## Assignment\_4

July 24, 2025

```
[34]: import warnings
      warnings.filterwarnings('ignore')
[32]: import numpy as np
      import pandas as pd
      import matplotlib.pyplot as plt
      import seaborn as sns
      from sklearn.impute import SimpleImputer
      from sklearn.model selection import train test split
      from sklearn.preprocessing import StandardScaler
      from sklearn.decomposition import PCA
      from sklearn.svm import SVC
      from sklearn.metrics import accuracy_score, precision_score, recall_score,
       [35]: # Load the dataset
      df = pd.read_csv("/content/cancer.csv")
      print("CSV Shape:", df.shape)
      df.head()
     CSV Shape: (569, 33)
[35]:
              id diagnosis
                            radius_mean
                                        texture_mean perimeter_mean area_mean \
      0
          842302
                         Μ
                                   17.99
                                                 10.38
                                                                122.80
                                                                           1001.0
           842517
                                   20.57
                                                 17.77
      1
                         Μ
                                                                132.90
                                                                           1326.0
      2 84300903
                         М
                                   19.69
                                                 21.25
                                                                130.00
                                                                           1203.0
                                                 20.38
                                                                77.58
      3 84348301
                         Μ
                                   11.42
                                                                            386.1
      4 84358402
                                   20.29
                                                 14.34
                                                                135.10
                                                                           1297.0
        smoothness_mean compactness_mean
                                           concavity_mean concave points_mean \
      0
                0.11840
                                   0.27760
                                                    0.3001
                                                                        0.14710
      1
                0.08474
                                   0.07864
                                                    0.0869
                                                                        0.07017
      2
                0.10960
                                   0.15990
                                                    0.1974
                                                                        0.12790
      3
                                                    0.2414
                0.14250
                                   0.28390
                                                                        0.10520
      4
                0.10030
                                   0.13280
                                                    0.1980
                                                                        0.10430
         ... texture_worst perimeter_worst area_worst smoothness_worst \
```

```
0
                    17.33
                                     184.60
                                                 2019.0
                                                                    0.1622
                                                 1956.0
                                                                    0.1238
      1
                    23.41
                                     158.80
      2 ...
                    25.53
                                     152.50
                                                 1709.0
                                                                    0.1444
      3 ...
                    26.50
                                      98.87
                                                  567.7
                                                                    0.2098
                    16.67
                                     152.20
                                                 1575.0
                                                                    0.1374
                                             concave points_worst symmetry_worst \
         compactness_worst concavity_worst
                                                             0.2654
      0
                    0.6656
                                      0.7119
                                                                             0.4601
                    0.1866
                                      0.2416
                                                             0.1860
                                                                             0.2750
      1
      2
                    0.4245
                                      0.4504
                                                             0.2430
                                                                             0.3613
      3
                                      0.6869
                    0.8663
                                                             0.2575
                                                                             0.6638
      4
                    0.2050
                                      0.4000
                                                             0.1625
                                                                             0.2364
         fractal_dimension_worst Unnamed: 32
      0
                         0.11890
                                           NaN
      1
                         0.08902
                                           NaN
      2
                         0.08758
                                           NaN
      3
                                           NaN
                         0.17300
      4
                         0.07678
                                           NaN
      [5 rows x 33 columns]
[36]: # Drop 'id' column and extract features
      X = df.drop(columns=['id', 'diagnosis'], axis=1)
      # Encode 'diagnosis': M = 1, B = 0
      Y = df['diagnosis'].map({'M': 1, 'B': 0}).values
      # Handle missing values using mean imputation
      imputer = SimpleImputer(strategy='mean')
      X = imputer.fit_transform(X)
      # Check shape
      print("X shape:", X.shape)
      print("Y shape:", Y.shape)
     X shape: (569, 30)
     Y shape: (569,)
[37]: # Confusion Matrix Plot Function
      def get_confusion_matrix(cnf_matrix):
          class_names = sorted(Y.unique())
          fig, ax = plt.subplots()
          tick_marks = np.arange(len(class_names))
          plt.xticks(tick_marks, class_names)
          plt.yticks(tick_marks, class_names)
          sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu", fmt='g')
```

```
plt.title('Confusion Matrix')
          plt.ylabel('Actual Label')
          plt.xlabel('Predicted Label')
          plt.show()
[38]: # Evaluation Metrics Function
      def get_results(y_test, y_pred):
          acc = accuracy_score(y_test, y_pred)
          prec = precision_score(y_test, y_pred)
          rec = recall_score(y_test, y_pred)
          print("Accuracy:", acc)
          print("Precision:", prec)
          print("Recall:", rec)
          return acc * 100, prec * 100, rec * 100
[39]: # PCA + SVM Training and Evaluation
      def svm model training pca(X, Y):
          n = X.shape[1]
          acc_list = []
          recall_list = []
          precision_list = []
          k_list = []
          for i in range(n):
             print("K =", i + 1)
             pca = PCA(n_components=i + 1)
             principalComponents = pca.fit_transform(X)
             X_train, X_test, y_train, y_test =
       strain_test_split(principalComponents, Y, test_size=0.20, random_state=99)
              classifier = SVC(kernel='linear')
              classifier.fit(X_train, y_train)
              y_pred = classifier.predict(X_test)
             result = get_results(y_test, y_pred)
             acc_list.append(result[0])
             precision_list.append(result[1])
              recall list.append(result[2])
             k_list.append(i + 1)
          high_acc = max(acc_list)
          high_acc_k = acc_list.index(high_acc) + 1
          print("----")
          print("Highest Classification Accuracy Achieved: {:.2f}% for K = {}".
       →format(high_acc, high_acc_k))
```

