proper Matrix operations to do the square and the summation, the code will be exactly the same here.

```
In [50]: def compute_cost(X, y, beta):
             m = X.shape[0]
             y_pred = np.matmul(X,beta)
             error = y_pred - y
             J = (1/(2*m))*np.matmul(error.T,error)
             return J[0][0]
In [51]: X = prepare_feature(df_features)
         target = prepare_target(df_target)
         assert isinstance(X, np.ndarray)
         assert isinstance(target, np.ndarray)
         assert X.shape == (506, 4)
         assert target.shape == (506, 1)
In [52]: ###
         ### AUTOGRADER TEST - DO NOT REMOVE
         ###
In [53]: beta = np.zeros((4,1))
         J = compute_cost(X, target, beta)
         print(J)
         assert np.isclose(J, 296.0734)
         beta = np.ones((4,1))
         J = compute_cost(X, target, beta)
         print(J)
         assert np.isclose(J, 270.4083)
         beta = np.array([-1, 2, 1, 2]).reshape((4,1))
```

```
J = compute_cost(X, target, beta)
    print(J)
    assert np.isclose(J, 314.8510)

296.07345849802374
270.40834049507566
314.8509513115608

In [54]: ###
    ### AUTOGRADER TEST - DO NOT REMOVE
    ###
```

**HW2.** Gradient Descent: Write a function called gradient\_descent\_multi() that takes in four parameters: - X: is a 2-D numpy array for the features - y: is a vector array for the target - alpha: is the learning rate - num\_iters: is the number of iteration to perform

The function should return two arrays: - beta: is coefficient at the end of the iteration - J\_storage: is the array that stores the cost value at each iteration

You can use some of the following functions: -np.matmul(array1, array2): which is to do matrix multiplication on two Numpy arrays. -compute\_cost(): which the function you created in the previous problem set to compute the cost.

Note that if you use proper matrix operations in your cohort sessions for the gradient descent function, the code will be the same here.

```
In [55]: def gradient_descent(X, y, beta, alpha, num_iters):
             m = X.shape[0]
             J storage = np.zeros(num iters)
             for i in range(num_iters):
                 yp = np.matmul(X,beta)
                 error = yp - y
                 beta = beta - (alpha/m) * np.matmul(X.T,error)
                 cost = compute_cost(X,y,beta)
                 J_storage[i] = cost
             return beta, J_storage
In [56]: iterations = 1500
         alpha = 0.01
         beta = np.zeros((4,1))
         beta, J_storage = gradient_descent(X, target, beta, alpha, iterations)
         print(beta)
         assert np.isclose(beta[0], 22.5328)
         assert np.isclose(beta[1], 5.4239)
         assert np.isclose(beta[2], -0.90367)
         assert np.isclose(beta[3], -2.95818)
```

**HW3.** Do the following tasks: - Get the features and the targets. - features: RM, DIS, INDUS - target: MEDV - Use the previous functions called predict() to calculated the predicted values given the features and the model. - Create a target numpy array from the data frame.

```
# Call predict()
pred = predict(df_features,beta)

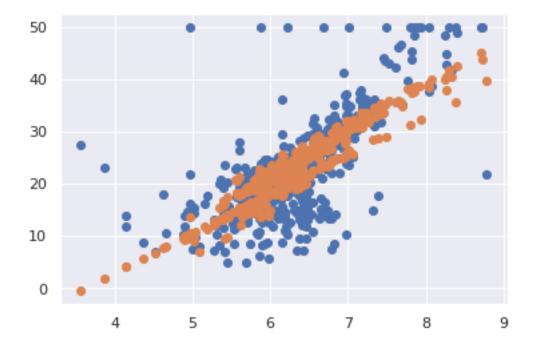
# Change target to numpy array
target = df_target.to_numpy()

###
### YOUR CODE HERE
###

In [60]: assert isinstance(pred, np.ndarray)
assert np.isclose(pred.mean(), 22.5328)
assert np.isclose(pred.std(), 6.7577)

In [61]: ###
### AUTOGRADER TEST - DO NOT REMOVE
###
```

Out[62]: <matplotlib.collections.PathCollection at 0x7fb727e09c10>



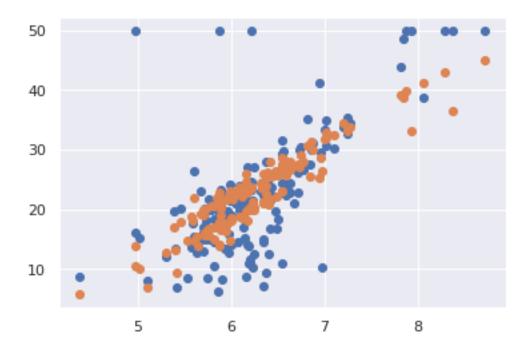
**HW4.** Splitting data: Do the following tasks: - Extract the following: - features: RM, DIS, and INDUS - target: MEDV - Use Week 9's function split\_data() to split the data into train and test using random\_state=100 and test\_size=0.3. - Normalize and prepare the features and the target. - Use the training data set and call gradient\_descent() to obtain the theta. - Use the test data set to get the predicted values.

You need to replace the None in the code below with other a function call or any other Python expressions.

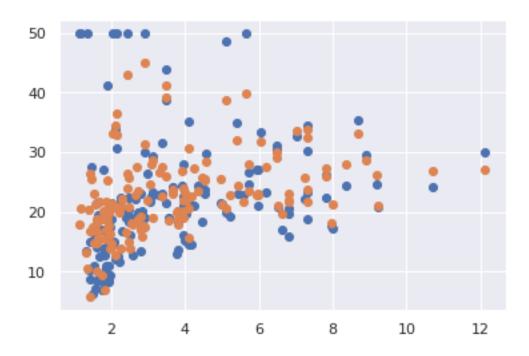
```
In [65]: # Extract the features and the target
         df_features, df_target = get_features_targets(df,["RM", "DIS", "INDUS"],["MEDV"])
         # Split the data set into training and test
         df_features_train, df_features_test, df_target_train, df_target_test = split_data(df_;
         # Normalize the features using z normalization
         df_features_train_z = normalize_z(df_features_train)
         # Change the features and the target to numpy array using the prepare functions
         X = prepare_feature(df_features_train_z) # concatenating for the y intercept
         target = prepare_target(df_target_train)
         iterations = 1500
         alpha = 0.01
         beta = np.zeros((4,1))
         # call the gradient_descent function
         beta, J_storage = gradient_descent(X, target, beta, alpha, iterations)
         # call the predict() method
         pred = predict(df_features_test,beta)
         print(beta)
[[22.66816258]
 [ 5.20934787]
 [-0.96089997]
 [-3.22203154]]
In [66]: ###
         ### AUTOGRADER TEST - DO NOT REMOVE
         ###
In [67]: assert isinstance(pred, np.ndarray)
         assert pred.shape == (151, 1)
```

```
assert np.isclose(pred.mean(), 22.66816)
assert np.isclose(pred.std(), 6.67324)
```

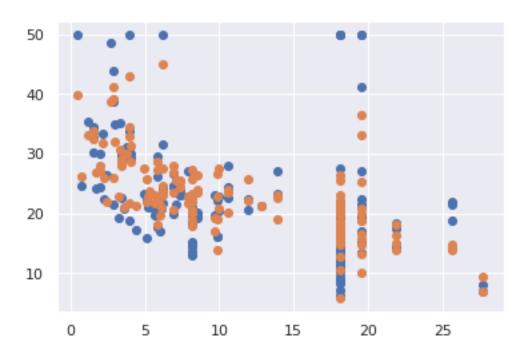
Out[69]: <matplotlib.collections.PathCollection at 0x7fb727e962d0>



Out[70]: <matplotlib.collections.PathCollection at 0x7fb727cefe10>



Out[71]: <matplotlib.collections.PathCollection at 0x7fb727c6ab50>

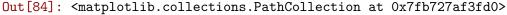


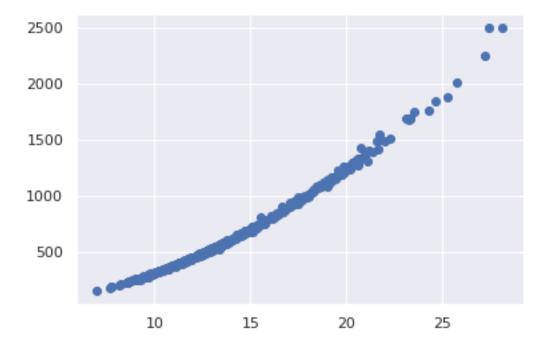
```
In [74]: target.shape
Out[74]: (506, 1)
   HW5. Calculate the coefficient of determination, r^2.
In [75]: # change target test set to a numpy array
         target = df_target.to_numpy()
         # Calculate r2 score by calling a function
         r2 = r2_score(df_target_test, pred)
         print(r2)
MEDV
        0.477135
dtype: float64
In [76]: assert np.isclose(r2, 0.47713)
In [77]: ###
         ### AUTOGRADER TEST - DO NOT REMOVE
          ###
   HW6. Calculate the mean squared error.
In [79]: # Calculate the mse
         mse = mean_squared_error(df_target_test, pred)
         ###
         ### YOUR CODE HERE
         ###
         print(mse)
MEDV 51.362988
/usr/lib/python3.7/site-packages/ipykernel_launcher.py:67: FutureWarning: Calling a ufunc on new packages/ipykernel_launcher.py:67:
Convert one of the arguments to a NumPy array (eg 'ufunc(df1, np.asarray(df2)') to keep the cu
In [80]: assert np.isclose(mse, 51.363)
In [34]: ###
         ### AUTOGRADER TEST - DO NOT REMOVE
```

###

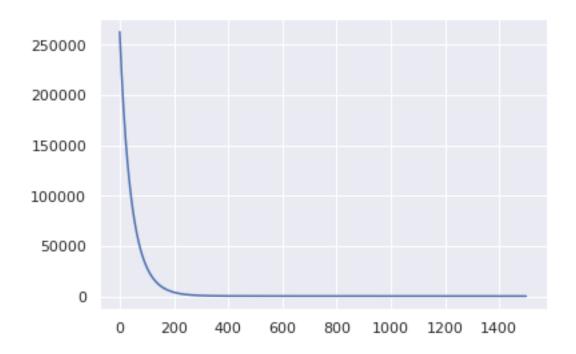
**HW7.** *Polynomial Transformation:* Redo the steps for breast cancer data but this time we will use quadratic model. Use the following columns: - x data: radius\_mean - y data: area\_mean

We will create a quadratic hypothesis for this x and y data. To do that write a function transform\_features(df, colname, colname\_transformed) that takes in a dataframe for the features, the original column name, and the transformed column name. The function should add another column with the name colname\_transformed with the value of column in colname transformed to its quadratic value.

