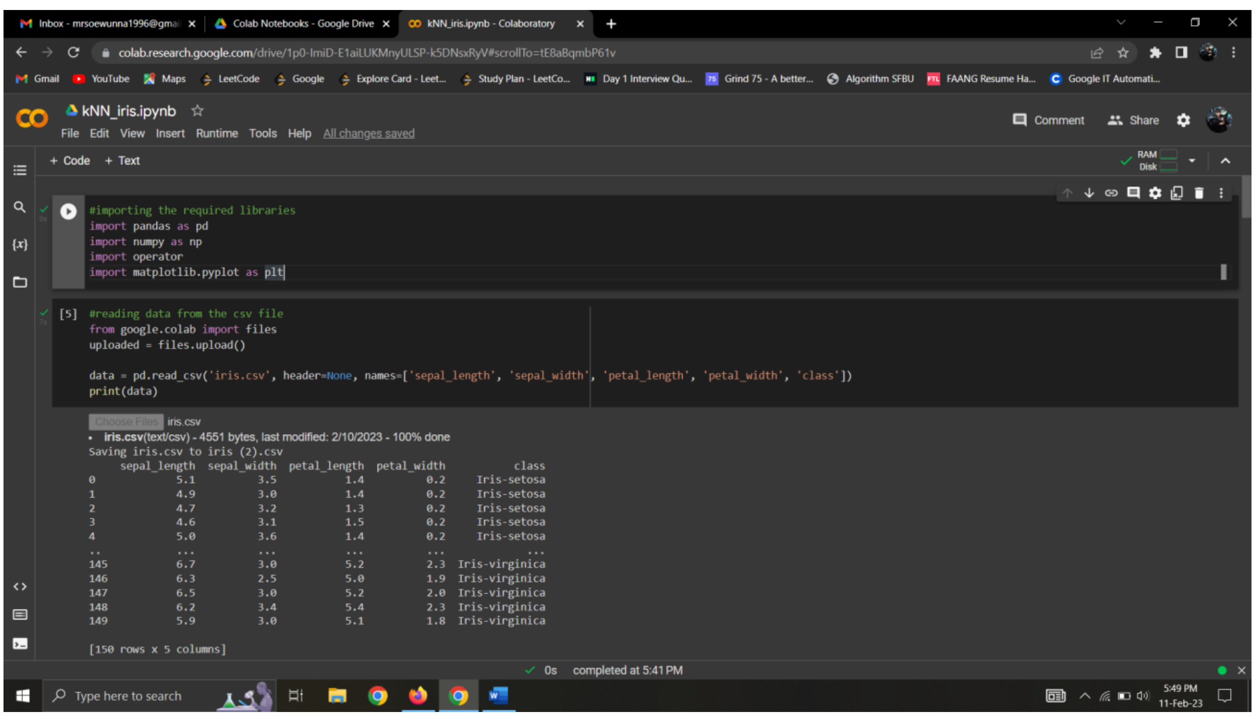
30. KNN + Confusion Matrix + Iris Data set + Colab
    - Process of adding notebooks to your portfolio
        1. Execute kNN_iris.ipynb on Colab to understand how to apply Confusion matrix on KNN-Classifier using Iris Data set
            - Add more comments to the kNN_iris.ipynb
                - Pick 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

