[1]:	<pre>label=label.astype(np.int32) plt.figure() plt.scatter(data_train[:,0],data_train[:,1],c=label) plt.title('Data visualization') Text(0.5, 1.0, 'Data visualization') Data visualization 4 3 2 1</pre>
[2]: [3]:	<pre>def euclidean_distance(row1, row2): return np.linalg.norm(row1-row2) def get_neighbors(train, label_train, test_row, nk): # insert your code here ng = []</pre>
[4]: [5]:	<pre>for i in range(train.shape[0]) : ng.append([euclidean_distance(train[i], test_row), label_train[i]]) ng = np.array(ng) ng = ng[ng[:,0].argsort()] ng = ng[:nk, 1] return ng def predict_classification(ng): ng = list(ng) if ng.count(1) >= ng.count(0): return 1; return 0; # test data generation data_test=np.concatenate((data1[-100:],data2[-100:])) label_test=np.concatenate((np.zeros(100),np.ones(100)))) label_test = label_test.astype(np.int32)</pre>
[6]:	<pre>K=2 pred_label=np.zeros(data_test.shape[0]) for i in range(data_test.shape[0]): neig=get_neighbors(data_train, label, data_test[i,:], K) pred_label[i]=predict_classification(neig) pred_label = pred_label.astype(np.int32) accuracy=(len(np.where(pred_label==label_test)[0])/len(label_test))*100 print('Testing Accuracy=', accuracy, '%') Testing Accuracy= 65.5 % Principal component analysis (PCA)</pre>
34]:	<pre>import numpy as np import matplotlib.pyplot as plt mean1=np.array([0,0]) mean2=np.array([1,0.1],[0.1,1]]) np.random.seed(0) data1=np.random.multivariate_normal(mean1, var, 500) data2=np.random.multivariate_normal(mean2, var, 500) data1=np.concatenate((data1, data2)) label=np.concatenate((np.zeros(data1.shape[0]), np.ones(data2.shape[0])))</pre>
	<pre>plt.figure() plt.scatter(data[:,0],data[:,1],c=label) plt.title('Data visualization') plt.show() plt.figure() plt.scatter(data[:,0],np.zeros(data.shape[0]),c=label) plt.title('distribution in x direction') plt.show() plt.figure() plt.scatter(data[:,1],np.zeros(data.shape[0]),c=label) plt.title('distribution in y direction') plt.show()</pre> Data visualization
	distribution in x direction
	0.000.020.042 0 2 4 6 distribution in y direction
35]:	#Data normalization # print(data[:5]) # perform data normalization here using mean substraction and std division data_mean = np.mean(data, axis=0) data_var = np.std(data, axis=0) # print(data_mean.shape, data_var.shape) data_norm = (data - data_mean) / data_var
	<pre>plt.figure() plt.scatter(data_norm[:,0],data_norm[:,1],c=label) plt.title('Data visualization') plt.show()</pre> Data visualization
37]:	# PCA # coverance matrix cov= data_norm.T @ data_norm # using sigular value decomposition u, s, v=np.linalg.svd(cov) trans_data = data_norm @ u print(trans_data.shape)
	<pre>var_pca1=np.var(trans_data[:,0]) var_pca2=np.var(trans_data[:,1]) print('variance along pca1 direction=',var_pca1) print('variance along pca2 direction=',var_pca2) plt.figure() plt.scatter(trans_data[:,0],trans_data[:,1],c=label) plt.title('Data visualization') plt.show() plt.figure() plt.scatter(trans_data[:,0],np.zeros(data.shape[0]),c=label) plt.title('distribution in pca1 direction') plt.show() plt.figure() plt.scatter(trans_data[:,1],np.zeros(data.shape[0]),c=label) plt.title('distribution in pca2 direction')</pre>
	(1000, 2) variance along pca1 direction= 1.8477663843459717 variance along pca2 direction= 0.15223361565402696 Data visualization 1.0 -0.5 -0.5
	-1.0 -
	-2 -1 0 1 2 distribution in pca2 direction 0.04 - 0.02 - -0.02 - -0.04 -