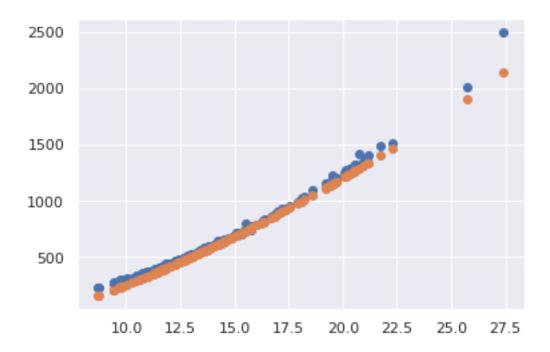




```
In [86]: df_features = transform_features(df_feature, "radius_mean", "radius_mean^2")
         assert (df_features.loc[:,"radius_mean^2"] == df_features.loc[:,"radius_mean"] ** 2).
In [39]: ###
         ### AUTOGRADER TEST - DO NOT REMOVE
In [88]: # split data using random_state = 100 and 30% test size
         df_features_train, df_features_test, df_target_train, df_target_test = split_data(df_
         # normalize features
         df_feature_train_z = normalize_z(df_features_train)
         # change to numpy array and append column for feature
         X = prepare_feature(df_feature_train_z) # concatenating for the y intercept
         target = prepare_target(df_target_train)
         iterations = 1500
         alpha = 0.01
         beta = np.zeros((3,1))
         # call gradient_descent() function
         beta, J_storage = gradient_descent(X, target, beta, alpha, iterations)
In []:
In [89]: ###
         ### AUTOGRADER TEST - DO NOT REMOVE
         ###
In [90]: assert np.isclose(beta[0], 646.0787)
         assert np.isclose(beta[1], 146.4801)
         assert np.isclose(beta[2], 201.9803)
In [91]: ###
         ### AUTOGRADER TEST - DO NOT REMOVE
         ###
In [92]: plt.plot(J_storage)
Out[92]: [<matplotlib.lines.Line2D at 0x7fb727abbe90>]
```



```
In [97]: type(df_target_test)
Out[97]: pandas.core.frame.DataFrame
In [99]: # change target to numpy array
         beta = np.array([[646.0787641], [146.4800792], [201.98031254]])
         target = df_target_test
         pred = predict(df_features_test,beta)
         # get predicted values
         ###
         ### YOUR CODE HERE
         ###
In [100]: ###
          ### AUTOGRADER TEST - DO NOT REMOVE
          ###
In [101]: plt.scatter(df_features_test["radius_mean"], target)
          plt.scatter(df_features_test["radius_mean"], pred)
Out[101]: <matplotlib.collections.PathCollection at 0x7fb7279e3ed0>
```



**HW8.** *Optional:* Redo the above tasks using Sci-kit learn libraries. You will need to use the following: - LinearRegression - train\_test\_split - r2\_score - mean\_squared\_error - PolynomialFeatures

## Redo HW 4 using Scikit Learn

```
In [53]: # Read the housing_processed.csv file
                       df = None
                       # extract the features from ["RM", "DIS", "INDUS"] and target from []"MEDV"]
                       df_features, df_target = None, None
                       # normalize
                       df features = None
                       ###
                       ### YOUR CODE HERE
                       ###
In [54]: # Split the data into training and test data set using scikit-learn function
                       df_features_train, df_features_test, df_target_train, df_target_test = None, No
                       # Instantiate LinearRegression() object
                       model = None
                       # Call the fit() method
                       pass
                       ###
                       ### YOUR CODE HERE
                       ###
                       print(model.coef_, model.intercept_)
                       assert np.isclose(model.coef_, [ 5.01417104, -1.00878266, -3.27301726]).all()
                       assert np.isclose(model.intercept_, 22.45962454)
In [55]: # Call the predict() method
                       pred = None
                       ###
                       ### YOUR CODE HERE
                       ###
In [56]: plt.scatter(df_features_test["RM"], df_target_test)
                       plt.scatter(df_features_test["RM"], pred)
In [57]: plt.scatter(df_features_test["DIS"], df_target_test)
                       plt.scatter(df_features_test["DIS"], pred)
In [58]: plt.scatter(df_features_test["INDUS"], df_target_test)
                       plt.scatter(df_features_test["INDUS"], pred)
In [59]: r2 = r2_score(df_target_test, pred)
                       print(r2)
                       assert np.isclose(r2, 0.48250)
In [60]: mse = mean_squared_error(df_target_test, pred)
                       print(mse)
                       assert np.isclose(mse, 52.41451)
```

### Redo HW7 Using Scikit Learn

```
In [61]: # Read the file breast_cancer_data.csv
                       df = None
                        # extract feature from "radius_mean" and target from "area_mean"
                       df_feature, df_target = None, None
                        ###
                        ### YOUR CODE HERE
                        ###
In [62]: # instantiate a PolynomialFeatures object with degree = 2
                       poly = None
                        # call its fit_transform() method
                       df_features = None
                        # call train_test_split() to split the data
                       df_features_train, df_features_test, df_target_train, df_target_test = None, No
                        # instantiate LinearRegression() object
                       model = None
                        # call its fit() method
                       pass
                        ### BEGIN SOLUTON
                       poly = PolynomialFeatures(2)
                       df_features = poly.fit_transform(df_feature)
                       df_features_train, df_features_test, df_target_train, df_target_test = train_test_spl
                       model = LinearRegression()
                       model.fit(df_features_train, df_target_train)
                        ### END SOLUTION
                       print(model.coef_, model.intercept_)
                        assert np.isclose(model.coef_, [0., 3.69735512, 2.9925278]).all()
                       assert np.isclose(model.intercept_, -32.3684598)
In [63]: # Call the predict() method
                       pred = None
                        ###
                        ### YOUR CODE HERE
                        ###
                       print(type(pred), pred.mean(), pred.std())
                       assert isinstance(pred, np.ndarray)
                       assert np.isclose(pred.mean(), 672.508465)
                        assert np.isclose(pred.std(), 351.50271)
```

# Week10\_Cohort

December 10, 2021

## 1 Week 10 Problem Set

#### 1.1 Cohort Session

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
   CS0. Do the following tasks before you start with the first cohort session.
   Task 1. Paste the following functions from your previous work: - get_features_targets() -
normalize_z() - prepare_feature() - prepare_target() - split_data()
In [2]: def normalize_z(df):
            dfout = (df - df.mean(axis=0)) / df.std(axis=0)
            return dfout
        def get_features_targets(df, feature_names, target_names):
            df_feature = df[feature_names]
            df_target = df[target_names]
            return df_feature, df_target
        def prepare_feature(df_feature): # creates X matrix
            feature = df_feature.to_numpy()
            array1 = np.ones((feature.shape[0], 1))
              array1 = np.ones(feature.shape) --> works too
            X = np.concatenate((array1, feature), axis=1)
            return X
        def prepare_target(df_target): # creates numpy array for y (target)
            return df_target.to_numpy()
        def split_data(df_feature, df_target, random_state=None, test_size=0.5):
            # assuming that index is consistent between features and target
            indices = df_target.index
            if random_state != None:
                np.random.seed(random_state)
            # k is the no. of rows in the test set
```

```
num_rows = len(indices)
k = int(test_size * num_rows)
# randomly choose indices for test set
test_indices = np.random.choice(indices, k, replace=False)

indices = set(indices)
test_indices = set(test_indices)
train_indices = indices - test_indices

df_feature_train = df_feature.loc[train_indices, :]
df_feature_test = df_feature.loc[test_indices, :]
df_target_train = df_target.loc[train_indices, :]
df_target_test = df_target.loc[test_indices, :]
return df_feature_train, df_feature_test, df_target_train, df_target_test
```

Task 2. Load the breast cancer data from breast\_cancer\_data.csv into a Data Frame.