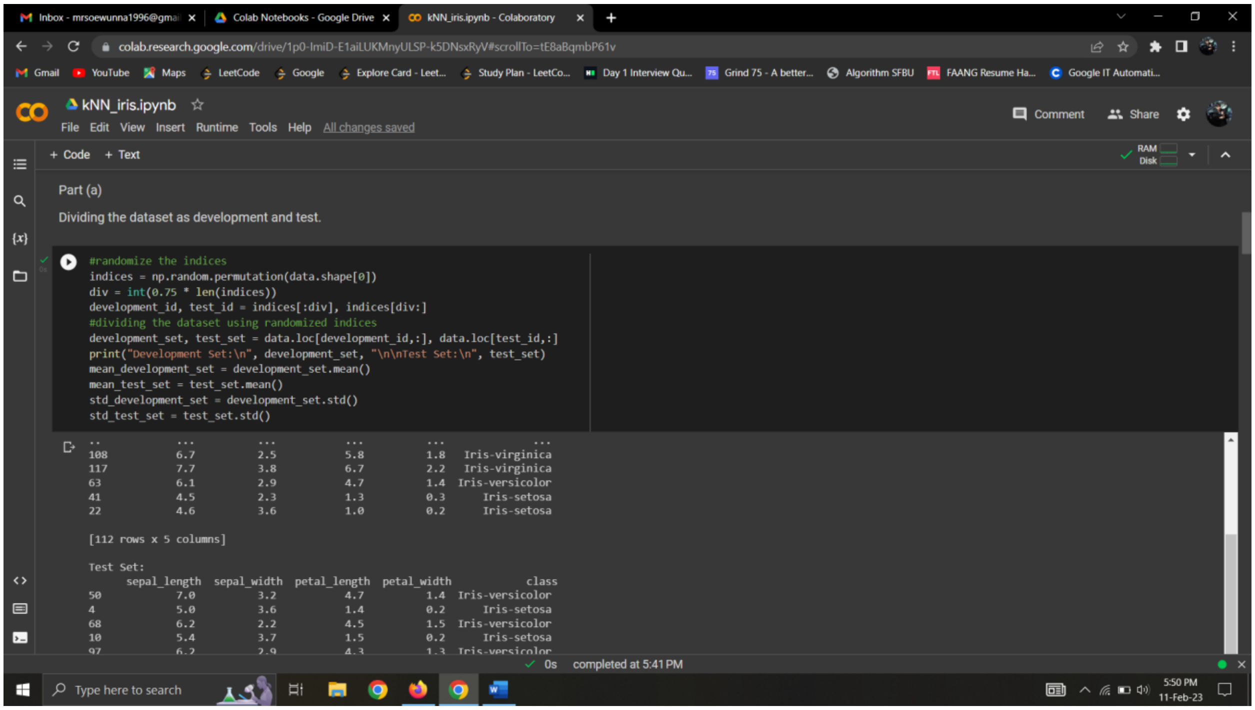
```
Machine Learning
   Supervised Learning
        KNN + Confusion Matrix + Iris Data set + Colab
```

        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

GitHub Link - https://github.com/SoeWunna29/Machine-Learning-Supervised-Learning-KNN-Confusion-Matrix-IRIS-Data-set-Colab.git

Opening note book file with Google Colab and importing csv file from the local drive.