return k\_list, acc\_list, precision\_list, recall\_list

```
[40]: # Plotting metrics over principal components
def plot_result_with(k_list, acc_list, precision_list, recall_list):
    plt.plot(k_list, acc_list, label='Accuracy')
    plt.plot(k_list, precision_list, label='Precision')
    plt.plot(k_list, recall_list, label='Recall')
    plt.xlabel("K")
    plt.ylabel("Metric Value")
    plt.title("PCA Dimensionality vs SVM Metrics")
    plt.legend()
    plt.show()
```

```
Problem 1:
        • 1.1
[41]: # Train and evaluate
      k_list, acc_list, precision_list, recall_list = svm_model_training_pca(X, Y)
     Accuracy: 0.9122807017543859
     Precision: 0.9375
     Recall: 0.7894736842105263
     K = 2
     Accuracy: 0.9473684210526315
     Precision: 0.9444444444444444
     Recall: 0.8947368421052632
     K = 3
     Accuracy: 0.9473684210526315
     Precision: 0.9444444444444444
     Recall: 0.8947368421052632
     K = 4
     Accuracy: 0.9736842105263158
     Precision: 0.9487179487179487
     Recall: 0.9736842105263158
     K = 5
     Accuracy: 0.9736842105263158
     Precision: 0.9487179487179487
     Recall: 0.9736842105263158
     K = 6
     Accuracy: 0.9736842105263158
     Precision: 0.9487179487179487
     Recall: 0.9736842105263158
     K = 7
     Accuracy: 0.9649122807017544
     Precision: 0.9473684210526315
```

Recall: 0.9473684210526315

Accuracy: 0.9649122807017544

Precision: 0.9473684210526315 Recall: 0.9473684210526315

K = 9

Accuracy: 0.956140350877193 Precision: 0.9459459459459459 Recall: 0.9210526315789473

K = 10

Accuracy: 0.956140350877193 Precision: 0.9459459459459459 Recall: 0.9210526315789473

K = 11

Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 12

Accuracy: 0.9649122807017544 Precision: 0.9473684210526315 Recall: 0.9473684210526315

K = 13

Accuracy: 0.9649122807017544 Precision: 0.9473684210526315 Recall: 0.9473684210526315

K = 14

Accuracy: 0.9649122807017544 Precision: 0.9473684210526315 Recall: 0.9473684210526315

K = 15

Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 16

Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 17

Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 18

Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 19

Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 20

Accuracy: 0.9736842105263158

Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 21

Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 22

Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 23

Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 24

Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 25

Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 26

Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 27

Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 28

Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 29

Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

K = 30

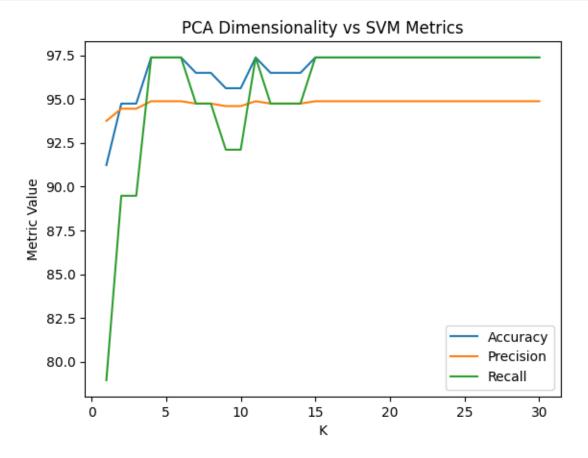
Accuracy: 0.9736842105263158 Precision: 0.9487179487179487 Recall: 0.9736842105263158