```
In [3]: # read breast_cancer_data.csv
        df = pd.read_csv("breast_cancer_data.csv")
        df
Out [3]:
                     id diagnosis
                                    radius_mean
                                                  texture_mean perimeter_mean
                                                                                   area_mean
                                           17.99
        0
                842302
                                Μ
                                                          10.38
                                                                           122.80
                                                                                       1001.0
        1
                842517
                                 Μ
                                           20.57
                                                          17.77
                                                                           132.90
                                                                                       1326.0
        2
              84300903
                                 М
                                           19.69
                                                          21.25
                                                                           130.00
                                                                                       1203.0
        3
              84348301
                                 Μ
                                           11.42
                                                          20.38
                                                                            77.58
                                                                                        386.1
        4
                                Μ
              84358402
                                          20.29
                                                          14.34
                                                                           135.10
                                                                                       1297.0
                                                            . . .
        564
                926424
                                           21.56
                                                          22.39
                                                                           142.00
                                                                                       1479.0
                                Μ
        565
                926682
                                Μ
                                          20.13
                                                          28.25
                                                                           131.20
                                                                                       1261.0
        566
                926954
                                           16.60
                                                          28.08
                                                                           108.30
                                                                                       858.1
                                 М
        567
                927241
                                 М
                                           20.60
                                                          29.33
                                                                           140.10
                                                                                       1265.0
        568
                 92751
                                            7.76
                                                          24.54
                                                                            47.92
                                                                                        181.0
              smoothness_mean
                                 compactness_mean
                                                    concavity_mean
                                                                      concave points_mean
        0
                       0.11840
                                          0.27760
                                                            0.30010
                                                                                   0.14710
        1
                       0.08474
                                           0.07864
                                                            0.08690
                                                                                   0.07017
        2
                       0.10960
                                           0.15990
                                                            0.19740
                                                                                   0.12790
        3
                       0.14250
                                           0.28390
                                                            0.24140
                                                                                   0.10520
        4
                       0.10030
                                           0.13280
                                                            0.19800
                                                                                   0.10430
                           . . .
                                                                 . . .
        564
                       0.11100
                                          0.11590
                                                            0.24390
                                                                                   0.13890
        565
                       0.09780
                                          0.10340
                                                            0.14400
                                                                                   0.09791
        566
                       0.08455
                                           0.10230
                                                            0.09251
                                                                                   0.05302
        567
                       0.11780
                                          0.27700
                                                            0.35140
                                                                                   0.15200
```

568		0.05263	0.04362	0.00000		0.00000
	r	adius_worst	texture_worst	perimeter_worst	area_worst	\
0		25.380	17.33	184.60	2019.0	
1		24.990	23.41	158.80	1956.0	
2		23.570	25.53	152.50	1709.0	
3		14.910	26.50	98.87	567.7	
4		22.540	16.67	152.20	1575.0	
564		25.450	26.40	166.10	2027.0	
565		23.690	38.25	155.00	1731.0	
566		18.980	34.12	126.70	1124.0	
567		25.740	39.42	184.60	1821.0	
568	• • •	9.456	30.37	59.16	268.6	
	smooth	ness_worst c	ompactness_wor	st concavity_wor	rst \	
0		0.16220	0.665	60 0.71	119	
1		0.12380	0.186	60 0.24	<del>1</del> 16	
2		0.14440	0.424	50 0.45	504	
3		0.20980	0.866	30 0.68	369	
4		0.13740	0.205			
 564		0.14100	0.211			
565		0.14100	0.192			
566		0.11390	0.309			
567		0.16500	0.868			
568		0.10300	0.064			
500		0.00990	0.004	44 0.00	000	
	concav	e points_wors	t symmetry_wo	rst fractal_dime	ension_worst	
0		0.265	4 0.4	601	0.11890	
1		0.186	0.2	750	0.08902	
2		0.243	0.3	613	0.08758	
3		0.257	5 0.6	638	0.17300	
4		0.162	5 0.2	364	0.07678	
			•	• • •		
564		0.221	6 0.2	060	0.07115	
565		0.162	0.2	572	0.06637	
566		0.141	8 0.2	218	0.07820	
567		0.265	0.4	087	0.12400	
568		0.000	0.2	871	0.07039	

[569 rows x 32 columns]

**Task 3.** Do the following tasks.

• Read the following columns

feature: radius\_meantarget: diagnosis

• Normalize the feature column using z normalization.

Task 4. Write a function replace\_target() to replace the diagnosis column with the following mapping: - M: 1, this means that malignant cell are indicated as 1 in our new column. - B: 0, this means that benign cell are indicated as 0 in our new column.

The function should takes in the following:

- df\_target: the target data frame
- target\_name: which is the column name of the target data frame
- map: which is a dictionary containing the map

It should returns a new data frame with the same column name but with its values changed according to the mapping.

```
In [5]: def replace_target(df_target, target_name, map_vals):
            df_out = df_target.copy()
            df_out.loc[:, target_name] = df_target[target_name].apply(lambda val: map_vals[val]
            return df out
In [6]: df_target = replace_target(df_target, "diagnosis", {'M': 1, 'B': 0})
        df_target
Out[6]:
             diagnosis
        0
        1
                      1
        2
                      1
        3
                      1
        4
                      1
        . .
                    . . .
        564
                      1
        565
                      1
        566
                      1
        567
                      1
                      0
        568
        [569 rows x 1 columns]
```

**Task 5.** Do the following tasks. - Change feature to Numpy array and append constant 1 column. - Change target to Numpy array

```
In [7]: # change feature data frame to numpy array and append column 1
    feature = prepare_feature(df_feature)

# change target data frame to numpy array
    target = prepare_target(df_target)
```

**CS1.** *Logistic function:* Write a function to calculate the hypothesis using a logistic function. Recall that the hypothesis for a logistic regression model is written as:

$$\mathbf{p}(x) = \frac{1}{1 + e^{-\mathbf{X}\mathbf{b}}}$$

The shape of the input is as follows:  $-\mathbf{b}$ : is a column vector for the parameters  $-\mathbf{X}$ : is a matrix where the number of rows are the number of data points and the number of columns must the same as the number of parameters in  $\mathbf{b}$ .

Note that you need to ensure that the output is a **column vector**.

You can use the following functions: -np.matmul(array1, array2): which is to perform matrix multiplication on the two numpy arrays. -np.exp(): which is to calculate the function  $e^x$ 

```
In [8]: # logistic function transforms x to z (p against x -> z against x (linear) -> p agains
        # z is a linear combination that transforms from x to z, p is the hypothesis
        def log_regression(beta, X):
            z = np.matmul(X, beta)
            return 1 / (1 + np.exp(-z))
In [9]: beta = np.array([0])
        x = np.array([0])
        ans = log_regression(beta, x)
        assert ans == 0.5
        beta = np.array([2])
        x = np.array([40])
        ans = log_regression(beta, x)
        assert np.isclose(ans, 1.0)
        beta = np.array([2])
        x = np.array([-40])
        ans = log_regression(beta, x)
        assert np.isclose(ans, 0.0)
        beta = np.array([[1, 2, 3]])
        x = np.array([[3, 2, 1]])
        ans = log_regression(beta.T, x)
        assert np.isclose(ans.all(), 1.0)
        beta = np.array([[1, 2, 3]])
        x = np.array([[3, 2, 1], [3, 2, 1]])
        ans = log_regression(beta.T, x)
        assert ans.shape == (2, 1)
        assert np.isclose(ans.all(), 1.0)
In [10]: ###
         ### AUTOGRADER TEST - DO NOT REMOVE
         ###
```

**CS2.** *Cost Function:* Write a function to calculate the cost function for logistic regression. Recall that the cost function for logistic regression is given by:

$$J(\beta) = -\frac{1}{m} \left[ \sum_{i=1}^{m} y^{i} \log(p(x^{i})) + (1 - y^{i}) \log(1 - p(x^{i})) \right]$$

You can use the following function in your code: -np.where(condition, then\_expression, else\_expression)

```
In [11]: # cost function: small penalty when y is close to 0
         def compute_cost_logreg(beta, X, y):
             np.seterr(divide = 'ignore')
             p = log_regression(beta, X)
             m = X.shape[0]
             J = (-1 / m) * np.sum(np.where(y == 1, np.log(p), np.log(1 - p)))
             np.seterr(divide = 'warn')
             return J
In [12]: y = np.array([[1]])
         X = np.array([[10, 40]])
         beta = np.array([1, 1]).T
         ans = compute_cost_logreg(beta, X, y)
         print(ans)
         assert np.isclose(ans, 0)
         y = np.array([[0]])
         X = np.array([[10, 40]])
         beta = np.array([[-1, -1]]).T
         ans = compute_cost_logreg(beta, X, y)
         print(ans)
         assert np.isclose(ans, 0)
-0.0
-0.0
In [13]: ###
         ### AUTOGRADER TEST - DO NOT REMOVE
         ###
```

**CS3.** *Gradient Descent:* Recall that the update functions can be written as a matrix multiplication.

$$\mathbf{b} = \mathbf{b} - \alpha \frac{1}{m} \mathbf{X}^T (\mathbf{p} - \mathbf{y})$$

Write a function called gradient\_descent\_logreg() that takes in five parameters: - X: is a 2-D numpy array for the features - y: is a vector array for the target - beta: is a column vector for the initial guess of the parameters - alpha: is the learning rate - num\_iters: is the number of iteration to perform

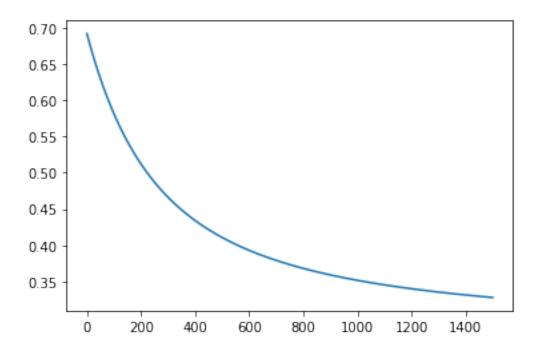
The function should return two arrays: - beta: is coefficient at the end of the iteration - J\_storage: is the array that stores the cost value at each iteration

The solution is similar to Linear Regression gradient descent function with two differences: - you need to use log\_regression() to calculate the hypothesis - you need to use compute\_cost\_logreg() to calculate the cost

