Homework 1

April 17, 2019

1 Homework 1

1.1 Initial Set-Up:

```
In [1]: # Read in data manipulation packages
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        # Use for data-preprocessing
        wine_dat = pd.read_csv('./wine_modified.csv')
        print('Wine modified dimensions:', wine_dat.shape)
        wine_dat.head()
        # Use for remaining sections
        X_train = pd.read_csv('./wine_train_data.csv')
        y_train = pd.read_csv('./wine_train_labels.csv')
        X_valid = pd.read_csv('./wine_val_data.csv')
        y_valid = pd.read_csv('./wine_val_labels.csv')
        X_test = pd.read_csv('./wine_test_data.csv')
        y_test = pd.read_csv('./wine_test_labels.csv')
        print('Traning data dimensions:',X_train.shape)
        print('Number of rows of training:', X_train.shape[0])
        print('Number of rows of validation:', X_valid.shape[0])
        print('Number of rows of testing:', X_test.shape[0])
Wine modified dimensions: (178, 14)
Traning data dimensions: (100, 13)
Number of rows of training: 100
Number of rows of validation: 39
Number of rows of testing: 39
```

1.2 Data Preprocessing:

```
Problem 1:
```

```
In [4]: # Where are the missing values?
    wine_dat.isnull().sum()
```

```
Out[4]: class
                                  10
        Alcohol
                                  0
        Malic acid
                                  12
        Ash
                                 112
        Alcalinity of ash
                                  12
        Magnesium
                                  22
        Total phenols
                                   0
        Flavanoids
                                  48
        Nonflavanoid phenols
                                  14
        Proanthocyanins
                                  12
                                  12
        Color intensity
        Hue
                                  14
        OD280/OD315
                                  11
        Proline
                                  14
        dtype: int64
In [25]: # Remove NaN in Class
         wine_clean = wine_dat.dropna(subset=['class'])
         # Remove Rows with > 7 missing
         wine_clean = wine_clean.dropna(thresh=wine_clean.shape[1]-7)
         # Report new number of rows
         print('New number of rows:',wine_clean.shape[0])
New number of rows: 154
   Problem 2:
In [26]: # Detect breakdown of missing values
         wine_clean.isnull().sum()/wine_clean.shape[0]
Out[26]: class
                                  0.000000
         Alcohol
                                  0.000000
         Malic acid
                                  0.000000
         Ash
                                  0.616883
         Alcalinity of ash
                                  0.000000
         Magnesium
                                  0.058442
         Total phenols
                                  0.000000
         Flavanoids
                                  0.227273
         Nonflavanoid phenols
                                  0.000000
         Proanthocyanins
                                  0.000000
         Color intensity
                                  0.000000
         Hue
                                  0.00000
         OD280/OD315
                                  0.000000
         Proline
                                  0.000000
         dtype: float64
In [27]: # Remove ash
         wine_clean.drop('Ash', axis=1, inplace=True)
```

```
# Print new shape
         print('New data dimensions:',wine_clean.shape)
         print('Removed Ash feature')
New data dimensions: (154, 13)
Removed Ash feature
In [28]: # Fill in missing data with mean
         features_detect = wine_clean.columns[pd.isnull(wine_clean).sum() > 0].tolist()
         print(features_detect, 'are features with missing values')
         wine_clean = wine_clean.fillna(wine_clean.mean())
         print('New standard deviations are:')
         wine_clean[features_detect].std()
['Magnesium', 'Flavanoids'] are features with missing values
New standard deviations are:
Out[28]: Magnesium
                        14.440377
         Flavanoids
                         0.873573
         dtype: float64
   Problem 3:
In [31]: # Remove rows that are within 3 standard deviations (~99.7%) of the data.
         wine_clean = wine_clean[np.abs(wine_clean.Alcohol - wine_clean.Alcohol.mean()) <= (3*wine_clean.Alcohol.mean())</pre>
         wine_clean = wine_clean[np.abs(wine_clean.Proline - wine_clean.Proline.mean()) <= (3*wine_clean.Proline.mean())</pre>
         print('Final dimensions are:',wine_clean.shape)
Final dimensions are: (148, 13)
```

While there are many different ways to classify an individual data point as an outlier, the most straightforward and indisputable approach is to remove rows where the value is above or below 3 standard deviations of the data. This value would need to be more extreme than 99.7% of the rest of the data. Hence, the data point is pretty safe to be classified as an outlier and removed.