\_\_\_\_\_

Highest Classification Accuracy Achieved: 97.37% for K = 4

1.2

## [56]: # Plot the results plot\_result\_with(k\_list, acc\_list, precision\_list, recall\_list)



1.3

```
# Apply PCA
             pca = PCA(n_components=n_pc)
             principalComponents = pca.fit_transform(X)
             # Train/Test split
             X_train, X_test, y_train, y_test = train_test_split(
                 principalComponents, Y, test_size=0.20, random_state=99
             )
             # Train SVM with specified kernel
             classifier = SVC(kernel=kernel list[i])
             classifier.fit(X_train, y_train)
             y_pred = classifier.predict(X_test)
             # Evaluate
             r = get_results(y_test, y_pred) # From previous function
             acc_list.append(r[0])
             precision_list.append(r[1])
             recall_list.append(r[2])
             print("----")
         # Find best kernel by accuracy
         high acc = max(acc list)
         n = acc_list.index(high_acc)
         high_acc_kernel = kernel_list[n]
         print("Highest Classification Accuracy Achieved: {:.6f}% for Kernel = {}".
       →format(high_acc, high_acc_kernel))
         return kernel_list, acc_list, precision_list, recall_list
[57]: # Plot the results and compare the accuracies for different kernels
     kernel_list, acc_list, precision_list, recall_list =
       ⇒svm_model_training_with_kernel(X, Y, 4)
     Kernel = linear
     Accuracy: 0.9736842105263158
     Precision: 0.9487179487179487
     Recall: 0.9736842105263158
     _____
     Kernel = poly
     Accuracy: 0.868421052631579
     Precision: 1.0
     Recall: 0.6052631578947368
     _____
```

Kernel = rbf

Accuracy: 0.9385964912280702

Recall: 0.868421052631579 \_\_\_\_\_ Kernel = sigmoid Accuracy: 0.9035087719298246 Precision: 0.8648648648649 Recall: 0.8421052631578947 \_\_\_\_\_ Highest Classification Accuracy Achieved: 97.368421% for Kernel = linear Problem 2 • 2.1 [59]: import pandas as pd import numpy as np from sklearn.model\_selection import train\_test\_split from sklearn.svm import SVR from sklearn.decomposition import PCA import warnings from sklearn.exceptions import DataConversionWarning # Suppress the y-shape warning from sklearn warnings.filterwarnings(action='ignore', category=DataConversionWarning) # Load dataset df = pd.read\_csv("/content/Housing.csv") print("CSV File Shape:") print(df.shape) df.head() CSV File Shape: (545, 13)[59]: price area bedrooms bathrooms stories mainroad guestroom basement 0 13300000 7420 4 2 3 yes no no 1 12250000 8960 4 4 4 yes no no 3 2 2 2 12250000 9960 yes no yes 3 12215000 7500 2 4 2 yes no yes 4 11410000 7420 1 2 yes yes yes hotwaterheating airconditioning parking prefarea furnishingstatus 0 2 furnished no yes yes 1 3 furnished yes no no semi-furnished 2 2 no no yes 3 3 furnished no yes yes 4 2 furnished no yes no