```
In [14]: def gradient_descent_logreg(X, y, beta, alpha, num_iters):
             m = X.shape[0]
             J_storage = np.zeros(num_iters)
             for n in range(num_iters):
                 p = log_regression(beta, X)
                 error = p - y
                 delta = np.matmul(X.T, error)
                 beta = beta - (alpha / m) * delta
                 # change the J value from 0 to sum cost (can also use an empty list and appen
                 J_storage[n] = compute_cost_logreg(beta, X, y)
             return beta, J_storage
In [15]: def gradient_descent_lin_reg(X, y, beta, alpha, num_iters):
             m = X.shape[0]
             J_storage = np.zeros(num_iters)
             for i in range(num_iters):
                 yp = np.matmul(X,beta)
                 error = yp - y
                 beta = beta - (alpha/m) * np.matmul(X.T,error)
                 cost = compute_cost(X,y,beta)
                 J_storage[i] = cost
             return beta, J_storage
In [16]: iterations = 1500
         alpha = 0.01
         beta = np.zeros((2,1))
         beta, J_storage = gradient_descent_logreg(feature, target, beta, alpha, iterations)
         print(beta)
         assert beta.shape == (2, 1)
         assert np.isclose(beta[0][0], -0.56630)
         assert np.isclose(beta[1][0], 1.93764)
[[-0.56630289]
 [ 1.93763591]]
In [17]: ###
         ### AUTOGRADER TEST - DO NOT REMOVE
         ###
```

## In [18]: plt.plot(J\_storage)

Out[18]: [<matplotlib.lines.Line2D at 0x7fc9a6cafcd0>]

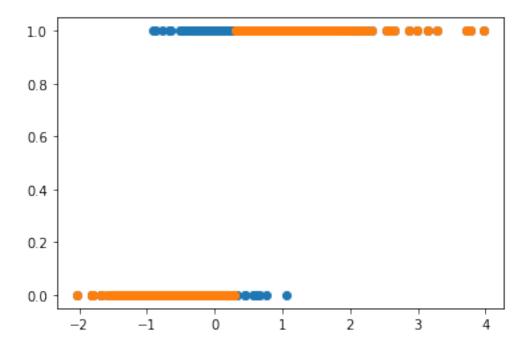


CS4. Predict: Write two functions predict() and predict\_norm() that calculate the straight line equation given the features and its coefficient. - predict(): this function should standardize the feature using z normalization, change it to a Numpy array, and add a column of constant 1s. You should use prepare\_feature() for this purpose. Lastly, this function should also call predict\_norm() to get the predicted y values. - predict\_norm(): this function should calculate the straight line equation after standardization and adding of column for constant 1.

You can use the following function in your code: - np.where()

plt.scatter(df\_feature, pred)

Out[23]: <matplotlib.collections.PathCollection at 0x7fc9a6b5fd90>



## **CS5.** *Multiple features and splitting of data set:*

Do the following task in the code below: - Read the following column names as the features: "radius\_mean", "texture\_mean", "perimeter\_mean", "area\_mean", "smoothness\_mean", "compactness\_mean", "concavity\_mean" - Read the column diagnosis as the target. Change the value from M and B to 1 and 0 respectively. - Split the data set with 30% test size and random\_state = 100. - Normalize the training feature data set using normalize\_z() function. - Convert to numpy array both the target and the features using prepare\_feature() and prepare\_target() functions. - Call gradient\_descent() function to get the parameters using the training data set. - Call predict() function on the test data set to get the predicted values.

```
In [24]: columns = ["radius_mean", "texture_mean", "perimeter_mean", "area_mean", "smoothness_n

# extract the features and the target columns

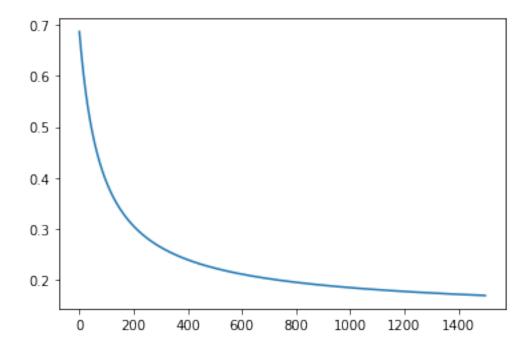
df_features, df_target = get_features_targets(df, columns, ["diagnosis"])
```

```
# replace the target values using from string to integer 0 and 1
         df_target = replace_target(df_target, "diagnosis", {'M': 1, 'B': 0})
         # split the data with random_state = 100 and 30% test size
         df_features_train, df_features_test, df_target_train, df_target_test = split_data(df_
         # normalize the features
         df_features_train_z = normalize_z(df_features_train)
         # change the feature columns to numpy array and append column of 1s
         features = prepare_feature(df_features_train_z)
         # change the target column to numpy array
         target = prepare_target(df_target_train)
         iterations = 1500
         alpha = 0.01
         # provide initial guess for theta
         beta = np.zeros((features.shape[1],1))
         # call the gradient descent method
         beta, J_storage = gradient_descent_logreg(features, target, beta, alpha, iterations)
         print(beta)
[[-0.6139379]
 [ 0.82529554]
 [ 0.72746485]
 [ 0.8236603 ]
[ 0.81647937]
 [ 0.5057749 ]
 [ 0.44176466]
 [ 0.78736842]]
In [25]: assert beta.shape == (8, 1)
         ans = np.array([[-0.6139379]],
                         [ 0.82529554],
                         [ 0.72746485],
                         [ 0.8236603 ],
                         [ 0.81647937],
                         [0.5057749],
                         [ 0.44176466],
                         [ 0.78736842]])
         assert np.isclose(beta, ans).all()
In [26]: ###
```

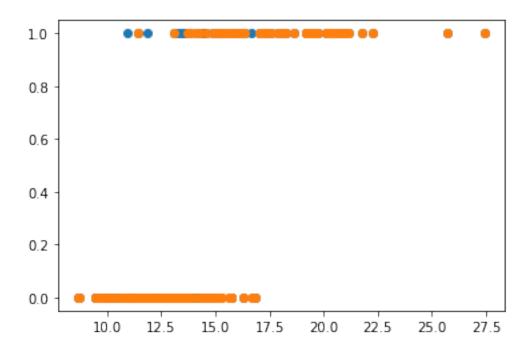
```
### AUTOGRADER TEST - DO NOT REMOVE
###
```

In [27]: plt.plot(J\_storage)

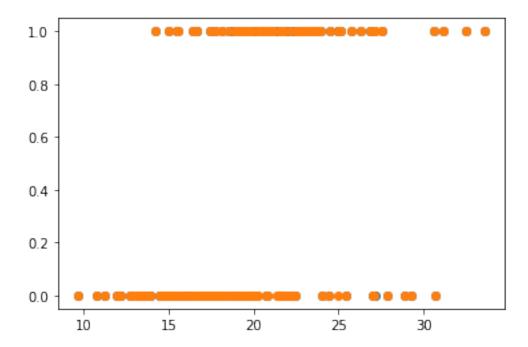
Out[27]: [<matplotlib.lines.Line2D at 0x7fc9a6a87410>]



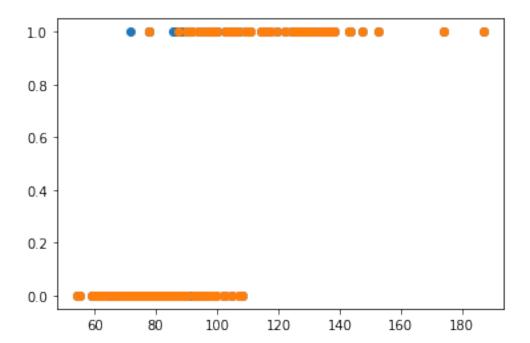
Out[29]: <matplotlib.collections.PathCollection at 0x7fc9a6a77d90>



Out[30]: <matplotlib.collections.PathCollection at 0x7fc9a6c7f6d0>



Out[31]: <matplotlib.collections.PathCollection at 0x7fc9a6953ed0>



**CS6.** Confusion Matrix: Write a function confusion\_matrix() that takes in: - ytrue: which is the true target values - ypred: which is the predicted target values - labels: which is a list of the category. In the above case it will be [1, 0]. Put the positive case as the first element of the list. The function should return a dictionary containing the matrix with the following format.

	predicted positive (1)	predicted negative (0)
actual positive (1) actual negative (0)	correct positive (1, 1) false positive (0, 1)	false negative (1, 0) correct negative (0, 0)

The keys to the dictionary are the indices: (0, 0), (0, 1), (1, 0), (1, 1).

You can use the following function in your code: - itertools.product(): this is to create a combination of all the labels.

## 1.1.1 Usage of itertools

• allows us to create different combinations of the numbers in array

**CS7.** *Metrics:* Write a function calc\_accuracy() that takes in a Confusion Matrix array and output a dictionary with the following keys and values: - accuracy: total number of correct predictions / total number of records - sensitivity: total correct positive cases / total positive cases - specificity: total false positives / total negative cases - precision: total of correct positive cases / total predicted positive cases

```
In [35]: def calc_accuracy(cm):
             tp = cm[(1, 1)]
             tn = cm[(0,0)]
             fp = cm[(0,1)]
             fn = cm[(1,0)]
             total = tp + tn + fp + fn
             accuracy = (tp + tn)/total
             sensitivity = tp/(tp+fn)
             specificity = tn/(fp+tn)
             precision = tp/(tp+fp)
             result = {'accuracy': accuracy, 'sensitivity': sensitivity,
                       'specificity': specificity, 'precision': precision}
             return result
In [36]: ans = calc_accuracy(result)
         expected = {'accuracy': 0.9235294117647059, 'sensitivity': 0.8260869565217391, 'speci
         assert np.isclose(ans['accuracy'], expected['accuracy'])
         assert np.isclose(ans['sensitivity'], expected['sensitivity'])
         assert np.isclose(ans['specificity'], expected['specificity'])
```

```
assert np.isclose(ans['precision'], expected['precision'])
        CS8. Optional: Redo the above tasks using Scikit Learn libraries. You will need to use the
following: - LogisticRegression - train_test_split - confusion_matrix
In [37]: from sklearn.linear_model import LogisticRegression
                          from sklearn.model_selection import train_test_split
                          from sklearn.metrics import confusion_matrix
In [38]: columns = ["radius_mean", "texture_mean", "perimeter_mean", "area_mean", "smoothness_"
                          # get the features and the columns
                          df_features = None
                          # replace target values with 0 and 1
                          df_target = None
                          ###
                          ### YOUR CODE HERE
In [39]: # split data set using random_state = 100 and 30% test size
                          df_features_train, df_features_test, df_target_train, df_target_test = None, No
                          # change feature to numpy array and append column of 1s
                          feature = None
                          # change target to numpy array
                          target = None
                          ###
                          ### YOUR CODE HERE
                          ###
In [40]: # create LogisticRegression object instance, use newton-cg solver
                         model = None
                          # build model
                          pass
                          # get predicted value
                          pred = None
                          ###
                          ### YOUR CODE HERE
                          ###
```

In [41]: # calculate confusion matrix

cm = None

