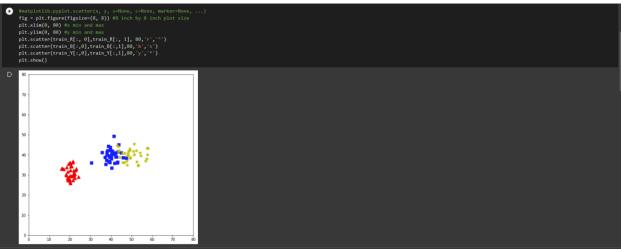
## **CPE383 Machine Learning: Quiz2**

- 1. 1.5 hr. Min Distance classifier on 3 Gaussian Classes. Modify your KNN program from quiz 1 with 3 classes to create 50 random points for each class: red, blue, and yellow from a 2D Gaussian distribution (see Gaussian Data.ipynb) with means: (20, 30), (40, 40), (50, 40) and (s\_x, s\_y) of (3, 10), (10, 10), (15, 15), for red, blue, and yellow, respectively. Use 70% of the dataset as training data and 30% as testing data.
  - A. 5 pts. Plot the 3 classes using the training data.





B. 5 pts. Using KNN with K = 5, report the total accuracy of the testing data.

C. Using the minimum distance classifier: 5 pts. Report the training data cluster mean for each class of red, blue, and yellow.

```
[48] mean, R - np.mean(train_M, axis=0)
mean, Y - np.mean(train_M, axis=0)
mean, Y - np.mean(train_M, axis=0)

centroid = [mean, R.tolist(), mean_M.tolist()]
centroid = np.array(centroid, dtype-np.floati2)
responses = [0, 1, 2]
responses = [0, 1, 2]
responses = np.array(responses, dtype-np.floati2)

print("mean of red =", centroid[0], "mean of blue =", centroid[1], "mean of yellow =", centroid[2])

mean of red = [19.931755 29.114399] mean of blue = (39.626453 40.266296) mean of yellow = [50.753605 41.74431]
```

D. Report the total accuracy of the testing data using this classifier.

```
ton = cv.al.@Nearest_create()
ton.train(centroid, cv.al.ROM_SMPUE, responses)
ret, results, neighbors, dist = ton.findhearest(test_data, 1)

correct = 0
for i in range(len(test_data)):
    resultcolor = colorHame[results[i].astype(int)]
    neighborcolors = colorHame[results[i].astype(int))

if (results[i].astype(int) == expect_result[i].astype(int)):
    correct += 1
    accuracy_percent = correct / len(expect_result)
    print("Miniam distance classifier accuracy_percent)
```

- 2. 4 hrs. Code Naive Bayes from Scratch. Write a program to read the Iris dataset, split into 2 parts: training and testing just like it was done in the example. Then write your own code to:
  - a. 5 pts. Find the mean and standard deviation for each of the 4 features of each of the 3 classes from the training data.  $\mu$ \_ik and  $\sigma$ \_ik for i = 1..4, k = 1..3. You will get pdfs P(x\_i | c\_k) for each class using the Gaussian distribution equation with  $\mu$ \_ik and  $\sigma$ \_ik for i = 1..4, k = 1..3. This gets you pdfs: P(x\_1, x\_2, x\_3, x\_4 | c\_1), P(x\_1, x\_2, x\_3, x\_4 | c\_2), P(x\_1, x\_2, x\_3, x\_4 | c\_3).

```
[1] import numpy as np import math from sklearm.addlests import load_iris from sklearm.addle_selection import train_test_split the_data = load_iris()

[2] label_names - the_data['target_names'] feature_names : the_data['fature_names'] all_labels = the_data['fature_names'] all_labels = the_data['fature_names'] all_features = the_data['fature_names'] all_features = the_data['fature_names'] all_features = the_data['fature_names'] selection_train_test_split all_features = the_data['fature_names'] selection_train_test_split selection_train_test_split selection_train_test_split_html

| Soliting_our_dataset_into_2 parts_for training_namt_test_split_selection_train_test_split_labels, test_size=0.2,random_state=0)
```

b. 5 pts. Find the P(c\_k) by counting the percent frequency of each class in your training data. Now we have P(c\_k | x\_1, x\_2, x\_3, x\_4)  $\propto$  P(x\_1, x\_2, x\_3, x\_4 | c\_k) \* P(c\_k).