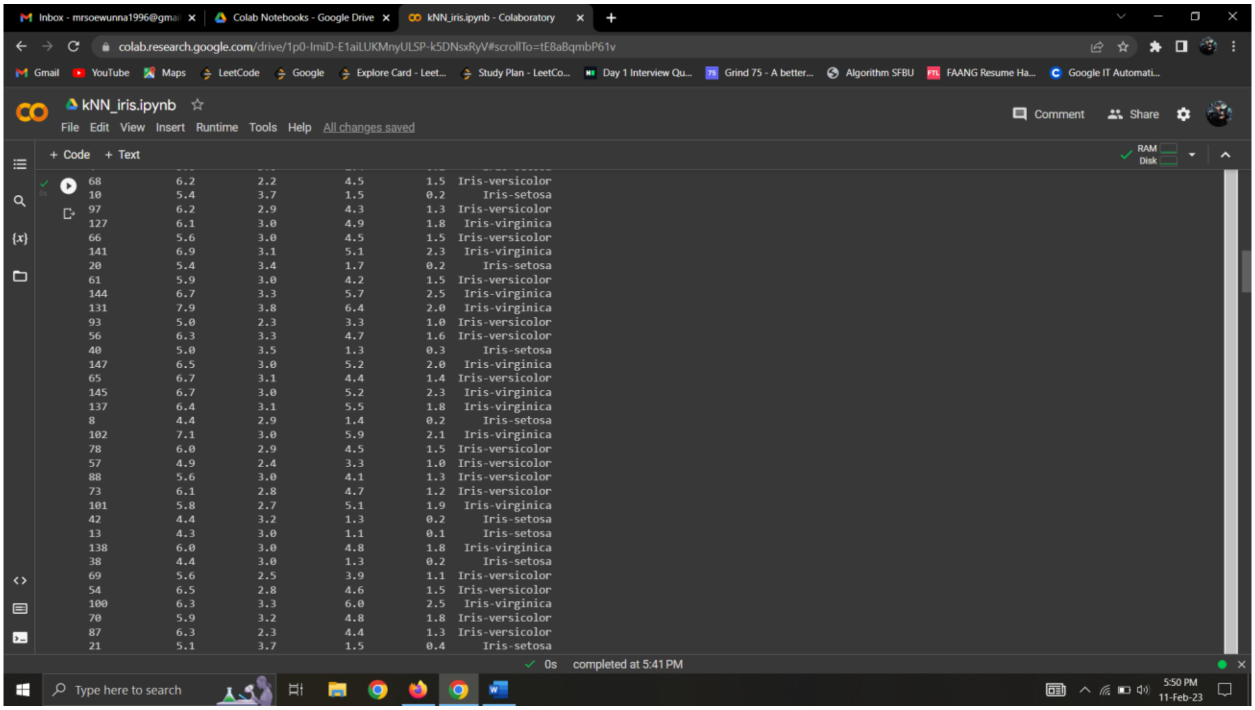


Part (a)