```
###
         ### YOUR CODE HERE
         ###
In [42]: expected = np.array([[58, 11], [6, 96]])
        assert (cm == expected).all()
        AssertionError
                                                  Traceback (most recent call last)
        <ipython-input-42-5489459f6fd4> in <module>
          1 expected = np.array([[58, 11], [6, 96]])
    ---> 2 assert (cm == expected).all()
        AssertionError:
In [ ]: plt.scatter(df_features_test["radius_mean"], df_target_test)
       plt.scatter(df_features_test["radius_mean"], pred)
In [ ]: plt.scatter(df_features_test["texture_mean"], df_target_test)
       plt.scatter(df_features_test["texture_mean"], pred)
In [ ]: plt.scatter(df_features_test["perimeter_mean"], df_target_test)
       plt.scatter(df_features_test["perimeter_mean"], pred)
```

# Week10\_Homework

December 10, 2021

## 1 Week 10 Problem Set

#### 1.1 Homeworks

```
In [3]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
  HW0. Do the following before starting the homework questions.
  Task 1. Paste the following functions from your cohort sessions: - get_features_target()
  normalize z() - normalize minmax() - replace target() - split_data()
prepare_feature() - prepare_target() - log_regression() - compute_cost_logreg() -
gradient_descent_logreg() - predict_norm() - predict() - confusion_matrix()
In [4]: def normalize_z(df):
            dfout = (df - df.mean(axis=0)) / df.std(axis=0)
            return dfout
        def get_features_targets(df, feature_names, target_names):
            df_feature = df[feature_names]
            df_target = df[target_names]
            return df_feature, df_target
        def prepare_feature(df_feature): # creates X matrix
            feature = df feature.to numpy()
            array1 = np.ones((feature.shape[0], 1))
              array1 = np.ones(feature.shape) --> works too
            X = np.concatenate((array1, feature), axis=1)
            return X
        def prepare_target(df_target): # creates numpy array for y (target)
            return df_target.to_numpy()
        def split_data(df_feature, df_target, random_state=None, test_size=0.5):
            # assuming that index is consistent between features and target
            indices = df_target.index
            if random_state != None:
                np.random.seed(random_state)
```

```
# k is the no. of rows in the test set
   num_rows = len(indices)
   k = int(test_size * num_rows)
    # randomly choose indices for test set
    test_indices = np.random.choice(indices, k, replace=False)
    indices = set(indices)
    test_indices = set(test_indices)
    train_indices = indices - test_indices
    df_feature_train = df_feature.loc[train_indices, :]
    df_feature_test = df_feature.loc[test_indices, :]
    df_target_train = df_target.loc[train_indices, :]
    df_target_test = df_target.loc[test_indices, :]
    return df_feature_train, df_feature_test, df_target_train, df_target_test
def replace_target(df_target, target_name, map_vals):
    df_out = df_target.copy()
    df_out.loc[:, target_name] = df_target[target_name].apply(lambda val: map_vals[val]
    return df_out
def normalize_minmax(dfin):
    dfout = (dfin - dfin.min(axis=0))/(dfin.max(axis=0)-dfin.min(axis=0))
    return dfout
def log_regression(beta, X):
    z = np.matmul(X, beta)
   hypothesis = 1 / (1 + np.exp(-z))
    return hypothesis
def compute_cost_logreg(beta, X, y):
   np.seterr(divide = 'ignore')
   p = log_regression(beta, X)
   m = X.shape[0]
    J = (-1 / m) * np.sum(np.where(y == 1, np.log(p), np.log(1 - p)))
   np.seterr(divide = 'warn')
    return J
def gradient_descent_logreg(X, y, beta, alpha, num_iters):
   m = X.shape[0]
    J_storage = np.zeros(num_iters)
    for n in range(num_iters):
        p = log_regression(beta, X)
```

```
error = p - y
        delta = np.matmul(X.T, error)
        beta = beta - (alpha / m) * delta
        # change the J value from 0 to sum cost (can also use an empty list and append
        J_storage[n] = compute_cost_logreg(beta, X, y)
    return beta, J_storage
def predict_norm(X, beta):
   p = log_regression(beta, X)
    return np.where(p \ge 0.5, 1, 0)
def predict(df_feature, beta):
    feature_z = normalize_z(df_feature)
    X = prepare_feature(feature_z)
    return predict_norm(X, beta)
import itertools
def confusion_matrix(ytrue, ypred, labels):
    output = {i : 0 for i in list(itertools.product([0,1],repeat = 2))}
    for idx in range(ytrue.shape[0]):
        actual = ytrue[idx,0]
        pred = ypred[idx,0] # or using a list index ypred[idx][0]
        output[(actual,pred)] +=1
    return output
```

**Task 2.** Load the Iris data set from iris\_data.csv into a Data Frame.

```
In [5]: # read iris_data.csv
       df = pd.read_csv("iris_data.csv")
       df.head()
          sepal_length sepal_width petal_length petal_width
Out[5]:
                                                                species
       0
                  5.1
                              3.5
                                           1.4
                                                       0.2 Iris-setosa
       1
                  4.9
                              3.0
                                           1.4
                                                       0.2 Iris-setosa
       2
                  4.7
                              3.2
                                           1.3
                                                       0.2 Iris-setosa
       3
                  4.6
                              3.1
                                           1.5
                                                      0.2 Iris-setosa
                              3.6
                                                       0.2 Iris-setosa
                  5.0
                                           1.4
```

**Task 3.** Do the following tasks.

- Read the following columns for the features: 'sepal\_length', 'sepal\_width', 'petal\_length', 'petal\_width'.
- Read the column species for the target.
- Replace the species column with the following mapping:
  - Iris-setosa: 0
  - Iris-versicolor: 1

**HW1.** *One-vs-All target:* Write a function that takes in a target data frame and returns a new dataframe where the size of the column is the same as the number of category. The function makes use of replace\_target() function to create one-vs-all target values.

For example, if we have three categories of class, the columns of the returned data frame will be as follows: - column target: this is the original target column - column 0: the target with values of 0 will be set to 1 while the rest will be replaced with 0. - column 1: the target with values of 1 will be set to 1 while the rest will be replaced with 0. - column 2: the target with values of 2 will be set to 1 while while the rest will be replaced with 0.

```
In [8]: def create_onevsall_columns(df_target, col):
            dfout = df_target.copy()
            num_classes = df_target[col].nunique()
            for i in range(num_classes):
                dfout[i] = dfout[col].apply(lambda y : np.where(y == i,1,0))
            return dfout
In [9]: df_targets = create_onevsall_columns(df_target, 'species')
       print(df_targets)
        result = np.unique(df_targets['species'], return_counts=True)
        assert (result[0] == [0, 1, 2]).all()
        assert (result[1] == [50, 50, 50]).all()
        result = np.unique(df_targets[0], return_counts=True)
        assert (result[0] == [0, 1]).all()
        assert (result[1] == [100, 50]).all()
        result = np.unique(df_targets[1], return_counts=True)
        assert (result[0] == [0, 1]).all()
        assert (result[1] == [100, 50]).all()
        result = np.unique(df_targets[2], return_counts=True)
        assert (result[0] == [0, 1]).all()
        assert (result[1] == [100, 50]).all()
     species 0 1 2
0
           0 1 0 0
```

```
0 1 0 0
1
2
        0 1 0
3
        0 1 0
4
        0 1 0
      2
         0 0
145
146
        2 0 0 1
147
        2 0 0 1
        2 0 0 1
148
149
        2 0 0 1
```

[150 rows x 4 columns]

**HW2.** Multiple features and splitting of data set: Do the following task in the code below: - Read the following columns for the features: sepal\_length,sepal\_width, petal\_length, petal\_width normalize it using normalize\_z(). - Read species as the target column and use create\_onevsall\_columns() to create the additional target columns to do multi class classification. - Split the data set with 30% test size and random\_state = 100. - Normalize the training feature data set using normalize\_z() function. - Convert to numpy array both the target and the features using prepare\_feature() and prepare\_target() functions. - Call gradient\_descent() function to get the parameters using the training data set.

```
In [10]: columns = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width']
         mapping = {'Iris-setosa': 0, 'Iris-versicolor': 1, 'Iris-virginica':2}
         # extract the features and the target
         df_features, df_target = get_features_targets(df, columns, ["species"])
         # change target values to integer using mapping
         df_target = replace_target(df_target, "species", mapping)
         # create one vs all columns for the target
         df_targets = create_onevsall_columns(df_target, 'species')
         # split the data using random_state = 100 and 30% test size
         df_features_train, df_features_test, df_targets_train, df_targets_test = split_data(di
         # normalize the training feature
         df_features_train_z = normalize_z(df_features_train)
In [11]: assert df_features_train_z.shape == (105, 4)
         assert np.isclose(df_features_train_z.min(), -2.52349).any()
         assert np.isclose(df_features_train_z.max(), 2.73284).any()
         assert np.isclose(df_features_train_z['sepal_width'].mean(), 0)
         assert np.isclose(df_features_train_z['sepal_width'].std(), 1, atol=0.01)
```

```
assert (np.unique(df_targets_train['species']) == [0, 1, 2]).all()
assert (np.unique(df_targets_train[0]) == [0, 1]).all()
assert (np.unique(df_targets_train[1]) == [0, 1]).all()
assert (np.unique(df_targets_train[2]) == [0, 1]).all()
```

**HW3.** Build Multi-class Model: Write a function build\_model\_multiclass() which takes in the following arguments: - df\_features: which is a Pandas data framecontaining the features. - df\_targets: which is a Pandas data frame containing the target for one vs all classification. - col\_target: the name of the column target in the original data frame which is also the key of the dictionary containing the original target numpy array. - iterations: the number of iterations to perform the gradient descent. By default it is set to 1500. - alpha: the learning rate in the gradient descent algorithm. By default it is set to 0.01.

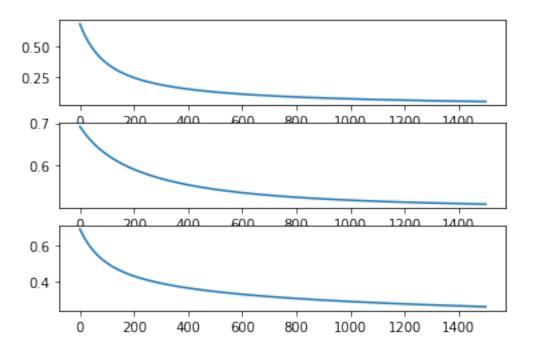
The function should return a dictionary of dictionary. The output dictionary has the following key and values: - key: the keys are the categories or the labels in the target. - values: the values are another dictionary for that particular label. This dictionary has two keys: beta and J\_storage, which gives the parameter value for that particular label and its cost minimization values at every iteration.

Hint: - you need to call prepare\_feature() and prepare\_target() to change the Pandas data frame to Numpy arrays. - in order to create a data frame instead of a series when accessing a column, use df[[c]] (will output data frame) instead of df[c] (will output series). - You need to use normalize\_minmax() on your target before passing it on to gradient\_descent\_logreg() because the function logistic regression has the normalized value of 0 to 1 in the y axis.