c. 5 pts. Then for each (x\_1, x\_2, x\_3, x\_4) in your test data: find the class k of 1, 2, or 3 for which P(c\_k | x\_1, x\_2, x\_3, x\_4) is maximum, put that k into array my\_predicted\_labels

```
[17] # Classify the testing data

my_predicted_labels = np.zeros(len(testing_labels))

for i in range(len(testing_labels)):

max_index = np.argmax(pdfs[z, i])

my_predicted_labels[i] = max_index

print(my_predicted_labels)

[2. 1. 0. 2. 0. 2. 0. 1. 1. 1. 1. 1. 1. 1. 0. 0. 2. 1. 0. 0.

2. 0. 0. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 0. 0. 2. 1. 0. 0.
```

d. 5 pts. Calculate and print the accuracy score from your implementation of Naive Bayes from scratch

```
[18] true_positive = 0
for i in range(len(testing_labels)):
    if testing_labels[i] -- my_predicted_labels[i]:
    true_positive + 1

my_predict_accuracy = true_positive / len(testing_labels)
print("My_predict_accuracy", my_predict_accuracy)

My_predict_accuracy 0.966666666666667
```

e. 5 pts. Use sklearn's GaussianNB classifier to report the accuracy score. Compare your result to sklearn's.

3. 1 hr. Try the digits datasets. Change the "Naive Bayes and KNN Iris and Cancer.ipynb" program to allow the user to also select the digits dataset by entering "digits", in addition to "iris" and "cancer". Present the output results for both Naive Bayes and KNN classifiers using Sklearn. What is the best value of K in KNN?

```
print ("Test data where predicted label equals the test label: \n", testing_labels == predicted_labels)
number_correct = (testing_labels == predicted_labels).sum()
print ("\nNumber of correct predictions: %d. Out of total test cases %d." %(number_correct, testing_labels.shape[@]) )
       7) from sklearn.metrics import accuracy_score
# Calculating the % Accuracy of the prediction, for Iris dataset random_state = 0 gives 97%, r
accuracy_sercent = 100*accuracy_score(texting_labels.predicted_labels)
print(Trediction Accuracy_1 % 0.27%X % accuracy_percent) %% escapes the formatting % to prin
          from sklearm.neighbors import KNeighborsClassifier
neighbor_size = []
errors_list = []
for k in runge (2, 20);
for k in runge (2, 20);
nodel = classifier = neighborsClassifier(n_neighbors = k)
nodel = classifier.fit(training features,training_labels) # or can also use:
predicted_labels = nodel.predict(testing_features) House the model obtained in
previous step to predict labels for testing features
accuracy_percent = 100*accuracy_score(testing_labels,predicted_labels)
# Calculation to # Accuracy of the mediction of the mediction.
                     # Calculating the % Accuracy of the prediction.

print("Prediction Accuracy for k - %2d : %5.2F%%" % (k, accuracy_percent)) #%% escapes the formatting % to print '%' neighbor_size append(k)

errors_list.append(100-accuracy_percent)
        print (" K = ", neighbor_size, "k", "Forms = ", errors_list)

Prediction Accuracy for k = 2: 98.06X

Prediction Accuracy for k = 3: 98.38X

Prediction Accuracy for k = 4: 97.36X

Prediction Accuracy for k = 6: 97.22X

Prediction Accuracy for k = 6: 97.22X

Prediction Accuracy for k = 6: 97.22X

Prediction Accuracy for k = 8: 99.36X

Prediction Accuracy for k = 8: 97.22X

Prediction Accuracy for k = 10: 97.22X

Prediction Accuracy for k = 11: 97.22X

Prediction Accuracy for k = 13: 97.22X

Prediction Accuracy for k = 16: 96.96X

Prediction Accuracy for k = 16: 96.96X

Prediction Accuracy for k = 16: 96.96X

Prediction Accuracy for k = 19: 96.07X

Prediction Accuracy for k = 19: 96.11X

Accuracy for k = 10: 96.11X
          # plot misclassification error versus k
import matplotlib.ppplot as plt
import misclassification error.
plt.fipport(figize = (i0, 6))
plt.plot(redightor_size, error_list) **x list and y list
plt.plate(fiscation freightor)
plt.ylate(fiscation freightor)
```