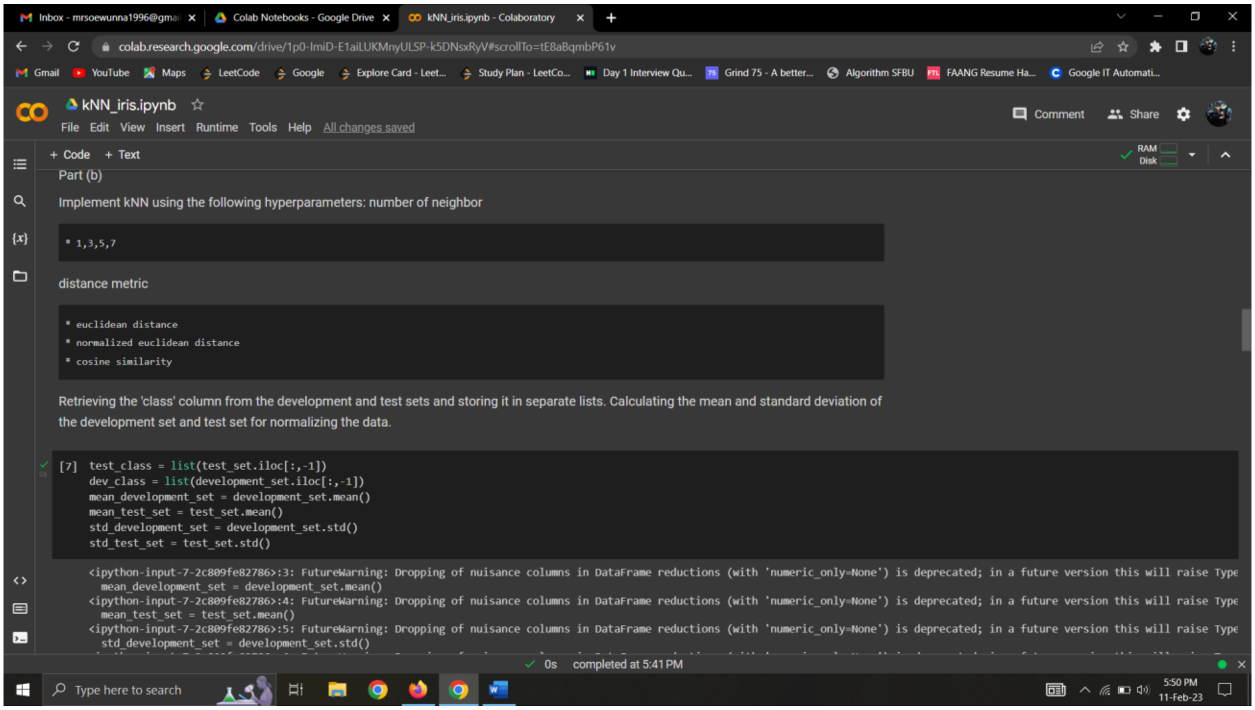
Dividing the dataset as development and test.

```
#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()
```

```
..       ...       ...       ...       ...              ...
108      6.7       2.5       5.8       1.8   Iris-virginica
117      7.7       3.8       6.7       2.2   Iris-virginica
63       6.1       2.9       4.7       1.4  Iris-versicolor
41       4.5       2.3       1.3       0.3      Iris-setosa
22       4.6       3.6       1.0       0.2      Iris-setosa

[112 rows x 5 columns]

Test Set:
     sepal_length  sepal_width  petal_length  petal_width            class
50           7.0          3.2           4.7          1.4  Iris-versicolor
4            5.0          3.6           1.4          0.2      Iris-setosa
68           6.2          2.2           4.5          1.5  Iris-versicolor
10           5.4          3.7           1.5          0.2      Iris-setosa
97           6.2          2.9           4.3          1.3  Iris-versicolor
```



```
68           6.2          2.2           4.5          1.5  Iris-versicolor
10           5.4          3.7           1.5          0.2      Iris-setosa
97           6.2          2.9           4.3          1.3  Iris-versicolor
127          6.1          3.0           4.9          1.8   Iris-virginica
66           5.6          3.0           4.5          1.5  Iris-versicolor
141          6.9          3.1           5.1          2.3   Iris-virginica
20           5.4          3.4           1.7          0.2      Iris-setosa
61           5.9          3.0           4.2          1.5  Iris-versicolor
144          6.7          3.3           5.7          2.5   Iris-virginica
131          7.9          3.8           6.4          2.0   Iris-virginica
93           5.0          2.3           3.3          1.0  Iris-versicolor
56           6.3          3.3           4.7          1.6  Iris-versicolor
40           5.0          3.5           1.3          0.3      Iris-setosa
147          6.5          3.0           5.2          2.0   Iris-virginica
65           6.7          3.1           4.4          1.4  Iris-versicolor
145          6.7          3.0           5.2          2.3   Iris-virginica
137          6.4          3.1           5.5          1.8   Iris-virginica
8            4.4          2.9           1.4          0.2      Iris-setosa
102          7.1          3.0           5.9          2.1   Iris-virginica
78           6.0          2.9           4.5          1.5  Iris-versicolor
57           4.9          2.4           3.3          1.0  Iris-versicolor
88           5.6          3.0           4.1          1.3  Iris-versicolor
73           6.1          2.8           4.7          1.2  Iris-versicolor
101          5.8          2.7           5.1          1.9   Iris-virginica
42           4.4          3.2           1.3          0.2      Iris-setosa
13           4.3          3.0           1.1          0.1      Iris-setosa
138          6.0          3.0           4.8          1.8   Iris-virginica
38           4.4          3.0           1.3          0.2      Iris-setosa
69           5.6          2.5           3.9          1.1  Iris-versicolor
54           6.5          2.8           4.6          1.5  Iris-versicolor
100          6.3          3.3           6.0          2.5   Iris-virginica
70           5.9          3.2           4.8          1.8  Iris-versicolor
87           6.3          2.3           4.4          1.3  Iris-versicolor
21           5.1          3.7           1.5          0.4      Iris-setosa
```



kNN_iris.ipynb

Part (b)

