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Week4_hw1

30. KNN + Confusion Matrix + Iris Data set + Colab
    - Process of adding notebooks to your portfolio
        1. Execute kNN_iris.ipynb on Colab to understand how to apply Confusion matrix on KNN-Classifier using Iris Data set
            - Add more comments to the kNN_iris.ipynb
                - Pick an Evaluation Metric: Confusion Matrix
                - KNN + Confusion Matrix
                - Classification
                    - Precision and Recall
                    - Precision/Recall Trade-off
            - References
                - iris_knn.ipynb
        2. Follow this procedure to create a PDF file for Iris.ipynb
        3. Add the PDF file to GitHub to improve your portfolio

```
Machine Learning
   Supervised Learning
        KNN + Confusion Matrix + Iris Data set + Colab
```

        4. Submit the PDF as the answer for the homework.
    - References
        - Adding notebooks to your portfolio
        - Understanding Confusion matrix and applying it on KNN-Classifier on Iris Data set
        - Iris.ipynb
        - Iris Dataset
            - Download Iris Dataset
        - Pick an Evaluation Metric: Confusion Matrix
        - KNN + Confusion Matrix
        - Run the code on Colab
            - References
                - Get Start with Colab

Solutions:

```
[1]  #importing the required libraries
     import pandas as pd
     import numpy as np
     import operator
     import matplotlib.pyplot as plt
```

```
[2]  #reading data from the csv file
     from google.colab import files
     uploaded = files.upload()

     data = pd.read_csv('iris.csv', header=None, names=['sepal_length', 'sepal_width', 'petal_length', 'petal_width', 'class'])
     print(data)
```

Choose Files iris.csv

- **iris.csv**(text/csv) - 3975 bytes, last modified: 2/5/2014 - 100% done

```
Saving iris.csv to iris.csv
     sepal_length  sepal_width  petal_length  petal_width      class
0    sepal.length  sepal.width  petal.length  petal.width    variety
1             5.1          3.5           1.4           .2     Setosa
2             4.9            3           1.4           .2     Setosa
3             4.7          3.2           1.3           .2     Setosa
4             4.6          3.1           1.5           .2     Setosa
..            ...          ...           ...          ...        ...
146           6.7            3           5.2          2.3  Virginica
147           6.3          2.5             5          1.9  Virginica
148           6.5            3           5.2            2  Virginica
149           6.2          3.4           5.4          2.3  Virginica
150           5.9            3           5.1          1.8  Virginica

[151 rows x 5 columns]
```

Part (a)

Dividing the dataset as development and test.

```
[3]  #randomize the indices
     indices = np.random.permutation(data.shape[0])
     div = int(0.75 * len(indices))
     development_id, test_id = indices[:div], indices[div:]
     #dividing the dataset using randomized indices
     development_set, test_set = data.loc[development_id,:], data.loc[test_id,:]
     print("Development Set:\n", development_set, "\n\nTest Set:\n", test_set)
     mean_development_set = development_set.mean()
     mean_test_set = test_set.mean()
     std_development_set = development_set.std()
     std_test_set = test_set.std()
```

```
     122          5.6         2.8          4.9           2   Virginica
     ..           ...         ...          ...         ...         ...
     59           6.6         2.9          4.6         1.3  Versicolor
     35           4.9         3.1          1.5          .2      Setosa
     43           4.4         3.2          1.3          .2      Setosa
     142          6.9         3.1          5.1         2.3   Virginica
     3            4.7         3.2          1.3          .2      Setosa

     [113 rows x 5 columns]

    Test Set:
          sepal_length  sepal_width  petal_length  petal_width       class
    116            6.4          3.2           5.3          2.3   Virginica
    26               5            3           1.6           .2      Setosa
    84               6          2.7           5.1          1.6  Versicolor
    49             5.3          3.7           1.5           .2      Setosa
    42             4.5          2.3           1.3           .3      Setosa
    37             5.5          3.5           1.3           .2      Setosa
    15             5.8            4           1.2           .2      Setosa
    107            4.9          2.5           4.5          1.7   Virginica
    74             6.1          2.8           4.7          1.2  Versicolor
    81             5.5          2.4           3.8          1.1  Versicolor
    145            6.7          3.3           5.7          2.5   Virginica
    70             5.6          2.5           3.9          1.1  Versicolor
    18             5.1          3.5           1.4           .3      Setosa
    120              6          2.2             5          1.5   Virginica
    91             5.5          2.6           4.4          1.2  Versicolor
    100            5.7          2.8           4.1          1.3  Versicolor
    23             4.6          3.6             1           .2      Setosa
    133            6.4          2.8           5.6          2.2   Virginica
    55             6.5          2.8           4.6          1.5  Versicolor
    134            6.3          2.8           5.1          1.5   Virginica
    118            7.7          3.8           6.7          2.2   Virginica
    86               6          3.4           4.5          1.6  Versicolor
    20             5.1          3.8           1.5           .3      Setosa
    124            6.3          2.7           4.9          1.8   Virginica
    17             5.4          3.9           1.3           .4      Setosa
    113            6.8            3           5.5          2.1   Virginica
    126            7.2          3.2             6          1.8   Virginica
    54             5.5          2.3             4          1.3  Versicolor
    143            5.8          2.7           5.1          1.9   Virginica
    112            6.4          2.7           5.3          1.9   Virginica
    97             5.7          2.9           4.2          1.3  Versicolor
    1              5.1          3.5           1.4           .2      Setosa
    129            6.4          2.8           5.6          2.1   Virginica
    119            7.7          2.6           6.9          2.3   Virginica
    0     sepal.length  sepal.width  petal.length  petal.width     variety
    12             4.8          3.4           1.6           .2      Setosa
    36               5          3.2           1.2           .2      Setosa
    24             5.1          3.3           1.7           .5      Setosa
```