```
In [12]: def build_model_multiclass(df_features, df_targets, col_target, iterations=1500, alpha
             output = {}
             # change the feature columns to numpy array and append column of 1s
             features = prepare_feature(df_features)
             # change the target column to numpy array
             # prepare target for every column in targets
             for column in df_targets.columns:
                 if column == col_target:
                     continue
                 values = {}
                 target = prepare_target(df_targets[[column]])
                 target = normalize_minmax(target)
                 # provide initial guess for theta
                 beta = np.zeros((features.shape[1],1))
                 # call the gradient descent method
                 beta, J_storage = gradient_descent_logreg(features, target, beta, alpha, iter
```

```
values["J_storage"] = J_storage
                 output[column] = values
             return output
In [13]: output = build_model_multiclass(df_features_train_z, df_targets_train, 'species')
         assert isinstance(output, dict)
         expected = np.array([[ -1.0198841], [ -0.69883077], [ 1.0774116], [-1.17170999], [-1
         assert np.isclose(output[0]['beta'], expected).all()
         expected = np.array([[ -0.63304937], [ 0.11684857], [-1.15346071], [ 0.18746937], [-0
         assert np.isclose(output[1]['beta'], expected).all()
         expected = np.array([[-1.31740148], [0.42271871], [0.18526839], [0.8831822], [1.179
         assert np.isclose(output[2]['beta'], expected).all()
In [14]: fig, axes = plt.subplots(len(output), 1)
         idx = 0
         for c in output:
             print(f'class model = {c:}', output[c]['beta'])
             axes[idx].plot(output[c]['J_storage'])
             idx += 1
class model = 0 [[-1.0198841]
 [-0.69883077]
 [ 1.0774116 ]
 [-1.17170999]
 [-1.12846826]]
class model = 1 [[-0.63304937]
 [ 0.11684857]
 [-1.15346071]
 [ 0.18746937]
 [-0.14534827]]
class model = 2 [[-1.31740148]
 [ 0.42271871]
 [ 0.18526839]
 [ 0.8831822 ]
 [ 1.17929455]]
```

values["beta"] = beta

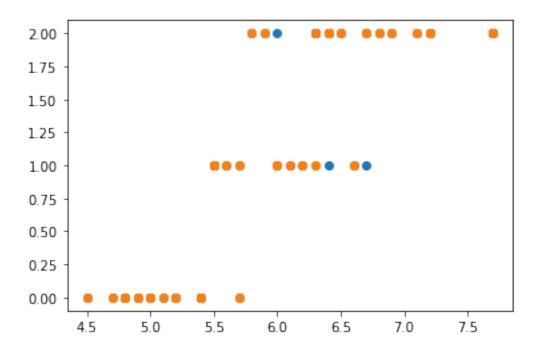


**HW4.** *Predict Multi-class:* Write a function predict\_multiclass() that takes in the data frame for the features and the parameters for the multi-class classification and return a Numpy array for the predicted target.

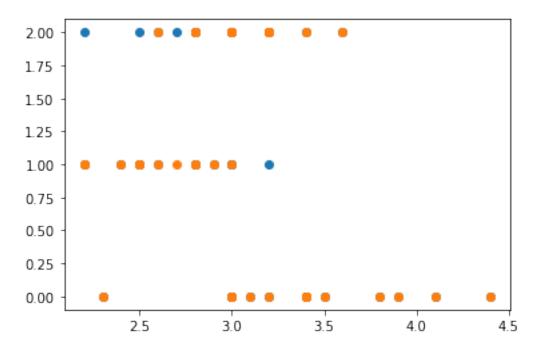
Recall that you need to do the following steps: - Normalize the features and change to numpy array - For each of the class, calculate the probability by using <code>log\_regression()</code> function. - For each record, find the class that gives the maximum probability. - Returns a Numpy array with the predicted target values

You can use the following function in your code: -np.argmax() to find the column name with the maximum value - df.apply(func, axis=1): which is to apply some function on a particular axis. Setting axis=1 means that the function is to be applied accross the columns of the data frame instead of the index or the rows.

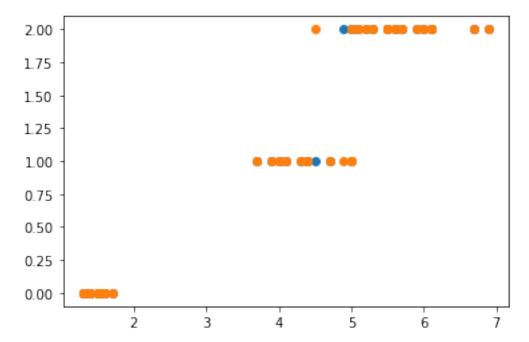
```
0.50949608])},
          2: {'beta': array([[-1.31740148],
                  [ 0.42271871],
                  [ 0.18526839],
                  [ 0.8831822 ],
                  [ 1.17929455]]),
           'J_storage': array([0.68991177, 0.68671789, 0.68356495, ..., 0.26207724, 0.26203146
                  0.26198572])}}
In [16]: def predict_multiclass(df_features, multi_beta):
             # normalize the training feature
             df_features_z = normalize_z(df_features)
             features = prepare_feature(df_features_z)
             num_features = len(multi_beta)
             pred = pd.DataFrame()
             for i in range(num_features):
                 beta = multi_beta[i]["beta"]
                 y_pred = log_regression(beta,features).ravel()
                 pred[i] = pd.Series(y_pred)
             pred['final'] = pred.apply(lambda x : np.argmax(x),axis = 1)
             return pred['final'].to_numpy().reshape(45,1)
In [17]: pred = predict_multiclass(df_features_test, output)
In [18]: pred.shape
Out[18]: (45, 1)
In [19]: pred = predict_multiclass(df_features_test, output)
         assert isinstance(pred, np.ndarray)
         assert pred.shape == (45, 1)
         assert pred.min() == 0
         assert pred.max() == 2
         assert np.median(pred) == 1
In [20]: plt.scatter(df_features_test['sepal_length'], df_targets_test['species'])
         plt.scatter(df_features_test['sepal_length'], pred)
Out[20]: <matplotlib.collections.PathCollection at 0x7f4cd7a91610>
```



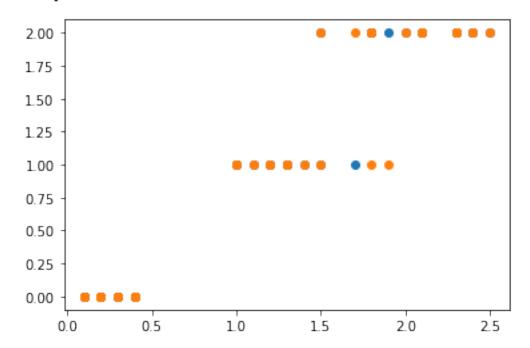
Out[21]: <matplotlib.collections.PathCollection at 0x7f4cd53c3a10>



Out[22]: <matplotlib.collections.PathCollection at 0x7f4cd5344e50>



Out[23]: <matplotlib.collections.PathCollection at 0x7f4cd52c9c50>



**HW5.** Confusion Matrix: Write a function to calculate the confusion matrix for multi-class label. If you write the solution in the Cohort session properly, the solution will be the same as in the Cohort session.

Make sure that you can output a dictionary where the keys are all the combinations of all the classes: (0, 0), (0, 1), (0, 2), (1, 0), (1, 1), (1, 2), (2, 0), (2, 1), (2, 2).

```
In [24]: import itertools
    def confusion_matrix(ytrue, ypred, labels):
        output = {i : 0 for i in list(itertools.product(labels,repeat = 2))}

    for idx in range(ytrue.shape[0]):
        actual = ytrue[idx,0]
        pred = ypred[idx,0] # or using a list index ypred[idx][0]
        output[(actual,pred)] +=1

    return output

In [25]: cm = confusion_matrix(df_targets_test.values, pred, [0, 1, 2])
        print(cm)
        assert cm == {(0, 0): 16, (0, 1): 0, (0, 2): 0, (1, 0): 0, (1, 1): 9, (1, 2): 2, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2, 4): 4, (2,
```

**HW6.** *Metrics:* Write a function calc\_accuracy() that takes in a Confusion Matrix array and output a dictionary with the following keys and values: - accuracy: total number of correct predictions / total number of records - sensitivity: total correct positive cases / total positive cases - precision: total of correct positive cases / total predicted positive cases

For multiple classes, we can also calculate *sensitivity* and *precision* for each of the class. For example, to calculate the sensitivity for class *i*, we use:

sensitivity<sub>i</sub> = 
$$\frac{M_{ii}}{\sum_{i} M_{ij}}$$

This means that we get the value at row i and column i which is the total correct case for class i and the sum over all the columns in row i which is the total cases for class i.

Similarly, we can calculate the precision for class *i* using:

$$precision_i = \frac{M_{ii}}{\sum_j M_{ji}}$$

**Notice that the indices are swapped for the denominator**. For precision, we instead of summing over all the columns, we sum over all the rows in column i which is the total cases when class i is *predicted*.

The output is a dictionary with one of the keys called accuracy and the rest of the keys are the label for the different classes, i.e. 0, 1, and 2 in our example here. The value for accuracy key is a float. On the other hand, the values for the other label keys is another dictionary that has sensitivity and precision as the keys.