26]:	PCA 1 dimension is sufficient, we can droup PCA 2 dimension class pca: # Constructor definit(self, name='reg',data=None,retain_dim=None): self.name = name # Create an instance variable self.data=data # self.retain_dim=retain_dim if retain_dim is not None else self.ret_dim(self.data) if retain_dim == None: self.retain_dim = self.ret_dim(self.data) else : self.retain_dim = retain_dim # compute pca transform value def pca_comp(self,data): data=self.pre_process(data) cov = data.T @ data
	<pre>u,=np.linalg.svd(cov) # singular value decomposition u_req = u[:, 0:self.retain_dim] # print("ureq_shape : ", u_req.shape) # print("ret_dim : ", self.retain_dim) trans_data= data @ u_req return trans_data,u_req # compute the required retain dimension def ret_dim(self,data): data=self.pre_process(data) cov=data.T @ data ,s,_=np.linalg.svd(cov) cur_sum = 0 total_sum = np.sum(s) # print(s.shape) ind = -1 for i in range(len(s)): cur_sum += s[i]; if cur_sum / total_sum > 0.9:</pre>
88]:	<pre>ind = i break return ind+1 def pre_process(self,data): data1=(data-np.mean(data,axis=0)) data=data1/(np.std(data1,axis=0)+10**(-30)) # avoid divide by zero return data # pca transformation PCA=pca(data=data) trans_data,trans_mat=PCA.pca_comp(data) plt.scatter(trans_data,np.zeros(trans_data.shape),c=label) plt.show()</pre>
39]:	#classification using pca #use k-nearest neighbour classifier after dimensionality reduction from sklearn.neighbors import KNeighborsClassifier
	<pre>k=5 knn = KNeighborsClassifier(n_neighbors=k) knn.fit(trans_data, label) print('KNN Training accuracy =',knn.score(trans_data,label)*100) # test data np.random.seed(0) data1=np.random.multivariate_normal(mean1,var,50) data2=np.random.multivariate_normal(mean2,var,50) data=np.concatenate((data1,data2)) tst_label=np.concatenate((np.zeros(data1.shape[0]),np.ones(data2.shape[0]))) print('KNN Testing accuracy =',knn.score(PCA.pre_process(data) @ trans_mat,tst_label)*100) KNN Training accuracy = 99.9 KNN Testing accuracy = 100.0</pre>
[]:	<pre>from google.colab import drive drive.mount('/gdrive') # MNIST data from keras.datasets import mnist import numpy as np import matplotlib.pyplot as plt (X_train, y_train), (X_test, y_test) = mnist.load_data() train_data = [] test_data = [] data_plot = [] train_label =[] test_label =[] for i in range(len(X_train)): if y_train[i] == 1 or y_train[i] == 5: data_plot.append(X_train[i])</pre>
	<pre>train_data.append(X_train[i].flatten()/255) train_label.append(y_train[i]) train_data = np.array(train_data) train_label = np.array(train_label) data_plot = np.array(data_plot) print("Train data shape",train_data.shape) for i in range(len(X_test)): if y_test[i] == 1 or y_test[i] == 5: test_data.append(X_test[i].flatten()/255) test_label.append(y_test[i]) test_data = np.array(test_data) test_label = np.array(test_label) plt.imshow(data_plot[1]) plt.show()</pre> Train data shape (12163, 784)
:1]:	print('Initial data dimension=', train_data.shape[1])
	<pre>PCA=pca(data=train_data) trans_data, trans_mat=PCA.pca_comp(train_data) print('Retained dimesion after PCA=', trans_mat.shape[1]) k=5 knn = KNeighborsClassifier(n_neighbors=k) knn.fit(trans_data, train_label) print('KNN Training accuracy =', knn.score(trans_data, train_label)*100) # final testing print('KNN Testing accuracy =', knn.score(PCA.pre_process(test_data) @ trans_mat, test_label)*100) Initial data dimension= 784 Retained dimesion after PCA= 173 KNN Training accuracy = 99.78623694812136 KNN Testing accuracy = 99.80266403552048</pre>