Part (b)

Implement kNN using the following hyperparameters: number of neighbor

* 1,3,5,7

distance metric

* euclidean distance
* normalized euclidean distance
* cosine similarity

Retrieving the 'class' column from the development and test sets and storing it in separate lists. Calculating the mean and standard deviation of the development set and test set for normalizing the data.

```
[4] test_class = list(test_set.iloc[:,-1])
    dev_class = list(development_set.iloc[:,-1])
    mean_development_set = development_set.mean()
    mean_test_set = test_set.mean()
    std_development_set = development_set.std()
    std_test_set = test_set.std()
```

```
[5] def euclideanDistance(data_1, data_2, data_len):
        dist = 0
        for i in range(data_len):
            dist = dist + np.square(data_1[i] - data_2[i])
        return np.sqrt(dist)

    def normalizedEuclideanDistance(data_1, data_2, data_len, data_mean, data_std):
        n_dist = 0
        for i in range(data_len):
            n_dist = n_dist + (np.square(((data_1[i] - data_mean[i])/data_std[i]) - ((data_2[i] - data_mean[i])/data_std[i])))
        return np.sqrt(n_dist)

    # Title: Cosine Similarty between 2 Number Lists
    # Author: dontloo
    # Date: 03.27.2017
    # Code version: 1
    # Availability: https://stackoverflow.com/questions/18424228/cosine-similarity-between-2-number-lists
    def cosineSimilarity(data_1, data_2):
        dot = np.dot(data_1, data_2[:-1])
        norm_data_1 = np.linalg.norm(data_1)
        norm_data_2 = np.linalg.norm(data_2[:-1])
        cos = dot / (norm_data_1 * norm_data_2)
        return (1-cos)
```

```python
def knn(dataset, testInstance, k, dist_method, dataset_mean, dataset_std):
    distances = {}
    length = testInstance.shape[1]
    if dist_method == 'euclidean':
        for x in range(len(dataset)):
            dist_up = euclideanDistance(testInstance, dataset.iloc[x], length)
            distances[x] = dist_up[0]
    elif dist_method == 'normalized_euclidean':
        for x in range(len(dataset)):
            dist_up = normalizedEuclideanDistance(testInstance, dataset.iloc[x], length, dataset_mean, dataset_std)
            distances[x] = dist_up[0]
    elif dist_method == 'cosine':
        for x in range(len(dataset)):
            dist_up = cosineSimilarity(testInstance, dataset.iloc[x])
            distances[x] = dist_up[0]
    # Sort values based on distance
    sort_distances = sorted(distances.items(), key=operator.itemgetter(1))
    neighbors = []
    # Extracting nearest k neighbors
    for x in range(k):
        neighbors.append(sort_distances[x][0])
    # Initializing counts for 'class' labels counts as 0
    counts = {"Iris-setosa" : 0, "Iris-versicolor" : 0, "Iris-virginica" : 0}
    # Computing the most frequent class
    for x in range(len(neighbors)):
        response = dataset.iloc[neighbors[x]][-1]
        if response in counts:
            counts[response] += 1
        else:
            counts[response] = 1
    # Sorting the class in reverse order to get the most frequest class
    sort_counts = sorted(counts.items(), key=operator.itemgetter(1), reverse=True)
    return(sort_counts[0][0])
```

Part c)

Using the development data set

Iterating all of the development data points and computing the class for each k and each distance metric

