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Exercise 1:

(a) Reduce the "ZIP-code"-dataset to two dimensions using Oja's algorithm and plot thepoint cloud of the data set highlighting each class.

(b) Try one of the previously implemented classifiers (k-NN or Logistic Regression) on thetwo-dimensional dataset.

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
```

```
training_data = np.array(pd.read_csv('Data/zip.train', sep=' ', header=None))
test_data = np.array(pd.read_csv('Data/zip.test', sep =' ',header=None))

X_train, y_train = training_data[:,1:-1], training_data[:,0]
X_test, y_test = test_data[:,1:], test_data[:,0]

print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(7291, 256)
(7291,)
(2007, 256)
(2007,)
```

```
import random

def normalize(v):
    norm = np.linalg.norm(v)

    if norm == 0:
        return v
    return v / norm

def PCA(data, size):
    # initialize w
    w = np.ones((size, ))
    w = normalize(w)
    counter = 1
    learning_rate = 0.1

    while(counter <= 1000):
        # pick a random x
```

```
        random_number = random.randint(0, data.shape[0]-1)
        x = data[random_number].reshape(size,)

        # update w
        temp = w + learning_rate * np.dot(w.T, x) * (x - (np.dot(w.T, x)) * w)
        w = temp

        # normalize w
        w = normalize(w)
        learning_rate = learning_rate / counter ** 0.5

        counter += 1
    #print(counter)
    return w
```

update x to x_new

```
def compress(data, size):
    w = PCA(data, size)
    for i in range(data.shape[0]):
        data[i] = (data[i] - (np.dot(w.T, data[i]) * w))
    return data
```

project dataset to eigen vector

```
def project(X, eig_vectors):
    return X @ eig_vectors.T
```

```
eig_vectors = PCA(X_train, 256)
eig_vector2 = PCA(compress(X_train, 256), 256)
print(eig_vectors.shape)
print(eig_vector2.shape)
# print(eig_vectors)
# print(eig_vector2)

eig_vectors = np.vstack([eig_vectors, eig_vector2])
print(eig_vectors.shape)
```

```
(256,)
(256,)
(2, 256)
```

```
X_train_2d = project(X_train, eig_vectors)
X_test_2d = project(X_test, eig_vectors)
print(X_train_2d.shape)
print(X_test_2d.shape)

print(X_train_2d[:5])
```

```
(7291, 2)
(2007, 2)
[[-4.18727744 -8.5283877 ]
 [-1.37963765 -2.62198044]
 [-1.15205182 -3.93146842]
 [-0.60833958 -0.28739138]
 [-2.15126905 -2.88241681]]
```

use homemade-KNN to predict the two-dimensional dataset

```
class KNearestNeighbors():
    def predict(self, X_test, k):       # As suggested, a function that takes in
k and a test image as a parameter.
        predict_results = []
        for i in X_test:
            squared_distances = self.squared_euclidean_distance(self.X, i)
            indices = np.argpartition(squared_distances, k)[:k]    # get the
indices of k values with smaller distances
            answer_indices = (self.y[indices])        # get the value of the
label corresponding to index
            #print(answer_indices)
            list = answer_indices.tolist()            # turn numpy array into a
normal list to use count
            majority = max(list, key=list.count)      # get the value with the
most occurrences
            #print(majority)
            predict_results += [majority]             # add it to a result list
        return(predict_results)

    def fit(self, x, y):     #fit X_train, y_train together
        self.X = x
        self.y = y

    def squared_euclidean_distance(self, x_1, x_2):
        return np.sum((x_1-x_2)**2, axis = 1)

    def correctness(self, right_answer, predict_result):
        return np.mean(right_answer == predict_result)

    def variance(self, prediction, y_new_test):
        return np.var(y_new_test != prediction)

kNN = KNearestNeighbors()
```

```
kNN.fit(X_train_2d, y_train)
```

```
prediction1 = kNN.predict(X_test_2d, 10)      # k=10
prediction2 = kNN.predict(X_test_2d, 20)
prediction3 = kNN.predict(X_test_2d, 50)
prediction4 = kNN.predict(X_test_2d, 100)
prediction5 = kNN.predict(X_test_2d, 200)
prediction6 = kNN.predict(X_test_2d, 500)

#print(prediction)
```

```
print(kNN.correctness(y_test, prediction1))
print(kNN.correctness(y_test, prediction2))
print(kNN.correctness(y_test, prediction3))
print(kNN.correctness(y_test, prediction4))
print(kNN.correctness(y_test, prediction5))
print(kNN.correctness(y_test, prediction6))
```