```
In [40]: cm
Out [40]: {(0, 0): 16,
          (0, 1): 0,
          (0, 2): 0,
          (1, 0): 0,
          (1, 1): 9,
          (1, 2): 2,
          (2, 0): 0,
          (2, 1): 3,
          (2, 2): 15
In [41]: def calc_accuracy(cm, labels):
             output = {'accuracy': 0}
             correct_predictions = 0
             total_predictions = 0
             for k,v in cm.items():
                 if k[0] == k[1]:
                     correct_predictions += v
                 total_predictions += v
             output['accuracy'] = correct_predictions/total_predictions
             for 1 in labels:
                 tp = cm[(1, 1)]
                 denom_sensititivity = 0
                 denom_precision = 0
                 for j in labels:
                     # getting sum of the row
                     denom_sensititivity += cm[(1, j)]
                     # getting sum of the column
                     denom_precision += cm[(j, 1)]
                 sensitivity = tp/denom_sensititivity
                 precision = tp/denom_precision
                 output[1] = {'sensitivity':sensitivity,'precision':precision}
             return output
In [42]: metrics = calc_accuracy(cm, [0,1,2])
         print(metrics)
         assert np.isclose(metrics['accuracy'], 0.88888)
         assert metrics[0] == {'sensitivity': 1.0, 'precision': 1.0}
         assert np.isclose(metrics[0]['sensitivity'], 1.0)
         assert np.isclose(metrics[0]['precision'], 1.0)
         assert np.isclose(metrics[1]['sensitivity'], 0.8181818)
         assert np.isclose(metrics[1]['precision'], 0.75)
         assert np.isclose(metrics[2]['sensitivity'], 0.833333)
         assert np.isclose(metrics[2]['precision'], 0.88235)
```

```
0 0
16
0 1
0
0 2
0
1 0
0
1 1
9
1 2
2
2 0
0
2 1
3
2 2
15
{'accuracy': 0.888888888888888, 0: {'sensitivity': 1.0, 'precision': 1.0}, 1: {'sensitivity':
   HW7. Optional: Redo the above tasks using Scikit Learn libraries. You will need to use the
following: - LogisticRegression - train_test_split - confusion_matrix
   You can refer to the followign discussion on the different minimization solver for
LogisticRegression() class. - Stack overflow - logistic regression python solvers' defintions
In [ ]: from sklearn.linear_model import LogisticRegression
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import confusion_matrix
In [ ]: columns = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width']
        mapping = {'Iris-setosa': 0, 'Iris-versicolor': 1, 'Iris-virginica':2}
        # get the features and the columns
        df_features = None
        # replace target values with integers using the mapping
        df_target = None
        ###
        ### YOUR CODE HERE
        ###
In []: # split data set using random state = 100 and 30% test size
        df_features_train, df_features_test, df_target_train, df_target_test = None, None, None
        # change feature to numpy array and append column of 1s
        feature = None
```

```
# change target to numpy array
        target = None
        ###
        ### YOUR CODE HERE
        ###
In [ ]: # create LogisticRegression object instance
        # set solver to 'newton-cg' and multi_class to 'auto'
       model = None
        # build model
       pass
        # get predicted value
       pred = None
        ###
        ### YOUR CODE HERE
In []: # calculate confusion matrix
        cm = None
        ###
        ### YOUR CODE HERE
        ###
       print(cm)
In [ ]: expected = np.array([[16, 0, 0], [0, 11, 0], [0, 1, 17]])
        assert (cm == expected).all()
In [ ]: plt.scatter(df_features_test["sepal_width"], df_target_test)
       plt.scatter(df_features_test["sepal_width"], pred)
In [ ]: plt.scatter(df_features_test["sepal_length"], df_target_test)
       plt.scatter(df_features_test["sepal_length"], pred)
In [ ]: plt.scatter(df_features_test["petal_width"], df_target_test)
       plt.scatter(df_features_test["petal_width"], pred)
In [ ]: plt.scatter(df_features_test["petal_length"], df_target_test)
       plt.scatter(df_features_test["petal_length"], pred)
```

# Week12\_Homework

December 10, 2021

## 1 Week 12 Problem Set

#### 1.1 Homework

**HW1.** *Comments:* Write a state machine whose inputs are the characters of a string. The string contains the code for a computer program. The output of the state machine are either: - the input character if it is part of a comment, or - None, otherwise.

Comment starts with a # character and continue to the end of the current line. If you want to create a string that contains a new line character, you can use \n.

For example,

```
inpstr = "def func(x): # comment\n return 1"
m = CommentsSM()
print(m.transduce(inpstr))
```

The expected output is:

```
[None, None, "#", " ", "c",
```

You should start by drawing a state transition diagram indicating the states and what inputs cause transition to which other states. Use the test case above to determine if your state transition diagram is correct. You should begin writing your program only when you are confident that your diagram is correct.

```
In [17]: from abc import ABC, abstractmethod

class StateMachine(ABC):
    def __init__(self):
        self.state = None

def start(self):
        self.state = self.start_state

def step(self, inp):
        self.state,out = self.get_next_values(self.state,inp)
        return out

def transduce(self, inp_list):
```

```
output_list = []
                 self.start()
                 for inp in inp_list:
                     if not self.is_done():
                         out = self.step(inp)
                         output_list.append(out)
                 print(output_list)
                 return output_list
             @abstractmethod
             def get_next_values(self, state, inp):
                 pass
             def done(self, state):
                 return False
             def is_done(self):
                 return self.done(self.state)
In [18]: class CommentsSM(StateMachine):
             def __init__(self):
                 self.start_state = 0
             # @ arqs
             # state : current state
             def get_next_values(self, state, inp):
                 next_state = state
                 output = None
                 if self.state == 0 and inp == "#":
                     next_state = 1
                     output = inp
                 elif self.state == 1 and inp == "\n":
                     next_state = 0
                 elif self.state == 1 and inp != "\n":
                     output = inp
                 return next_state, output
In [19]: inpstr = "def func(x): # comment\n return 1"
        m = CommentsSM()
         out = m.transduce(inpstr)
         assert out == [None, None, None
[None, None, '#', '', 'c',
```

**HW2.** *First Word:* Write a state machine whose inputs are the characters of a string and which outputs either: - the input character if it is part of the first word on a line, or - None, otherwise

For the purposes here, a word is any sequence of consecutive characters that does not contain spaces or end-of-line characters. In this problem, comments have no special status. This means that if the line begins with #, then the first word is #.

```
that if the line begins with #, then the first word is #.
   For example,
inpstr = "def func(x): # comment\n
                                      return 1"
m = FirstWordSM()
print(m.transduce( inpstr))
   The expected output is:
["d", "e", "f", None, None,
In [47]: class FirstWordSM(StateMachine):
             def __init__(self):
                  self.start_state = 2
             def get_next_values(self, state, inp):
                  next_state = state
                  output = None
                  t = []
                  if self.state == 2:
                      if inp == " ":
                          next_state = 0
                      elif inp == ' n':
                          next_state = 1
                      elif inp != " ":
                          output = inp
                  elif self.state == 0 and inp == "\n":
                      next_state = 1
                  elif self.state == 1 and inp != " ":
                      next_state = 2
                      output = inp
                  return next_state, output
```

```
In [48]: inpstr = "def func(x, y): # comment\n pass\n return 1"
                                                                                         m = FirstWordSM()
                                                                                          out = m.transduce(inpstr)
                                                                                           assert out == ["d", "e", "f", None, 
 ['d', 'e', 'f', None, No
                                                                                 AssertionError
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          Traceback (most recent call last)
                                                                                  <ipython-input-48-b0b23635bf50> in <module>
                                                                                                      2 m = FirstWordSM()
                                                                                                    3 out = m.transduce(inpstr)
                                         ----> 4 assert out == ["d", "e", "f", None, None, None, None, None, None, None, None, None
                                                                                 AssertionError:
In [49]: inpstr = "def func(x): # comment\n return 1"
                                                                                          m = FirstWordSM()
                                                                                          out = m.transduce(inpstr)
                                                                                           assert out == ["d", "e", "f", None, 
 ['d', 'e', 'f', None, No
In []: ###
                                                                                   ### AUTOGRADER TEST - DO NOT REMOVE
```

**HW3.** *Robot:* Write a State Machine class that represent a robot. The dimension of the world and the robot initial position should be specified during the class instantiation. The robot can take in the following input: - "left" - "right" - "up" - "down"

The initial position of the robot is specified during the object instantiation and the input should modify the position of the robot. The robot position must not change if it exceed the boundary. At each step, the robot should output the updated position.

### In [ ]: class Position:

###

```
def __init__(self, x=0, y=0):
    self.x = x
    self.y = y

def __str__(self):
    return f"({self.x:}, {self.y:})"
```

```
class Dimension:
            def __init__(self, width=0, height=0):
                self.width = width
                self.height = height
            def __str__(self):
                return f"width: {self.width:}, height: {self.height:}"
In [ ]: class RobotSM(StateMachine):
            # @arqs
            \# init\_pos : Position
            # dimension : Dimension
            def __init__(self, init_pos, dimension):
                self.world_dim = dimension
                self.movement_map = {
                    "right" : (1,0),
                    "up" : (0,1),
                    "down" : (0,-1),
                    "left" : (-1,0)
                }
                self.start_state = init_pos
                self.bounded = 1
            def get_next_values(self, state, inp):
                next_state = self.compute_position(state,inp)
                output = next_state
                return next_state,output
            def compute_position(self,state, inp):
                # inp : Position
                # out : Position
                if self.bounded == 0:
                    return state
                if not self.check_dimension:
                    return state
                state.x += self.movement_map[inp][0]
                state.y += self.movement_map[inp][1]
                return state
            def check_dimension(self,state):
```

```
# check if the element is out of out of boundary
                if state.x > self.world_dim.width or state.x < 0 or state.y > self.world_dim.he
                    self.bounded = 0
                    return False
                return True
In []: robot = RobotSM(Position(0, 0), Dimension(5, 5))
        robot.start()
        robot.transduce(["right", "right", "up", "up", "up", "left", "down"])
       pos = robot.state
       print(pos)
        assert pos.x == 1 and pos.y == 2
In []: robot = RobotSM(Position(0, 0), Dimension(5, 5))
       robot.start()
        robot.transduce(["right", "right", "up", "up", "up", "left", "down"])
        pos = robot.state
        assert pos.x == 1 and pos.y == 2
In []: ###
        ### AUTOGRADER TEST - DO NOT REMOVE
        ###
```

**HW4.** Search SM: Write a function sm\_search that takes in the following arguments: -sm\_to\_search: is the State Machine instance to search. This argument is of the type MapSM as defined in CS4. You should use the get\_next\_values() of this State Machine instance to explore the next state in your search. -initial\_state: is the start state of the search. If it is not provided, it should be assigned to the start\_state of sm\_search. - goal\_test: is a function that returns True if the argument is the end state of the search. If it is not provided, it should be eassigned to the done function of the state machine.

This function performs a **breadth-first-search** algorithm to explore the next states.

The output is a list of Step instances from the init\_state to the end state which is determined by the goal\_test function.

This problem requires you to complete the following: - Queue class from Problem Set 4 HW2. - MapSM class in CS4. - SearchNode and Step classes in CS5.