Implement kNN using the following hyperparameters: number of neighbor

* 1,3,5,7

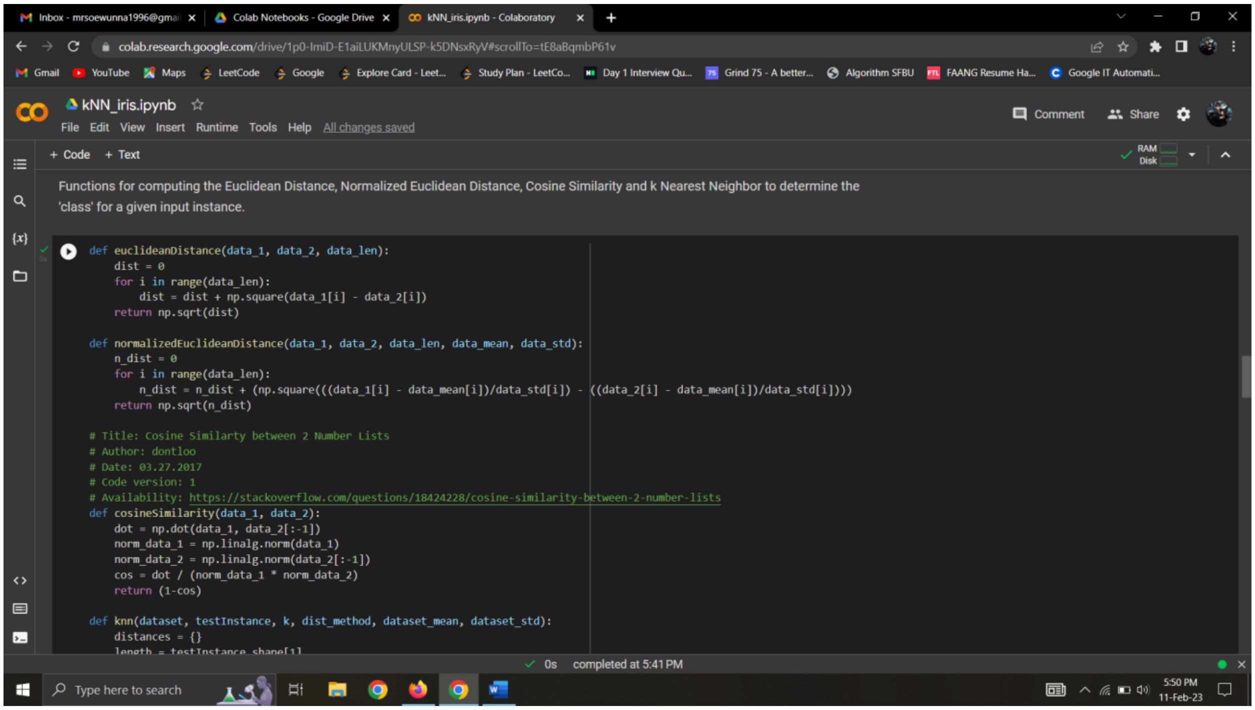
distance metric

* 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.

```
[7] 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()
```

```
<ipython-input-7-2c809fe82786>:3: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise Type
  mean_development_set = development_set.mean()
<ipython-input-7-2c809fe82786>:4: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise Type
  mean_test_set = test_set.mean()
<ipython-input-7-2c809fe82786>:5: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise Type
  std_development_set = development_set.std()
```



kNN_iris.ipynb

Functions for computing the Euclidean Distance, Normalized Euclidean Distance, Cosine Similarity and k Nearest Neighbor to determine the 'class' for a given input instance.

```
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)

def knn(dataset, testInstance, k, dist_method, dataset_mean, dataset_std):
    distances = {}
    length = testInstance.shape[1]
```

```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
```