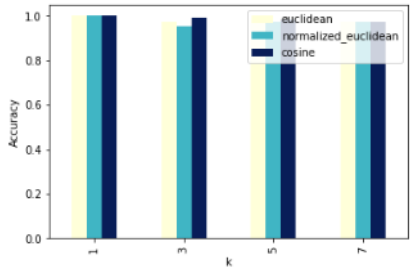
```python
[12] # Creating a list of list of all columns except 'class' by iterating through the development set
     row_list = []
     for index, rows in development_set.iterrows():
         my_list =[rows.sepal_length, rows.sepal_width, rows.petal_length, rows.petal_width]
         row_list.append([my_list])
     # k values for the number of neighbors that need to be considered
     k_n = [1, 3, 5, 7]
     # Distance metrics
     distance_methods = ['euclidean', 'normalized_euclidean', 'cosine']
     # Performing kNN on the development set by iterating all of the development set data points and for each k and each distance metri
     obs_k = {}
     for dist_method in distance_methods:
         development_set_obs_k = {}
         for k in k_n:
             development_set_obs = []
             for i in range(len(row_list)):
                 development_set_obs.append(knn(development_set, pd.DataFrame(row_list[i]), k, dist_method, mean_development_set, std_d
             development_set_obs_k[k] = development_set_obs
         # Nested Dictionary containing the observed class for each k and each distance metric (obs_k of the form obs_k[dist_method][k]
         obs_k[dist_method] = development_set_obs_k
         print(dist_method.upper() + " distance method performed on the dataset for all k values!")
     #print(obs_k)
```

```
EUCLIDEAN distance method performed on the dataset for all k values!
NORMALIZED_EUCLIDEAN distance method performed on the dataset for all k values!
COSINE distance method performed on the dataset for all k values!
```

```
[13] # Calculating the accuracy of the development set by comparing it with the development set 'class' list created earlier
     accuracy = {}
     for key in obs_k.keys():
         accuracy[key] = {}
         for k_value in obs_k[key].keys():
             #print('k = ', key)
             count = 0
             for i,j in zip(dev_class, obs_k[key][k_value]):
                 if i == j:
                     count = count + 1
                 else:
                     pass
             accuracy[key][k_value] = count/(len(dev_class))

     # Storing the accuracy for each k and each distance metric into a dataframe
     df_res = pd.DataFrame({'k': k_n})
     for key in accuracy.keys():
         value = list(accuracy[key].values())
         df_res[key] = value
     print(df_res)

     # Plotting a Bar Chart for accuracy
     draw = df_res.plot(x='k', y=['euclidean', 'normalized_euclidean', 'cosine'], kind="bar", colormap='YlGnBu')
     draw.set(ylabel='Accuracy')

     # Ignoring k=1 if the value of accuracy for k=1 is 100%, since this mostly implies overfitting
     df_res.loc[df_res['k'] == 1.0, ['euclidean', 'normalized_euclidean', 'cosine']] = np.nan

     # Fetching the best k value for using all hyper-parameters
     # In case the accuracy is the same for different k and different distance metric selecting the first of all the same
     column_val = [c for c in df_res.columns if not c.startswith('k')]
     col_max = df_res[column_val].max().idxmax()
     best_dist_method = col_max
     row_max = df_res[col_max].argmax()
     best_k = int(df_res.iloc[row_max]['k'])
     if df_res.isnull().values.any():
         print('\n\n\nBest k value is\033[1m', best_k, '\033[0mand best distance metric is\033[1m', best_dist_method, '\033[0m. Ignoring k=1 if the value of accuracy for k=1 is 100%, since this mostly implies overfitting')
     else:
         print('\n\n\nBest k value is\033[1m', best_k, '\033[0mand best distance metric is\033[1m', best_dist_method, '\033[0m.')
```

```
   k  euclidean  normalized_euclidean    cosine
0  1   1.000000              1.000000  1.000000
1  3   0.973214              0.955357  0.991071
2  5   0.982143              0.973214  0.982143
3  7   0.973214              0.973214  0.973214
```

Best k value is **3** and best distance metric is **cosine** . Ignoring k=1 if the value of accuracy for k=1 is 100%, since this mostly implies overfitting



Part d)

Using the test dataset

```
[14] print('\n\n\nBest k value is\033[1m', best_k, '\033[0mand best distance metric is\033[1m', best_dist_method, '\033[0m')
```

```
Best k value is 3 and best distance metric is cosine
```

Using the best k value and best distance metric to determine the class for all rows in the test dataset

```
[15] # Creating a list of list of all columns except 'class' by iterating through the development set
     row_list_test = []
     for index, rows in test_set.iterrows():
         my_list =[rows.sepal_length, rows.sepal_width, rows.petal_length, rows.petal_width]
         row_list_test.append([my_list])
     test_set_obs = []
     for i in range(len(row_list_test)):
         test_set_obs.append(knn(test_set, pd.DataFrame(row_list_test[i]), best_k, best_dist_method, mean_test_set, std_test_set))
     #print(test_set_obs)

     count = 0
     for i,j in zip(test_class, test_set_obs):
         if i == j:
             count = count + 1
         else:
             pass
     accuracy_test = count/(len(test_class))
     print('Final Accuracy of the Test dataset is ', accuracy_test)
```

```
Final Accuracy of the Test dataset is  0.9473684210526315
```

GitHub:

https://github.com/momer22/Machine-Learning-Supervised-Learning-KNN-Confusion-Matrix-Iris-Data-set-Colab