```
In []: class Queue:
    def __init__(self):
        self.__items = []

    def enqueue(self, item):
        self.__items.append(item)

    def dequeue(self):
        return self.__items.pop(0) if not self.is_empty else None

    def peek(self):
        return self.__items[0]
```

```
@property
            def is_empty(self):
                return len(self.__items) == 0
            @property
            def size(self):
                return len(self.__items)
In [ ]: # Copy over the implementation of StateSpaceSearch from Cohort
        from abc import abstractmethod
        class StateSpaceSearch(StateMachine):
            @property
            @abstractmethod
            def statemap(self):
                pass
            @property
            @abstractmethod
            def legal_inputs(self):
                pass
In [ ]: class MapSM(StateSpaceSearch):
            def __init__(self, start):
                self.start_state = start
            @property
            def statemap(self):
                # There are 4 actions : 0,1,2,3 -- encoded
                statemap = {"S": ["A", "B"],
                            "A": ["S", "C", "D"],
                            "B": ["S", "D", "E"],
                            "C": ["A", "F"],
                            "D": ["A", "B", "F", "H"],
                            "E": ["B", "H"],
                            "F": ["C", "D", "G"],
                            "H": ["D", "E", "G"],
                            "G": ["F", "H"]}
                return statemap
            @property
            def legal_inputs(self):
                max_neighbour = -1
                for _,neighbours in self.statemap.items():
                    max_neighbour = max(max_neighbour,len(neighbours))
                return set(range(max_neighbour))
```

```
def get_next_values(self, state, inp):
                neighbours = self.statemap.get(state,None)
                # default values
                next_state = state
                output = state
                  if not neighbours:
                      return next_state, output
                if inp < len(neighbours) and neighbours:</pre>
                    next_state = neighbours[inp]
                    output = next_state
                return next_state, output
In [ ]: class Step:
            def __init__(self, action, state):
                self.action = action
                self.state = state
            def __eq__(self, other):
                return self.action == other.action and self.state == other.state
            def str (self):
                return f"action: {self.action:}, state: {self.state:}"
        class SearchNode:
            def __init__(self, action, state, parent):
                self.state = state
                self.action = action
                self.parent = parent
            # @return : list of Step instances
            # S -> A-> C
            # C.path() --> [Step(None,S),Step(ActionA,A),Step(ActionC,C))]
            # Recursively calling from C.path()
            # C.path()
            # A.path()
            # S.path()
            def path(self):
                # using recursion
                # base state
                if self.parent is None:
```

```
return [Step(self.action, self.state)]
                else:
                    return self.parent.path() + [Step(self.action,self.state)]
            # @ args
            # state -> string
            # @return
            # boolean
            def in_path(self, state):
                if self.state == state: # asking if the state is the expected state
                    return True
                elif self.parent == None: # not in path anymore
                    return False
                else:
                    # recursion to check the parent is equals to the state
                    return self.parent.in_path(state) # passing the parent object as self.stat
            def __eq__(self, other):
                if self is None and other is None:
                    return True
                elif self is None:
                    return False
                elif other is None:
                    return False
                else:
                    return self.state == other.state and self.parent == other.parent and \
                           self.action == other.action
In [ ]: def sm_search(sm_to_search, initial_state=None, goal_test=None):
            # check if initial_state is provided
            # if it is, use it
            # otherwise, get the start state of sm_to_search
            if initial_state == None:
                # replace None to take the start state of sm_to_search
                init_state = sm_to_search.start_state
            else:
                init_state = initial_state
            # check if goal_test is provided, if it is, use it
            # otherwise, use the done method as the goal function
            if goal_test == None:
                goal_func = sm_to_search.done
            else:
                goal_func = goal_test
            # create a Queue instance to store the node to explore
            bfs_queue = Queue()
```

```
# if the initial state is the goal state,
# then we are done and exit
if goal_func(init_state):
    return [Step(None, init_state)]
# otherwise, add the current node into the agenda
# Start bfs from root
# We create SearchNode Instance with state as init state
bfs_queue.enqueue(SearchNode(None, init_state, None))
# explore as long as the Queue is not empty
while not bfs_queue.is_empty:
    # Take out the parent from the Queue
    current_node = bfs_queue.dequeue()
    # create a list to keep track which child state have been explored
    visited = \Pi
    # get all the legal input values
    actions = sm_to_search.legal_inputs
    #iterate over all legal inputs
    for a in actions: # a will be 0,1,2,3
        # get the next possible state using the current action
        # get next values returns (nextstate, output). next state is a string
        next_state = sm_to_search.get_next_values(current_node.state, a)[0]
        # create a new search node from the new_s
        next_state_search_node = SearchNode(a,next_state,current_node) # Search no
        # if the new state is the goal state, then we exit and return the path
        if goal func(next state):
            return next_state_search_node.path()
        # Checking 2 conditions before adding them to the queue. dont want to repe
        # do not explore states that have already been explored or about to be exp
        # if the next_state is already in the list of new child state, ignore it
        elif next_state in visited:
            continue
        # if the next state is in the path of the current node, ignore it
        # doesnt this mean that its already visited. so wouldnt the first conditio
        elif current_node.in_path(next_state):
            continue
```

```
# otherwise, add the new state into the list
                    # and the new node into the Queue
                    else:
                        # step 1. add the new state into the new_child_state
                        visited.append(next_state)
                        # step 2. add the new node into the Queue
                        bfs_queue.enqueue(next_state_search_node)
            return None
In [ ]: mapSM = MapSM("S")
        ans = sm_search(mapSM , "S" , lambda s: s=="H" )
        steps = [(step.action, step.state) for step in ans]
        assert steps == [(None, "S"), (0, "A"), (2, "D"), (3, "H")]
        for step in ans:
            print(step)
In []: ###
        ### AUTOGRADER TEST - DO NOT REMOVE
        ###
```

# Week12\_Cohort

December 10, 2021

### 1 Week 12 Problem Set

### 1.1 Cohort Sessions

**CS1.** Define an Abstract Class for a State Machine, called StateMachine. The class has two properties: - state: which is the current state of the machine - start\_state: which is the initial state of the machine

The class should define the following methods: - start(): this method set the state property using the value in start\_state. Once state has a value, the machine is considered started. - step(inp): this method takes in the current input and returns the current output. This method should move the state machine to the next state based on the current input and its current state. You should call get\_next\_values(state, inp) in your implementation. - done(state): this method always return False. A child class can override thid method to give a different condition to end the state machine. - is\_done(): is to be used internally to check if the state machine should terminate or not. This method simply calls done(state) and pass on the current state. The method transduce(inp\_list) calls this method to check if it should terminates or not. - transduce(inp\_list): this method calls start() to initialize the state with the start\_state and run the state machine by calling step(inp) for every item in the inp\_list. The method runs the state machine and produces the output list according to the number of input in the inp\_list or when the state machine terminates according to the output of is\_done() method. This method should call is\_done() to see if it should terminate at a particular state.

This class should be an Abstract Class. Implement the following way: - SM class inherits from abc.ABC, which is Python's Abstract Base Class (ABC). - Any implementation of State Machine's instances must declare the following property: start\_state. - Any implementation of State Machine's instances must implement the following abstract method: get\_next\_values() that takes in the current state and the current input and output a tuple of the next\_state and the current output.

```
In [3]: from abc import ABC, abstractmethod
    class StateMachine(ABC):
        def __init__(self):
            self.state = None

    def start(self):
        self.state = self.start_state
    def step(self, inp):
```

```
self.state,out = self.get_next_values(self.state,inp)
                return out
            def transduce(self, inp_list):
                output_list = []
                self.start()
                for inp in inp_list:
                    if not self.is_done():
                        out = self.step(inp)
                        output_list.append(out)
                return output_list
            @abstractmethod
            def get_next_values(self, state, inp):
                pass
            def done(self, state):
                return False
            def is_done(self):
                return self.done(self.state)
In [4]: class Test(StateMachine):
            start_state = 0
            def get_next_values(self, state, inp):
                next_state = state + inp
                output = next_state
                return next_state, output
            def done(self, state):
                if state == -1:
                    return True
                else:
                    return False
        class NoImplement(StateMachine):
            def __init__(self):
                start_state = 0
        t1 = Test()
        t1.start()
        assert t1.state == 0
        out = t1.step(2)
        print(out)
        print(t1.state)
```

```
assert t1.state ==2 and out == 2
        t2 = Test()
        out = t2.transduce([1,2,3,4])
        print(out)
        assert out == [1, 3, 6, 10]
        t3 = Test()
        out = t3.transduce([1, -2, 3])
        assert out == [1, -1]
        try:
            t4 = NoImplement()
            raise AssertionError
        except TypeError:
            pass
2
[1, 3, 6, 10]
In [5]: class Test(StateMachine):
            start_state = 0
            def get_next_values(self, state, inp):
                next_state = state + inp
                output = next_state
                return next_state, output
            def done(self, state):
                if state == -1:
                    return True
                else:
                    return False
        class NoImplement(StateMachine):
            def __init__(self):
                start_state = 0
        t1 = Test()
        t1.start()
        assert t1.state == 0
        out = t1.step(2)
        assert t1.state ==2 and out == 2
        t2 = Test()
        out = t2.transduce([1,2,3,4])
```