1.3 Decision Trees:

Problem 4:

```
In [4]: from sklearn.tree import DecisionTreeClassifier, export_graphviz
    import pydotplus
    from sklearn.neighbors import KNeighborsClassifier
    from sklearn import preprocessing

# For final predictions:
    X_train_fin = pd.concat([X_train,X_valid],ignore_index=True)
```

```
y_train_fin = pd.concat([y_train,y_valid],ignore_index=True)
                  best_acc = 0
                  computations = ['gini', 'entropy']
                  for i in computations:
                           clf = DecisionTreeClassifier(i)
                           clf.fit(X_train, y_train)
                           accuracy = np.sum(clf.predict(X_valid)==y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].value
                           print('For criterion =', i, 'the validation accuracy = ' + str(accuracy))
                           if (accuracy > best_acc):
                                    best_acc = accuracy
                                    best_computation = i
                  print("")
                  print('The best criterion is', best_computation, 'with a validation accuracy of', best_a
                  clf = DecisionTreeClassifier(criterion=best_computation)
                  clf.fit(X_train_fin, y_train_fin)
                  predictions = clf.predict(X_test)
                  fin_accuracy = np.sum(predictions==y_test['class'].values)*1/len(y_test['class'].values)
                  print('Final accuracy on total training data = ' + str(fin_accuracy))
For criterion = gini the validation accuracy = 0.948717948718
For criterion = entropy the validation accuracy = 0.974358974359
The best criterion is entropy with a validation accuracy of 0.974358974359
Final accuracy on total training data = 0.820512820513
      Problem 5:
In [13]: best_acc = 0
                    min_sample = [2,5,10,20]
                    for i in min_sample:
                              clf = DecisionTreeClassifier(best_computation,min_samples_split=i)
                              clf.fit(X_train, y_train)
                              accuracy = np.sum(clf.predict(X_valid)==y_valid['class'].values)*1/len(y_valid['class'].values)
                              print('For min sample =', i, 'the validation accuracy = ' + str(accuracy))
                              if (accuracy > best_acc):
                                       best_acc = accuracy
                                       best_sample = i
                    print("")
                    print('The best sample is', best_sample, 'with a validation accuracy of', best_acc)
```

```
clf = DecisionTreeClassifier(criterion=best_computation,min_samples_split = best_sample)
                    clf.fit(X_train_fin, y_train_fin)
                   predictions = clf.predict(X_test)
                    fin_accuracy = np.sum(predictions==y_test['class'].values)*1/len(y_test['class'].values
                    print('\n')
                   print('Final accuracy = ' + str(fin_accuracy))
For min sample = 2 the validation accuracy = 0.948717948718
For min sample = 5 the validation accuracy = 0.948717948718
For min sample = 10 the validation accuracy = 0.923076923077
For min sample = 20 the validation accuracy = 0.948717948718
The best sample is 2 with a validation accuracy of 0.948717948718
Final accuracy = 0.820512820513
      Problem 6:
In [15]: sample_size = [20,40,60,80,100]
                   acc_list = []
                   for i in sample_size:
                             clf = DecisionTreeClassifier(best_computation,min_samples_split=best_sample)
                             clf.fit(X_train[:i], y_train[:i])
                             accuracy = np.sum(clf.predict(X_valid)==y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].values)*1/len(y_valid['class'].value
                             print('For training data sample size =', i, 'the validation accuracy = ' + str(accu
                             acc_list.append(accuracy)
For training data sample size = 20 the validation accuracy = 0.641025641026
For training data sample size = 40 the validation accuracy = 0.846153846154
For training data sample size = 60 the validation accuracy = 0.871794871795
For training data sample size = 80 the validation accuracy = 0.871794871795
For training data sample size = 100 the validation accuracy = 0.948717948718
In [21]: # Generate Line Plot
                   plt.plot(sample_size,acc_list)
                    # Label the axes
                   plt.xlabel('Sample Size')
                   plt.ylabel('Accuracy')
                    #Figure Title
                   plt.title('More Training Data Achieves Greater Accuracy')
                   plt.show()
```



1.4 KNN

Problem 7:

```
In [22]: # Use Standard Scaler from Sklearn to normalize data in full training data:
    normalize = preprocessing.StandardScaler().fit(X_train_fin)
    X_train_fin_norm = normalize.transform(X_train_fin)

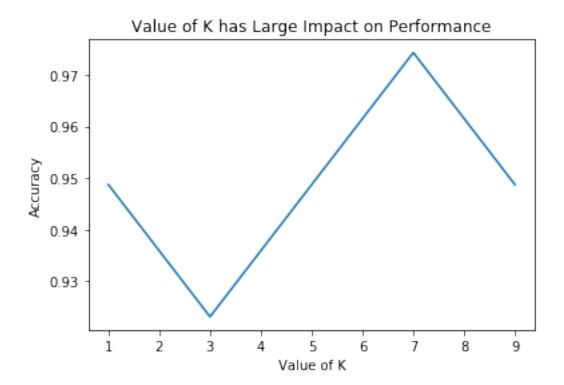
# Apply normalizing of aggregate training set to other data-sets:
    X_train_norm = normalize.transform(X_train)
    X_valid_norm = normalize.transform(X_valid)
    X_test_norm = normalize.transform(X_test)

In [28]: # Build KNN classifier
    clf = KNeighborsClassifier(n_neighbors=3,metric = 'euclidean')
    clf.fit(X_train_fin_norm, y_train_fin.values.ravel())
    predictions = clf.predict(X_test_norm)
    accuracy = np.sum(predictions == y_test['class'].values)*1.0/len(y_test['class'].values
    print('Test accuracy with k = 3 is', accuracy)
Test accuracy with k = 3 is 0.871794871795
```

