

PCA-KNN based fruit image recognition

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Dataset: https://www.kaggle.com/moltean/fruits/version/44?almost-there=true&token=CfDJ8LdUzqlsSWBPr4Ce3rb9VL94NDb4cA1DaPdZIO02viMgZayoqaDonA1njtJgjTUWCIBe5VErc_Gk6qEfOsCtUoelQgpmoxhlA3_dUz338NuQTnhcwylzBoMgDEbIZr1uAyA8RTH7Ifd2p-HJB42HcnNx6KsqxgwWyAjf3qC3H-Kssn06d_fio4J8ch4Z_K4rA19gzoMEt7X0D03ZqbSORwAbZWILYVpXuWntyEGYxEiXh4v-6cpOhtfeEKGWhlHNjmgTqEcnYgQyHAhONBGqfZUmVOJlnWPRx5YQDwSO6IRgWGYU1WGaezKcg89VWRa2qUmXtC7-lw1vEHhbmSsG0xvE9aIr4WyBAkaAU8M1K5Ejuiygnhj9j1nf8ipwAG4_f50t5OB2hT0uNs2TjmXFhsuWIB1Ar1cP0QQd5j_fb57FUt33AqnHyS0aPnSOwjRE9OTIfRH_rC62G92Qo_RjeECAEu7qU2eJX27L6OrCVkj5lidik5AlIZXt-fqW3wY7gPvYglMxY55ie0Y2IQgs6QfIgY5TV-xem2q02DelcqVWzlsPFGsm2OD824fl_qXxWP0U1kefCi-5-9xNBGwWnsjA#

Used Dataset of four different fruits namely: {0: 'Apple Braeburn', 1: 'Avocado', 2: 'Banana', 3: 'Dates'}

Training Data consists of total 1899 images, whereas testing data consists of total 639 images.

Step-1 Loading the Training Data and extracting the labels of each:

Used open CV (cv2) to load the image data and extract the labels of each image, resized the image to 28*28. Here is the code.

```

In [16]: 1 # Training Data set
2 fruit_images = []
3 labels = []
4 for fruit_dir_path in glob.glob("/Users/ashwinbabu/Downloads/fruits-proj/Training/*"):
5     # Extracting the labels from the folder name
6     fruit_label = fruit_dir_path.split("/")[-1]
7     print(fruit_label)
8     for image_path in glob.glob(os.path.join(fruit_dir_path, "*.jpg")):
9         # Loads a color image
10        image = cv2.imread(image_path, cv2.IMREAD_COLOR)
11        # Resize the image
12        image = cv2.resize(image, (28, 28))
13        # Changing the color space
14        image = cv2.cvtColor(image, cv2.COLOR_RGB2BGR)
15
16        fruit_images.append(image)
17        labels.append(fruit_label)
18 fruit_images = np.array(fruit_images)
19 labels = np.array(labels)
20 print('Total Training data images: ', len(fruit_images))

```

```

Avocado
Dates
Apple Braeburn
Banana
Total Training data images: 1899

```

```

In [3]: 1 label_to_id_dict = {v:i for i,v in enumerate(np.unique(labels))}
2 id_to_label_dict = {v: k for k, v in label_to_id_dict.items()}
3 print(id_to_label_dict)
4 label_ids = np.array([label_to_id_dict[x] for x in labels])

{0: 'Apple Braeburn', 1: 'Avocado', 2: 'Banana', 3: 'Dates'}