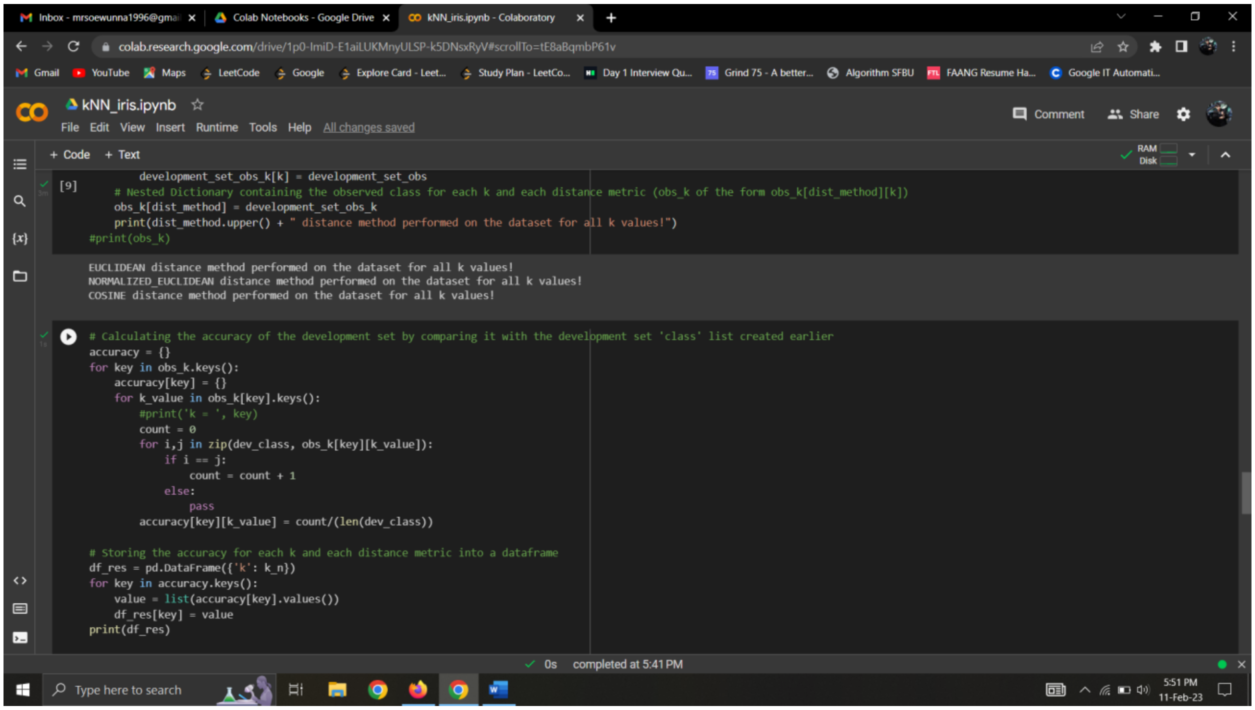
```python
[8]
    # Sorting the class in reverse order to get the most frequest class
    sort_counts = sorted(counts.items(), key=operator.itemgetter(1), reverse=True)
    return(sort_counts[0][0])
```

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

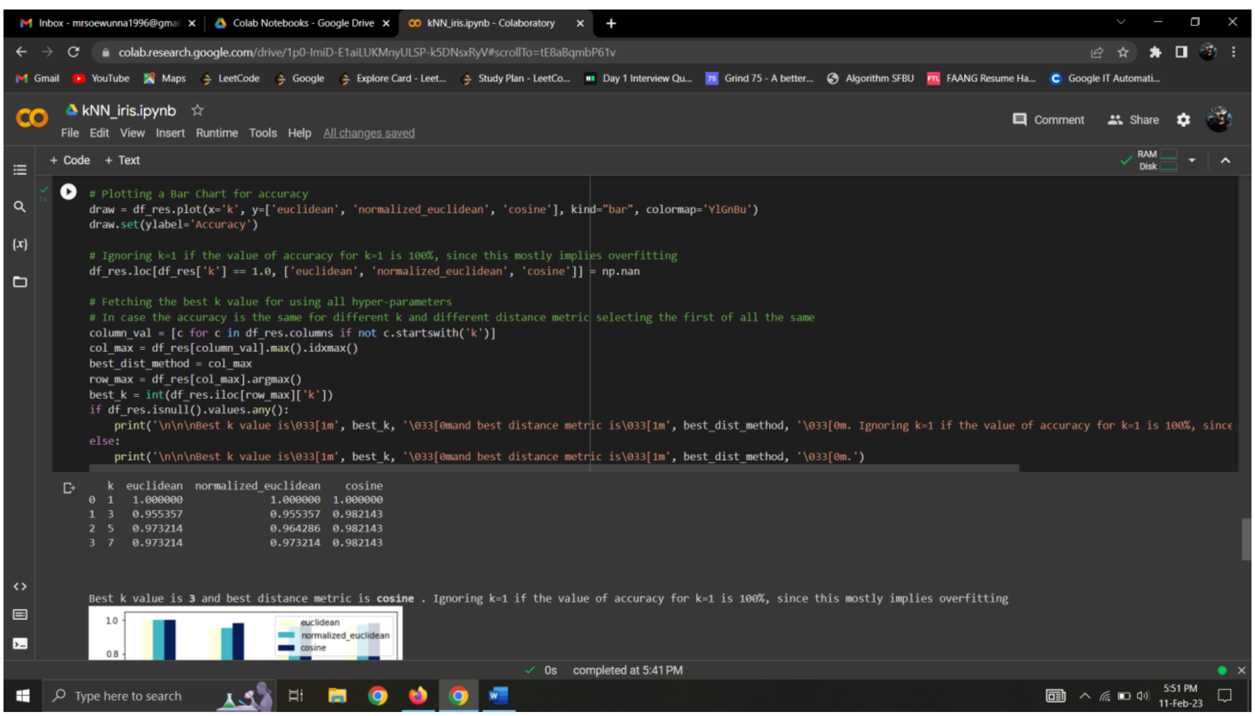
```python
# Creating a list of list of all columns except 'class' by iterating through the development set
row_list = []
for index, rows in development_set.iterrows():
    my_list =[rows.sepal_length, rows.sepal_width, rows.petal_length, rows.petal_width]
    row_list.append([my_list])
# k values for 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 metric
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_development_set))
        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
```



```
        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)
```