```
0.1554559043348281
0.1574489287493772
0.17040358744394618
0.16741405082212257
0.1604384653712008
0.13054309915296464
```

The lower prediction accuracy here is due to the loss of too much information by compressing the 256 dimensional data into 2 dimensions.

Visualising the data

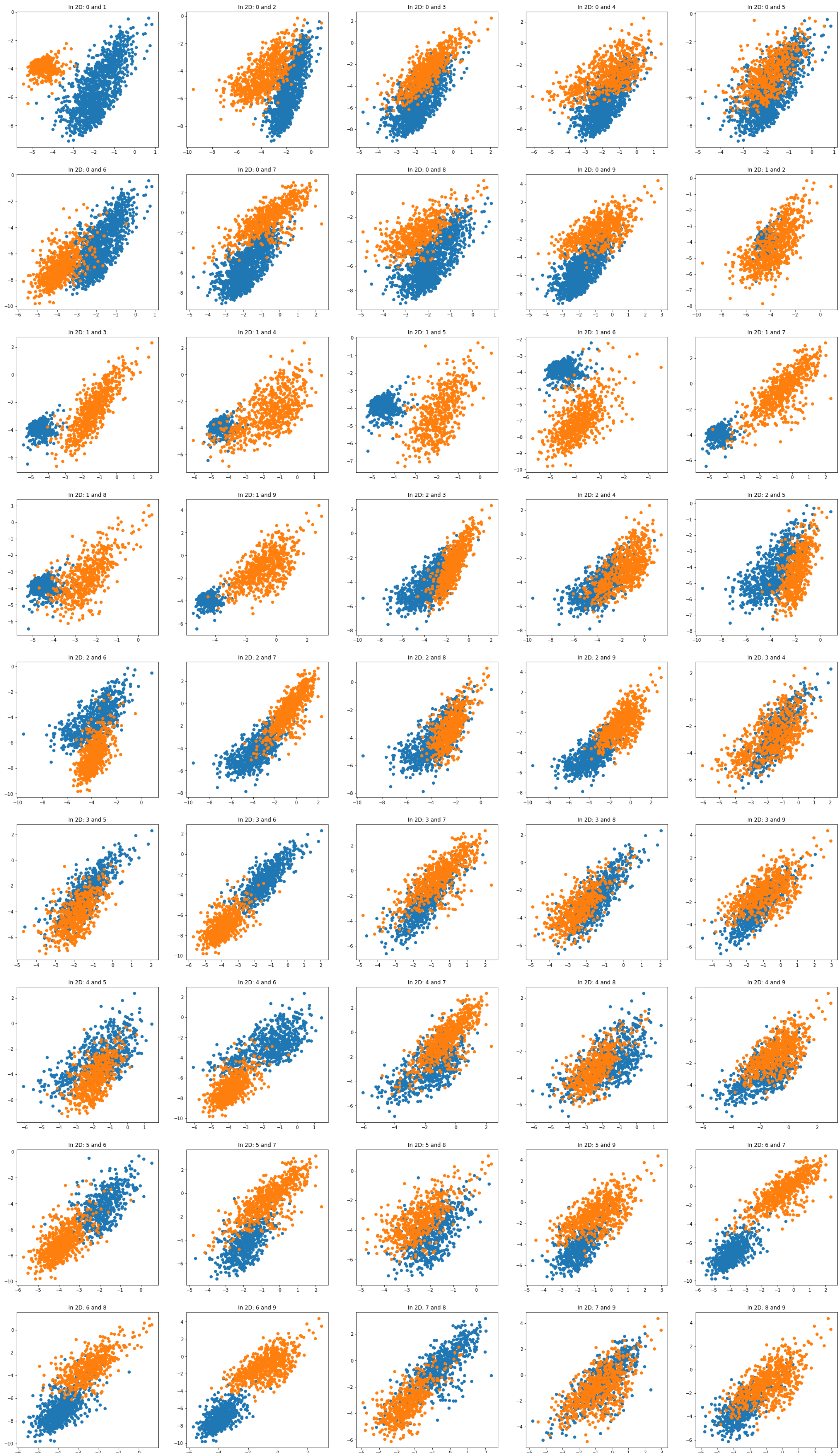
```
class Visualizer:
    def show_2d(self, X, y):
        classes = 10             # 0 to 9 , 10 classes
        fig = plt.figure(figsize=(33, 66))
        num = 0                  # count the num of picture
        for i in range(classes):
            for j in range(i+1, classes):
                num += 1
                plt.subplot(10, 5, num)
                self.plot_classes(X, y, i, j)
                plt.title("In 2D: %d and %d" % (i, j))
        plt.show()

    def eigenfaces(self, eig_vectors):
        num_faces = 2            # two eigen vectors, two eigen faces :)
        images = eig_vectors.reshape(num_faces, 50, 37)
        fig = plt.figure(figsize=(5, 10))
        for i in range(0, num_faces):
            ax = plt.subplot(1, 2, i+1)
            plt.imshow(images[i])
            plt.title("Eigen_face %d:" % (i+1))
        plt.show()

    def plot_classes(self, X, y, i, j):
        filtered_by_i = X[y==i]
        filtered_by_j = X[y==j]
        plt.scatter(filtered_by_i[:,0], filtered_by_i[:,1])
        plt.scatter(filtered_by_j[:,0], filtered_by_j[:,1])
```