85]:	<pre>import numpy as np import matplotlib.pyplot as plt # data generation mean1=np.array([0,0]) mean2=np.array([4,5]) var=np.array([[1,0.1],[0.1,1]]) np.random.seed(0) data1=np.random.multivariate_normal(mean1, var, 500) data2=np.random.multivariate_normal(mean2, var, 500) data2=np.concatenate((data1, data2)) label=np.concatenate((np.zeros(data1.shape[0]), np.ones(data2.shape[0]))) plt.figure()</pre>
35]:	<pre>plt.scatter(data[:,0],data[:,1],c=label) plt.title('Data visualization') plt.figure() plt.scatter(data[:,0],np.zeros(data.shape[0]),c=label) plt.title('distribution in x direction') plt.figure() plt.scatter(data[:,1],np.zeros(data.shape[0]),c=label) plt.title('distribution in y direction')</pre> Text(0.5, 1.0, 'distribution in y direction') Data visualization 8 6 4
	2
	-0.02
37]:	<pre># perform 2-class and m-class LDA def LDA(data, label): id={} data_l={} mean_l={} cov_l={} S_w=np.zeros((data.shape[1], data.shape[1])) cls=np.unique(label) for i in cls: id[i]=np.where(label==i)[0] data_l[i]=data[id[i].]</pre>
	<pre>data_l[i]=data[id[i],:] mean_l[i]=np.mean(data_l[i],axis=0) temp = data_l[i]-mean_l[i]; cov_l[i] = temp.T@temp S_w=S_w+cov_l[i] S_w = S_w/len(data_l) if len(data_l)==2: temp = mean_l[0]-mean_l[1] temp = np.array([temp]) S_b = temp.T @ temp; temp = np.linalg.pinv(S_w)@S_b u,_,_=np.linalg.svd(temp) w = u[:,:len(data_l)-1] else: S_t = np.cov(data,rowvar=False) S_b = S_t-S_w temp = np.linalg.pinv(S_w)@S_b</pre>
8]:	<pre>u,_,_ = np.linalg.svd(temp) w = u[:,:len(data_l)-1] return w a = LDA(data, label) # after LDA projection w=LDA(data, label) plt.figure() plt.scatter(data @ w,np.zeros(data.shape[0]),c=label) plt.show()</pre>
5]:	#classification using pca #use k-nearest neighbour classifier after dimensionality reduction from sklearn.neighbors import KNeighborsClassifier LDA_data= data @ w k=5 knn = KNeighborsClassifier(n_neighbors=k) knn.fit(LDA_data, label)
	<pre>knn.fit(LDA_data, label) print('KNN Training accuracy =',knn.score(LDA_data,label)*100) # test data np.random.seed(0) data1=np.random.multivariate_normal(mean1,var,50) data2=np.random.multivariate_normal(mean2,var,50) data_tst=np.concatenate((data1,data2)) tst_label=np.concatenate((np.zeros(data1.shape[0]),np.ones(data2.shape[0]))) print('KNN Testing accuracy =',knn.score(data_tst@ w,tst_label)*100) KNN Training accuracy = 100.0 KNN Testing accuracy = 100.0</pre>
9]:	1. 3 class Sythetic data 2. Homework: Mnist 3 class and 10 class import numpy as np import matplotlib.pyplot as plt mean1=np.array([0,0]) mean2=np.array([4,5]) mean3=np.array([-5,-4]) var=np.array([[1,0.1],[0.1,1]]) np.random.seed(0) data1=np.random.multivariate_normal(mean1, var, 500) data2=np.random.multivariate_normal(mean2, var, 500) data3=np.random.multivariate_normal(mean3, var, 500) data3=np.concatenate((data1, data2, data3)) label=np.concatenate((np.zeros(data1.shape[0]), np.ones(data2.shape[0]), np.ones(data3.shape[0])+1)) nlt_figure()
9]:	<pre>plt.figure() plt.scatter(data[:,0],data[:,1],c=label) plt.title('Data visualization') plt.figure() plt.scatter(data[:,0],np.zeros(data.shape[0]),c=label) plt.title('distribution in x direction') plt.figure() plt.scatter(data[:,1],np.zeros(data.shape[0]),c=label) plt.title('distribution in y direction')</pre> Text(0.5, 1.0, 'distribution in y direction') Data visualization 8 6 4 6 7 7 8 7 8 7 8 7 8 7 8 7 8 7 8 7 8 8 7 8 7 8 7 8 8 7 8 8 7 8 8 7 8 8 7 8
	4 2 0 0 -2 -4 -6 -8 -6 -4 -2 0 2 4 6 distribution in x direction
	0.00
	0.00