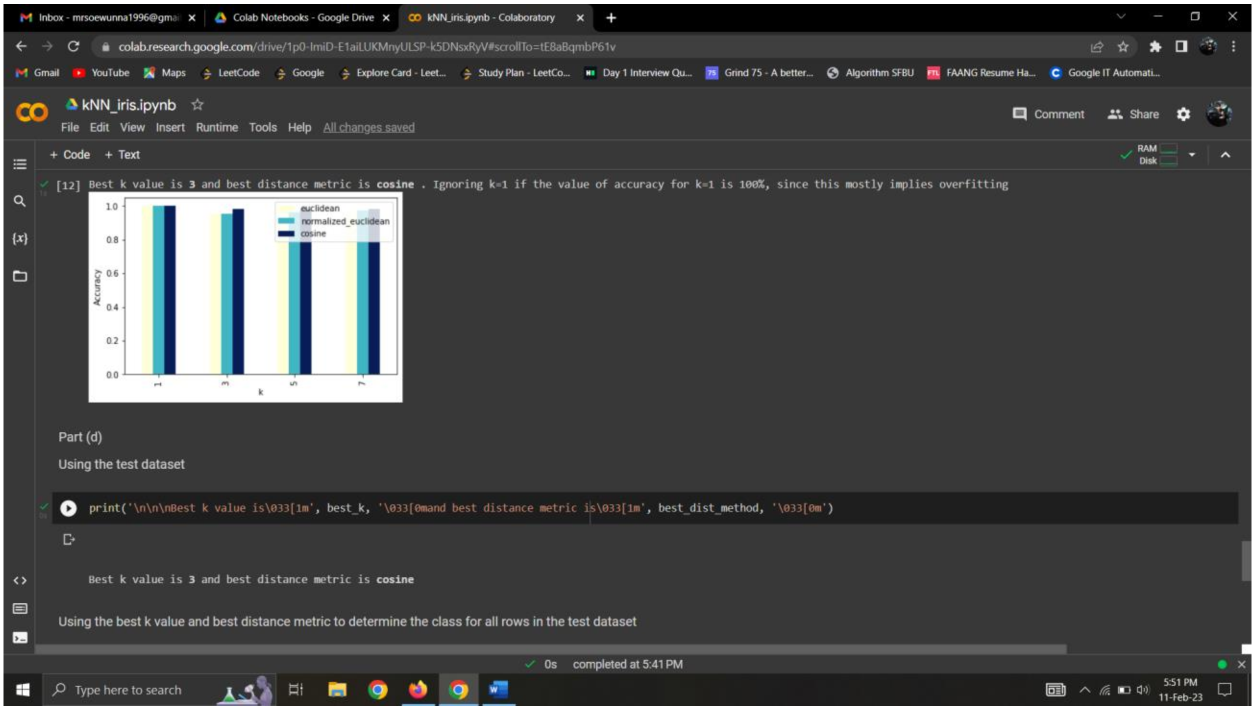
```
EUCLIDEAN distance method performed on the dataset for all k values!
NORMALIZED_EUCLIDEAN distance method performed on the dataset for all k values!
COSINE distance method performed on the dataset for all k values!
```