```

Step-2 Implementing PCA as a function: First Flatten the image data to 1899 by (28*28*3), then standardize the data, find co-variance matrix, find eigen value, eigen vector and lastly plotted the proportion of variance graph to decide how many Principal components to pick, in my case I picked 2 principal components, transform the data to 2-D using the eigen vector and eigen value. Here is the code.

```

In [6]: 1 # PCA implementation
2 def pca(data):
3     # First Flattening the image data to 1899 by 2352(28*28*3)
4     image_flattened = ([i.flatten() for i in data])
5     image_flattened = np.asarray(image_flattened,dtype=float)
6
7     # Standardizing the data by calculating the mean and standard deviation
8     # Subtracting with the mean to center the data and dividing by the standard deviation
9     for x in range(len(image_flattened[0])):
10         mean = np.mean(image_flattened[:,x])
11         std = np.std(image_flattened[:,x])
12         for y in range(len(image_flattened)):
13             if std != 0.0:
14
15                 image_flattened[y][x] = (image_flattened[y][x] - mean)/std
16             else:
17                 image_flattened[y][x] = (image_flattened[y][x] - mean)
18
19
20
21     # Finding the co-variance matrix
22     co_var = np.cov(image_flattened.T)
23
24
25     # Computing the eigen-value and eigen-vector from co-variance matrix
26     eig_val_cov, eig_vec_cov = np.linalg.eig(co_var)
27
28
29
30
31     # Make a list of (eigenvalue, eigenvector) tuples
32     eig_pairs = [(np.abs(eig_val_cov[i]), eig_vec_cov[:,i]) for i in range(len(eig_val_cov))]
33
34
35
36     # Sort the (eigenvalue, eigenvector) tuples from high to low
37     eig_pairs.sort(key=lambda x: x[0], reverse=True)
38
39
40     # Taking the top 2 features (components)
41     matrix_w = np.hstack((eig_pairs[0][1].reshape(2352,1), eig_pairs[1][1].reshape(2352,1)))
42
43     # Training data converted to 2-D space
44     transformed = matrix_w.T.dot(image_flattened.T)
45
46     # print(len(transformed[0]))
47     # print(transformed.T)
48
49     final_data = transformed.T
50     final_data = final_data.real
51     final_data[:,1] = np.multiply(final_data[:,1],-1)
52
53     """
54     Plottling the propotion of variance graph and keeping the threshold 40% and adding features until 40% of total
55     variability which is PC1 and PC2 together in this case (45%)
56     """
57
58     eig_val_cov = np.real(eig_val_cov)
59     eig_val_sorted = np.sort(eig_val_cov)[::-1]
60     eig_val = []
61     total = np.sum(eig_val_sorted)
62
63     for x in range(len(eig_val_sorted)):
64         temp = []
65         if eig_val_cov[x] !=0:
66             temp.append(eig_val_cov[x]/(total))
67             temp.append(x+1)
68             eig_val.append(temp)
69
70     eig_val = np.asarray(eig_val)
71
72
73
74
75
76
77
78
79     eig_val = np.asarray(eig_val)
80
81     for x in range(len(eig_val)):
82         plt.plot(eig_val[x][1],eig_val[x][0], 'ro-',linewidth=2)
83     plt.title("The proportion of variance plot")
84     plt.xlabel('Principal Component')
85     plt.ylabel('Eigenvalue')
86     plt.show()
87
88     return final_data

```

I performed PCA using the sklearn library on my data to check if gives the same answer like my own function implementation of PCA and here are the results:

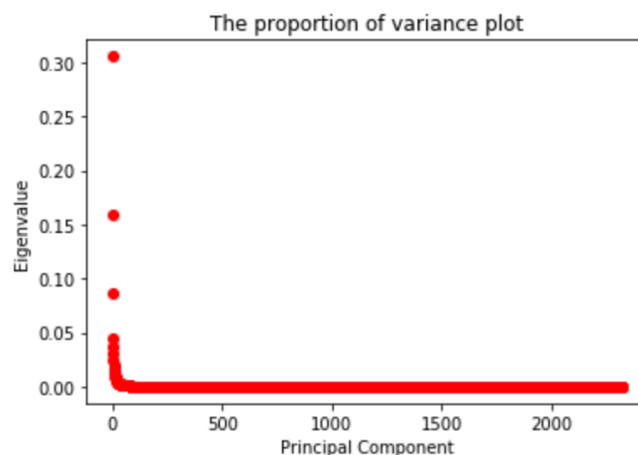
Using my function:

```
[ [-13.79713764  -5.44450968]
  [-18.24821148  -7.06634674]
  [-32.94622328  -5.69887025]
  ...
  [ 35.48930194 -11.50028708]
  [ 20.2922983  -18.09956562]
  [ 44.32998711  -9.79990508]]
```

Using the sklearn library:

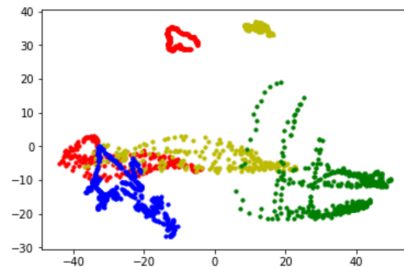
```
[ [-13.79713764  -5.44450968]
  [-18.24821148  -7.06634674]
  [-32.94622328  -5.69887025]
  ...
  [ 35.48930194 -11.50028708]
  [ 20.2922983  -18.09956562]
  [ 44.32998711  -9.79990508]]
```

The scree plot (proportion of variance) looks like this:



The transformed Training data looks like this:

```
In [9]: 1 # graphing the new 2-d Training Data
2 for x in range(len(train)):
3     if train[x][-1] == 0.0:
4         plt.scatter(train[x][0], train[x][1], s=10, c='b', marker="o", label='first')
5     elif train[x][-1] == 1.0:
6         plt.scatter(train[x][0], train[x][1], s=10, c='r', marker="o", label='second')
7     elif train[x][-1] == 2.0:
8         plt.scatter(train[x][0], train[x][1], s=10, c='g', marker="o", label='third')
9     else:
10        plt.scatter(train[x][0], train[x][1], s=10, c='y', marker="o", label='fourth')
11 plt.show()
```



Step-3 Load the Testing data, resize to 28* 28 and perform PCA on it as well. The code looks like this.

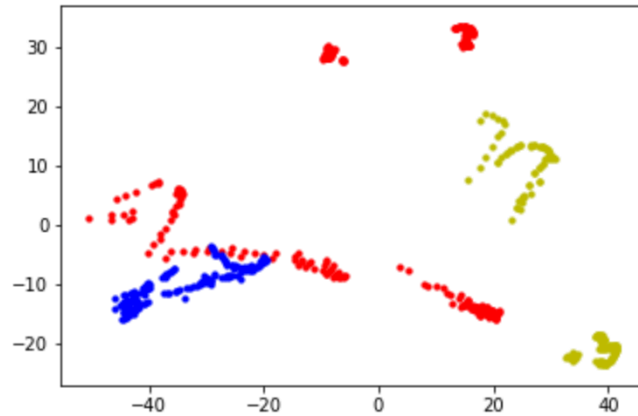
```
In [10]: 1 #Testing Data set
2 fruit_test_images = []
3 labels_test = []
4 for fruit_dir in glob.glob("/Users/ashwinbabu/Downloads/fruits-proj/Test/*"):
5     fruit_label_test = fruit_dir.split("/")[-1]
6     print(fruit_label_test)
7     for image_path_t in glob.glob(os.path.join(fruit_dir, "*.jpg")):
8         image = cv2.imread(image_path_t, cv2.IMREAD_COLOR)
9
10        image = cv2.resize(image, (28, 28))
11        image = cv2.cvtColor(image, cv2.COLOR_RGB2BGR)
12
13        fruit_test_images.append(image)
14        labels_test.append(fruit_label_test)
15 fruit_test_images = np.array(fruit_test_images)
16 labels_test = np.array(labels_test)
17 print(len(fruit_test_images))
18
```

```
Avocado
Dates
Apple Braeburn
Banana
639
```

```
In [11]: 1 label_to_id_dict_test = {v:i for i,v in enumerate(np.unique(labels_test))}
2 id_to_label_dict_test = {v: k for k, v in label_to_id_dict_test.items()}
3 print(id_to_label_dict_test)
4 label_test_ids = np.array([label_to_id_dict_test[x] for x in labels_test])

{0: 'Apple Braeburn', 1: 'Avocado', 2: 'Banana', 3: 'Dates'}
```

The testing data after performing PCA looks like this in 2-D



Step-4 KNN implementation

Find K-nearest data points (using Euclidean distance) and take a majority vote to predict the label