```
visualizer = Visualizer()
```

```
visualizer.show_2d(X_train_2d, y_train)
```


In 2D: 0 and 1
In 2D: 0 and 2
In 2D: 0 and 3
In 2D: 0 and 4
In 2D: 0 and 5
In 2D: 0 and 6
In 2D: 0 and 7
In 2D: 0 and 8
In 2D: 0 and 9
In 2D: 1 and 2
In 2D: 1 and 3
In 2D: 1 and 4
In 2D: 1 and 5
In 2D: 1 and 6
In 2D: 1 and 7
In 2D: 1 and 8
In 2D: 1 and 9
In 2D: 2 and 3
In 2D: 2 and 4
In 2D: 2 and 5
In 2D: 2 and 6
In 2D: 2 and 7
In 2D: 2 and 8
In 2D: 2 and 9
In 2D: 3 and 4
In 2D: 3 and 5
In 2D: 3 and 6
In 2D: 3 and 7
In 2D: 3 and 8
In 2D: 3 and 9
In 2D: 4 and 5
In 2D: 4 and 6
In 2D: 4 and 7
In 2D: 4 and 8
In 2D: 4 and 9
In 2D: 5 and 6
In 2D: 5 and 7
In 2D: 5 and 8
In 2D: 5 and 9
In 2D: 6 and 7
In 2D: 6 and 8
In 2D: 6 and 9
In 2D: 7 and 8
In 2D: 7 and 9
In 2D: 8 and 9

Exercise 2:

Use your implementation of PCA on the greyscale-version of the "LFWcrop Face"-Dataset1.Visualize the first two principal components as Eigenfaces.

```
from sklearn.datasets import fetch_lfw_people
import numpy as np
from matplotlib import pyplot as plt


# ###############################################################################
# Download the data, if not already on disk and load it as numpy arrays

lfw_people = fetch_lfw_people(min_faces_per_person=70, resize=0.4)

# introspect the images arrays to find the shapes (for plotting)
n_samples, h, w = lfw_people.images.shape

# for machine learning we use the 2 data directly (as relative pixel
# positions info is ignored by this model)
X = lfw_people.data
n_features = X.shape[1]
print("X shape",X.shape)
print("")

# the label to predict is the id of the person
y = lfw_people.target
print(y.shape)
print(y[:5])
print("")

target_names = lfw_people.target_names
print(target_names[:5])
print("")

n_classes = target_names.shape[0]

print("Total dataset size:")
print("n_samples: %d" % n_samples)
print("n_features: %d" % n_features)
print("n_classes: %d" % n_classes)
print("image_height: %d" % h)
print("image_width: %d" % w)


def show_faces(X):
    num_samples = 28
    indices = np.random.choice(range(len(X)), num_samples)
#     indices = np.array([0,1,2,3,4,5])
    print(indices.shape)
    sample_digits = X[indices]

    fig = plt.figure(figsize=(20, 6))

    for i in range(num_samples):
```

```
        ax = plt.subplot(4, 7, i + 1)
        img = sample_digits[i].reshape((h, w))
        plt.imshow(img, cmap='gray')
        plt.axis('off')
show_faces(X)
```

```
X shape (1288, 1850)

(1288,)
[5 6 3 1 0]

['Ariel Sharon' 'Colin Powell' 'Donald Rumsfeld' 'George W Bush'
 'Gerhard Schroeder']

Total dataset size:
n_samples: 1288
n_features: 1850
n_classes: 7
image_height: 50
image_width: 37
(28,)
```

get the two eigen vectors

```
eig_vectors = PCA(X, n_features)
eig_vector2 = PCA(compress(X, n_features), n_features)
print(eig_vectors.shape)
print(eig_vector2.shape)
# print(eig_vectors)
# print(eig_vector2)

eig_vectors = np.vstack([eig_vectors, eig_vector2])
print(eig_vectors.shape)
```

```
(1850,)
(1850,)
(2, 1850)
```

```
X_2d = project(X, eig_vectors)
print(X_2d.shape)
print(X_2d[:5])
```

```
(1288, 2)
[[ 178.80440658 -837.04171197]
 [ 163.18371272 -925.26076418]
 [ 144.7472842  -621.57920617]
 [ 205.22405949 -986.95171417]
 [ 230.78712547 -804.45722147]]
```

Visualize the first two principal components as Eigenfaces !

```
visualizer.eigenfaces(eig_vectors)
```