Precision: 0.9428571428571428

```
[60]: # Convert binary categorical columns
      svar_list = ['mainroad', 'guestroom', 'basement', 'hotwaterheating',
      ⇔'airconditioning', 'prefarea']
      def binary_mapping(x):
          return x.map({'yes': 1, 'no': 0})
      df[svar_list] = df[svar_list].apply(binary_mapping)
      df.head()
[60]:
           price area bedrooms bathrooms stories mainroad guestroom
      0 13300000 7420
                                                              1
      1 12250000 8960
                                                    4
                                4
                                           4
                                                              1
                                                                         0
                                           2
                                                    2
      2 12250000 9960
                                3
                                                              1
                                                                         0
      3 12215000 7500
                                4
                                           2
                                                    2
                                                              1
                                                                         0
      4 11410000 7420
                                                    2
                                4
                                           1
                                                                         1
        basement hotwaterheating airconditioning parking prefarea \
      0
               0
                                                  1
                                                           3
      1
                0
                                0
                                                                     0
      2
                                                  0
                                                           2
                1
                                 0
                                                                     1
      3
                1
                                 0
                                                  1
                                                           3
                                                                     1
                1
                                 0
                                                  1
                                                                     0
        furnishingstatus
      0
               furnished
               furnished
      1
          semi-furnished
      3
               furnished
               furnished
[61]: # Extract Features and Target
      num_vars = ['area', 'bedrooms', 'bathrooms', 'stories', 'mainroad',
                  'guestroom', 'basement', 'hotwaterheating',
                  'airconditioning', 'parking', 'prefarea']
      target_column = 'price'
      data = df[num_vars]
      X = data.to_numpy()
      Y = df[[target_column]].to_numpy()
      # Impute missing values
      from sklearn.impute import SimpleImputer
      imputer = SimpleImputer(strategy='mean')
      X = imputer.fit_transform(X)
```

```
print("Input shape:", X.shape)
      print("Target shape:", Y.shape)
     Input shape: (545, 11)
     Target shape: (545, 1)
[62]: # Cost Function for SVR
      def compute_cost(y, y_pred):
          m = len(y)
          errors = np.subtract(y, y_pred)
          sqrErrors = np.square(errors)
          J = 1 / (2 * m) * np.sum(sqrErrors)
          return J
[63]: # Train SVR Model (No PCA)
      from sklearn.svm import SVR
      from sklearn.model_selection import train_test_split
      def svr_model_training(X, Y):
          X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.20, __
       →random state=99)
          classifier = SVR()
          classifier.fit(X_train, y_train)
          Y_pred = classifier.predict(X_test)
          loss = compute_cost(y_test, Y_pred)
          print("Loss:", loss)
[64]: #Run
      svr_model_training(X, Y)
     Loss: 238290456164115.3
[65]: # PCA + SVR Training Across K
      from sklearn.decomposition import PCA
      def svr_model_training_pca(X, Y):
          n = X.shape[1]
          loss_list = []
          k_list = []
          for i in range(n):
              print("K =", i+1)
              pca = PCA(n_components=i+1)
              principalComponents = pca.fit_transform(X)
              X_train, X_test, y_train, y_test =
       strain_test_split(principalComponents, Y, test_size=0.20, random_state=9)
```

```
classifier = SVR(kernel='linear')
              classifier.fit(X_train, y_train)
             Y_pred = classifier.predict(X_test)
             loss = compute_cost(y_test, Y_pred)
             print("Loss:", loss)
             loss_list.append(loss)
             k_list.append(i+1)
         low_loss = min(loss_list)
         low_loss_k = loss_list.index(low_loss) + 1
         print("----")
         print("Lowest Loss Achieved:", low_loss, "for K number =", low_loss_k)
         return k_list, loss_list
[66]: # Run
     k_list, loss_list = svr_model_training_pca(X, Y)
     K = 1
     Loss: 250088245443913.44
     K = 2
     Loss: 250064272993220.78
     K = 3
     Loss: 250063469523478.62
     K = 4
     Loss: 250063984078365.66
     Loss: 250065669922950.5
     K = 6
     Loss: 250065169858786.6
     K = 7
     Loss: 250065604004005.22
     K = 8
     Loss: 250067194202934.53
     K = 9
     Loss: 250067274612974.3
     K = 10
     Loss: 250067050044776.47
     K = 11
     Loss: 250067033255061.38
     Lowest Loss Achieved: 250063469523478.62 for K number = 3
[67]: # Compare Kernels (with PCA)
      def svr_model_training_with_kernel(X, Y, n_pc):
```

```
kernel_list = ["linear", "poly", "rbf"]
         loss_list = []
         y_pred_list = []
         pca = PCA(n_components=n_pc)
         principalComponents = pca.fit_transform(X)
         for i in kernel_list:
             print("Kernel =", i)
             X_train, X_test, y_train, y_test =
       strain_test_split(principalComponents, Y, test_size=0.20, random_state=99)
             classifier = SVR(kernel=i)
             classifier.fit(X_train, y_train)
             Y_pred = classifier.predict(X_test)
             y_pred_list.append(Y_pred)
             loss = compute_cost(y_test, Y_pred)
             loss_list.append(loss)
             print("Loss:", loss)
             print("----")
         low_loss = min(loss_list)
         n = loss_list.index(low_loss)
         low_loss_kernel = kernel_list[n]
         print("Lowest Loss Achieved:", low_loss, "for Kernel =", low_loss_kernel)
         return kernel_list, y_pred_list, loss_list
[68]: # Run
     kernel_list, y_pred_list, y_test = svr_model_training_with_kernel(X, Y, n_pc=3)
     Kernel = linear
     Loss: 306023058583913.25
     Kernel = poly
     Loss: 238440221378996.94
     Kernel = rbf
     Loss: 238289370339162.38
     _____
     Lowest Loss Achieved: 238289370339162.38 for Kernel = rbf
```