1.

```

1  # K-Nearest Neighbours Implementation
2  def euclideanDistance(item1, item2, length):
3      cal_dist = 0
4      for x in range(length):
5          cal_dist += pow((item1[x] - item2[x]), 2)
6      return math.sqrt(cal_dist)
7
8
9  def checkNeighbors(trainingData, test, k):
10     distance_measure = []
11     length = len(test)-1
12     for x in range(len(trainingData)):
13         dist = euclideanDistance(test, trainingData[x], length)
14         distance_measure.append((dist, trainingData[x]))
15     distance_measure.sort(key=operator.itemgetter(0))
16
17     neighbors = []
18     for x in range(k):
19         neighbors.append(distance_measure[x][1])
20
21     return neighbors
22
23  def determineClass(neighbors):
24     classMajority = {}
25     for x in range(len(neighbors)):
26         classification = str(neighbors[x][-1])
27
28         if classification in classMajority:
29             classMajority[classification] += 1

```

```

30         else:
31             classMajority[classification] = 1
32
33     sortedMajority = max(classMajority.items(), key=operator.itemgetter(1))[0]
34     return sortedMajority[0][0]
35
36
37 def accuracy(test, prediction):
38     identified=0
39
40     for x in range(len(test)):
41
42
43         b = float(prediction[x])
44
45         if test[x][-1] == b:
46             identified +=1
47     # print(identified)
48     return (identified/float(len(test))) * 100.0

```

Main function to perform KNN and output the results:

K=3

```

In [15]: 1 # calling the functions of KNN --> predicting labels --> accuracy
2 def main():
3     # New data that has been converted to 2-D space
4     trainingData = train
5     testData = test
6     print('Training Data: ' + repr(len(trainingData)))
7     print('Test Data: ' + repr(len(testData)))
8     # Predicting the class
9     predictions = []
10    k=input('Enter value for k: ')
11    k = int(k)
12
13    for x in range(len(testData)):
14        neighbors = checkNeighbors(trainingData, testData[x], k)
15        result = determineClass(neighbors)
16        predictions.append(result)
17    # print('--> predicted=' + repr(result) + '-->actual=' + repr(testData[x][-1]))
18    accuracy_1 = accuracy(testData, predictions)
19    print('Accuracy:' + repr(accuracy_1) + '%')
20
21    main()

```

```

Training Data: 1899
Test Data: 639
Enter value for k: 3
Accuracy:73.55242566510172%

```

k=5

```

In [17]: 1 # calling the functions of KNN --> predicting labels --> accuracy
2 def main():
3     # New data that has been converted to 2-D space
4     trainingData = train
5     testData = test
6     print('Training Data: ' + repr(len(trainingData)))
7     print('Test Data: ' + repr(len(testData)))
8     # Predicting the class
9     predictions = []
10    k=input('Enter value for k: ')
11    k = int(k)
12
13    for x in range(len(testData)):
14        neighbors = checkNeighbors(trainingData, testData[x], k)
15        result = determineClass(neighbors)
16        predictions.append(result)
17    # print('--> predicted=' + repr(result) + '-->actual=' + repr(testData[x][-1]))
18    accuracy_1 = accuracy(testData, predictions)
19    print('Accuracy: ' + repr(accuracy_1) + '%')
20
21    main()

Training Data: 1899
Test Data: 639
Enter value for k: 5
Accuracy:74.80438184663537%

```

K=1

```

In [18]: 1 # calling the functions of KNN --> predicting labels --> accuracy
2 def main():
3     # New data that has been converted to 2-D space
4     trainingData = train
5     testData = test
6     print('Training Data: ' + repr(len(trainingData)))
7     print('Test Data: ' + repr(len(testData)))
8     # Predicting the class
9     predictions = []
10    k=input('Enter value for k: ')
11    k = int(k)
12
13    for x in range(len(testData)):
14        neighbors = checkNeighbors(trainingData, testData[x], k)
15        result = determineClass(neighbors)
16        predictions.append(result)
17    # print('--> predicted=' + repr(result) + '-->actual=' + repr(testData[x][-1]))
18    accuracy_1 = accuracy(testData, predictions)
19    print('Accuracy: ' + repr(accuracy_1) + '%')
20
21    main()

Training Data: 1899
Test Data: 639
Enter value for k: 1
Accuracy:68.38810641627543%

```

Outcomes of this project:

This project helped me learn how to handle image data, I had no prior experience handling image data. I learned how to use cv2 to load the image data. Dimension reduction is a very important topic in machine learning (without much loss of information). Learned how to reduce

dimension, how many components to choose, meaning of scree plot, importance of variance, co-variance matrix. The importance of eigen-value, eigen-vector and numpy operations.