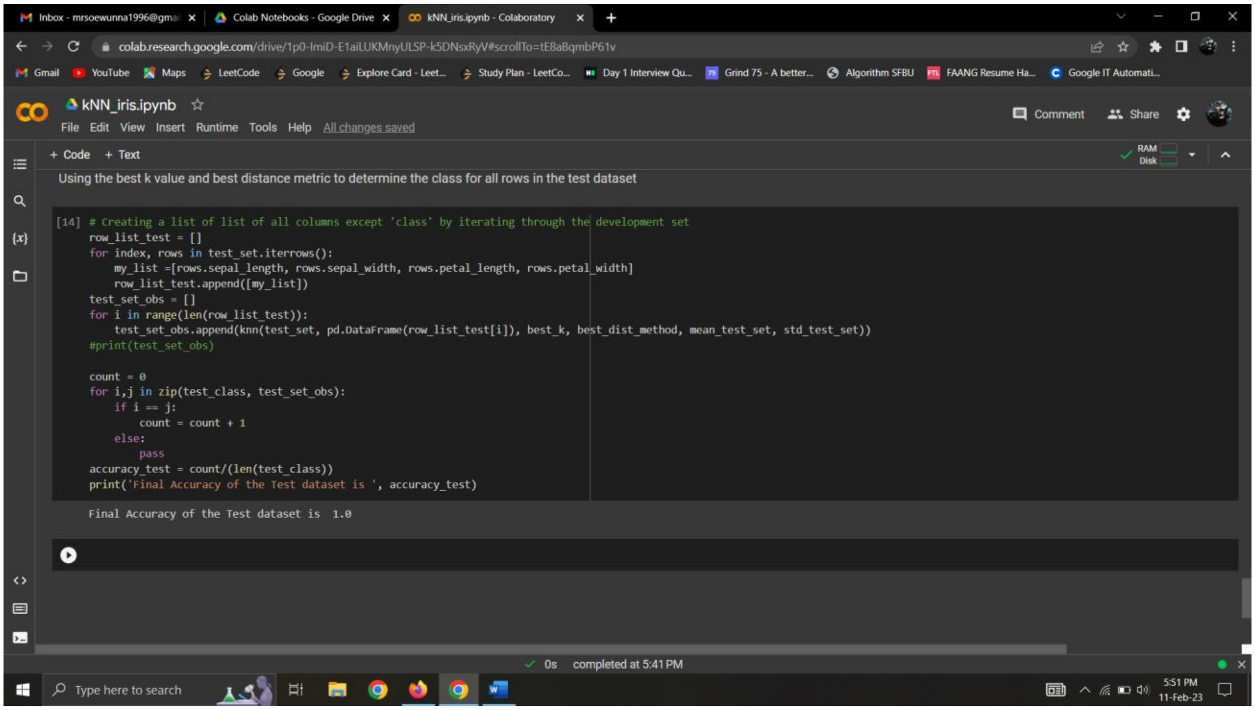
```
# Calculating the accuracy of the development set by comparing it with the development set 'class' list created earlier
accuracy = {}
for key in obs_k.keys():
    accuracy[key] = {}
    for k_value in obs_k[key].keys():
        #print('k = ', key)
        count = 0
        for i,j in zip(dev_class, 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
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   0.955357              0.955357  0.982143
2  5   0.973214              0.964286  0.982143
3  7   0.973214              0.973214  0.982143


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
```


kNN_iris.ipynb
File Edit View Insert Runtime Tools Help All changes saved
[12] 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
euclidean
normalized_euclidean
cosine
Accuracy
k
Part (d)
Using the test dataset
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
0s completed at 5:41 PM


kNN_iris.ipynb
File Edit View Insert Runtime Tools Help All changes saved
Using the best k value and best distance metric to determine the class for all rows in the test dataset
[14] # 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 1.0
0s completed at 5:41 PM