Problem 8:

```
In [31]: best_acc = 0
         dist_metric = ['euclidean', 'manhattan', 'chebyshev']
         for i in dist_metric:
             clf = KNeighborsClassifier(n_neighbors=3,metric = i)
             clf.fit(X_train_norm, y_train)
             accuracy = np.sum(clf.predict(X_valid_norm) == y_valid['class'].values)*1/len(y_valid
             print('For distance metric =', i, 'the validation accuracy = ' + str(accuracy))
             if (accuracy > best_acc):
                 best_acc = accuracy
                 best_dist = i
         print("")
         print('The best distance metric is', best_dist, 'with a validation accuracy of', best_a
         clf = KNeighborsClassifier(n_neighbors=3,metric = best_dist)
         clf.fit(X_train_fin_norm, y_train_fin.values.ravel())
         predictions = clf.predict(X_test_norm)
         fin_accuracy = np.sum(predictions==y_test['class'].values)*1/len(y_test['class'].values
         print('\n')
         print('Final accuracy = ' + str(fin_accuracy))
For distance metric = euclidean the validation accuracy = 0.923076923077
For distance metric = manhattan the validation accuracy = 0.948717948718
For distance metric = chebyshev the validation accuracy = 0.923076923077
The best distance metric is manhattan with a validation accuracy of 0.948717948718
Final accuracy = 0.974358974359
/Users/kkannapp/anaconda/lib/python3.6/site-packages/ipykernel_launcher.py:6: DataConversionWarn
  Problem 9:
In [32]: k_{list} = [1,3,5,7,9]
         acc_list = []
         best_acc = 0
         for i in k_list:
             clf = KNeighborsClassifier(n_neighbors=i,metric = 'euclidean')
             clf.fit(X_train_norm, y_train)
             accuracy = np.sum(clf.predict(X_valid_norm)==y_valid['class'].values)*1/len(y_valid_norm)
             print('For k =', i, 'the validation accuracy = ' + str(accuracy))
             acc_list.append(accuracy)
             if (accuracy > best_acc):
                 best_acc = accuracy
```

```
best_k = i
         print("")
         print('The best k-value is', best_k, 'with a validation accuracy of', best_acc)
         clf = KNeighborsClassifier(n_neighbors=best_k,metric = 'euclidean')
         clf.fit(X_train_fin_norm, y_train_fin.values.ravel())
         predictions = clf.predict(X_test_norm)
         fin_accuracy = np.sum(predictions==y_test['class'].values)*1/len(y_test['class'].values)
         print('\n')
         print('Final accuracy = ' + str(fin_accuracy))
For k = 1 the validation accuracy = 0.948717948718
For k = 3 the validation accuracy = 0.923076923077
For k = 5 the validation accuracy = 0.948717948718
For k = 7 the validation accuracy = 0.974358974359
For k = 9 the validation accuracy = 0.948717948718
The best k-value is 7 with a validation accuracy of 0.974358974359
Final accuracy = 0.923076923077
/Users/kkannapp/anaconda/lib/python3.6/site-packages/ipykernel_launcher.py:7: DataConversionWarn
  import sys
In [34]: # Generate Line Plot
        plt.plot(k_list,acc_list)
         # Label the axes
         plt.xlabel('Value of K')
         plt.ylabel('Accuracy')
         #Figure Title
         plt.title('Value of K has Large Impact on Performance')
         plt.show()
```



Problem 10:

/Users/kkannapp/anaconda/lib/python3.6/site-packages/ipykernel_launcher.py:6: DataConversionWarn

```
In [37]: # Generate Line Plot
     plt.plot(sample_size,acc_list)
```

For sample size = 100 the validation accuracy = 0.923076923077

```
# Label the axes
plt.xlabel('Sample Size')
plt.ylabel('Accuracy')

#Figure Title
plt.title('Shuffling Data Important, Predictions could be Unrealistic')
plt.show()
```