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```

Ans: The best K is 1 with 98.89% accuracy

4. 10 pts. 1.5 hr. Normalize data option. Add an option to "Naive Bayes and KNN Iris and Cancer.ipynb" to ask the user whether to normalize the dataset by converting each feature into a Z-distribution by making mean = 0, and standard deviation = 1. For this problem, compare the accuracy results for the breast cancer dataset on the sklearn's KNN classifier using normalized vs. unnormalized data.

```
# Training our classifier
from sklearn.naive buyes import GaussianHB
classifier = GaussianHH() #classifier is now an object of the Gaussian Naive Buyes class
model = classifier.fit(training_features_training_labels)
model = classifier.fit(training_features_training_labels)
                     print ('\Predicted class labels: \n', predicted_labels)
print('\Normect festing class labels: \n', testing_labels)
print('\Normect festing class labels: \n', label_names[predicted_labels])
print('\Normect class lames: \n', label_names[predicted_labels])
                        print ("Test data where predicted label equals the test label: \n", testing_labels == predicted_labels)
number_correct = (testing_labels == predicted_labels).sum()
print ("Numbure of correct predictions: 26. Out of total test cases 36." %(number_correct, testing_labels.shape[0]) )
from sklearn.metrics import accuracy_score
                          From StatesPinetrics import accuracy_score of the prediction. For Iris dataset random_state = # gives 97%, random_state 40 gives 100%, random_state 5 gives 90%. 

accuracy_percent - 1009 accuracy_score(testing_labels.predicted_labels)
print("Prediction_Accuracy: %3.27%% % accuracy_percent) #%% escapes the formatting % to print %"

Prediction_Accuracy: 90.00%.
                     from sklearn.neighbors import EMeighborsclassifier
neighbor size - []
errors_list = []
for k in range (2, 20):
classifier - Meighborsclassifier(n.neighbors = k)
model = classifier.fit(training_features_training_labels) # or can also use:
predicted_labels = model_newide(tresting_features) # use the model obtained in previous step to predict labels for testing_features
accuracy_percent = 100*accuracy_score(testing_labels_predicted_labels) # or can also use:
predicted_labels = model_newide(tresting_features) # use the model obtained in previous step to predict labels for testing_features
accuracy_percent = 100*accuracy_score(testing_labels_predicted_labels)
# Calculation the % Accuracy of the prediction.
                                  # Calculating the % Accuracy of the prediction.

print("Prediction Accuracy for k - %2d : %5.2F%% % (k, accuracy_percent)) #% escapes the formatting % to print '%' neighbor_size.append(k)

errors_list.append(100-accuracy_percent)
                   print (* k * , neighbor_size, "W", "En
Rewilltiam Accornsy for k = 2 : 30 - 47%.
Rewilltiam Accornsy for k = 3 : 30 - 12%.
Rewilltiam Accornsy for k = 5 : 30 - 10%.
Prediction Accornsy for k = 6 : 30 - 30%.
Prediction Accornsy for k = 7 : 30 - 72%.
Prediction Accornsy for k = 7 : 30 - 72%.
Prediction Accornsy for k = 3 : 306 - 40%.
Prediction Accornsy for k = 10 : 306 - 40%.
Prediction Accornsy for k = 11 : 306 - 40%.
Prediction Accornsy for k = 12 : 306 - 40%.
Prediction Accornsy for k = 13 : 306 - 40%.
Prediction Accornsy for k = 16 : 306 - 40%.
Prediction Accornsy for k = 16 : 306 - 40%.
Prediction Accornsy for k = 10 : 306 - 40%.
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Prediction Accornsy for k = 10 : 306 - 40%.
Prediction Accornsy for k = 10 : 306 - 40%.
Prediction Accornsy for k = 10 : 306 - 40%.
Prediction Accornsy for k = 10 : 306 - 40%.
                          Prediction Accuracy for k - 19 : 96.49%
K = [2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19]
Errors = [16.56315789473665, 8.77192982456141, 7.8947364210526, 6.1403568771929844, 6.1403568771929845, 5.26315789473685, 5.26315789473685, 3.5087719298245617, 5.26315789473685, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617, 3.5087719298245617,
                        # plot misclassification error versus k
import matplotlib.ppplot as plt
jutt.figure(figize = (00, 6)
plt.plot(relighbor_size, errors_list) #x list and y list
plt.plot(relighbor_size, errors_list) #x list and y list
plt.plate(misclassification Error Percent')
plt.ylade(figize)
plt.pld(frue)
plt.prid(frue)
plt.prid(frue)
```

```
- 0 curacy - 0 in range(s, math.ceil(math.sqrt(len(training_labels)))):
ifider - Dissiphorsclassifier(n_melghbors - k)
i- classifier-fit(training_features,training_labels)  # or con also use:
cited_labels - model_medit(ettering_features) size the model obtained in previous step to predict labels for testing features and concentrations of according to the content - labels contents_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_convertes_con
c granty = 0
in range(r) = 0
in range(r)
```

Ans: The best K of normalized data is 16, different from unnormalized that is 9