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ML-LAB3

A1)

Evaluate the intraclass spread and interclass distances between the classes in your dataset. If your data deals with multiple classes, you can take any two classes. Steps below (refer below diagram for understanding):

```
import numpy as np

import pandas as pd


data = pd.read_csv(r"C:\Users\vanga\Downloads\archive (10)\Agrofood_co2_emission.csv")


features = data.drop(columns=[data.columns[-2]]).select_dtypes(include=[np.number]).values

labels = data.iloc[:, -2].values


unique_classes = np.unique(labels)

labels_series = pd.Series(labels)
```

```
class_1 = features[labels_series == unique_classes[0]]
class_2 = features[labels_series == unique_classes[1]]

centroid_1 = np.mean(class_1, axis=0)
centroid_2 = np.mean(class_2, axis=0)

spread_1 = np.std(class_1, axis=0)
spread_2 = np.std(class_2, axis=0)

interclass_distance = np.linalg.norm(centroid_1 - centroid_2)

print(f"Interclass Distance: {interclass_distance}")
print(f"Centroid of Class 1: {centroid_1}")
print(f"Centroid of Class 2: {centroid_2}")
print(f"Spread of Class 1: {spread_1}")
print(f"Spread of Class 2: {spread_2}")
```

output:

```
Interclass Distance: 673116.9587643914
Centroid of Class 1: [ 2.00200000e+03  5.25653230e+03  4.39844830e+03  6.19190350e+03
  1.01998400e+03  5.11917382e+04  7.71000000e+02  1.39057513e+04
 -7.97183079e+05  0.00000000e+00  3.30239753e+04  7.14644570e+03
  9.44550480e+03  1.12223960e+04  3.00024135e+04  2.57117318e+04
  2.48273495e+04  1.36980783e+05  7.71615450e+03  4.60095510e+03
  1.44233043e+04  0.00000000e+00  0.00000000e+00  1.74626516e+04
  3.87072170e+07  1.06487665e+08  6.78472090e+07  7.77429270e+07
  1.31833333e+00]
Centroid of Class 2: [ 2.00100000e+03  4.15422340e+03  3.26106440e+03  6.09476510e+03
  1.11563200e+03  5.12012611e+04  7.31000000e+02  1.38148964e+04
 -7.97183079e+05  0.00000000e+00  3.53737190e+04  7.08022070e+03
  1.03505555e+04  1.08775433e+04  2.97197477e+04  2.47101319e+04
  2.45878214e+04  1.36408994e+05  7.70823310e+03  4.58992940e+03
  1.44714001e+04  0.00000000e+00  0.00000000e+00  2.33018189e+04
  3.88661250e+07  1.06948739e+08  6.82287880e+07  7.80067420e+07
  9.37250000e-01]
Spread of Class 1: [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0.]
Spread of Class 2: [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0.]
```

A2)

Take any feature from your dataset. Observe the density pattern for that feature by plotting the histogram. Use buckets (data in ranges) for histogram generation and study.

import matplotlib.pyplot as plt

import seaborn as sns

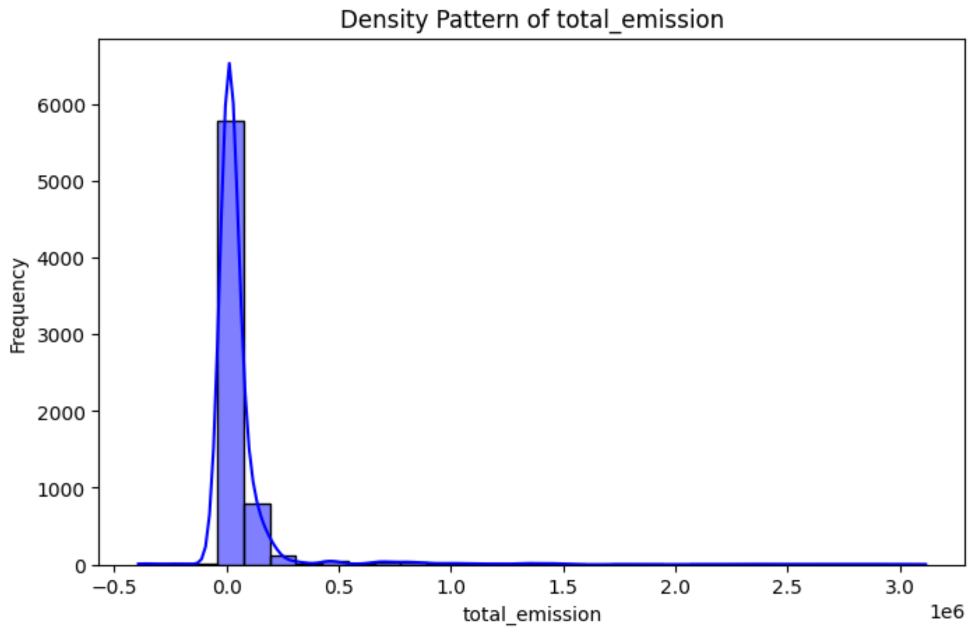
import numpy as np

Load dataset

import pandas as pd

```
df = pd.read_csv("Agrofood_co2_emission.csv")

# Select a numerical feature
feature = "total_emission"

# Drop missing values to avoid issues
data = df[feature].dropna()

# Plot histogram
plt.figure(figsize=(8, 5))
sns.histplot(data, bins=30, kde=True, color="blue")  # kde=True
adds a smooth density curve
plt.xlabel(feature)
plt.ylabel("Frequency")
plt.title(f"Density Pattern of {feature}")
plt.show()
```

output:



Calculate the mean and variance from the available data.

```
mean_value = np.mean(data)

variance_value = np.var(data)


print(f"Mean of {feature}: {mean_value}")

print(f"Variance of {feature}: {variance_value}")
```

output:

Mean of total_emission: 64091.24414739476
Variance of total_emission: 52119322663.65157

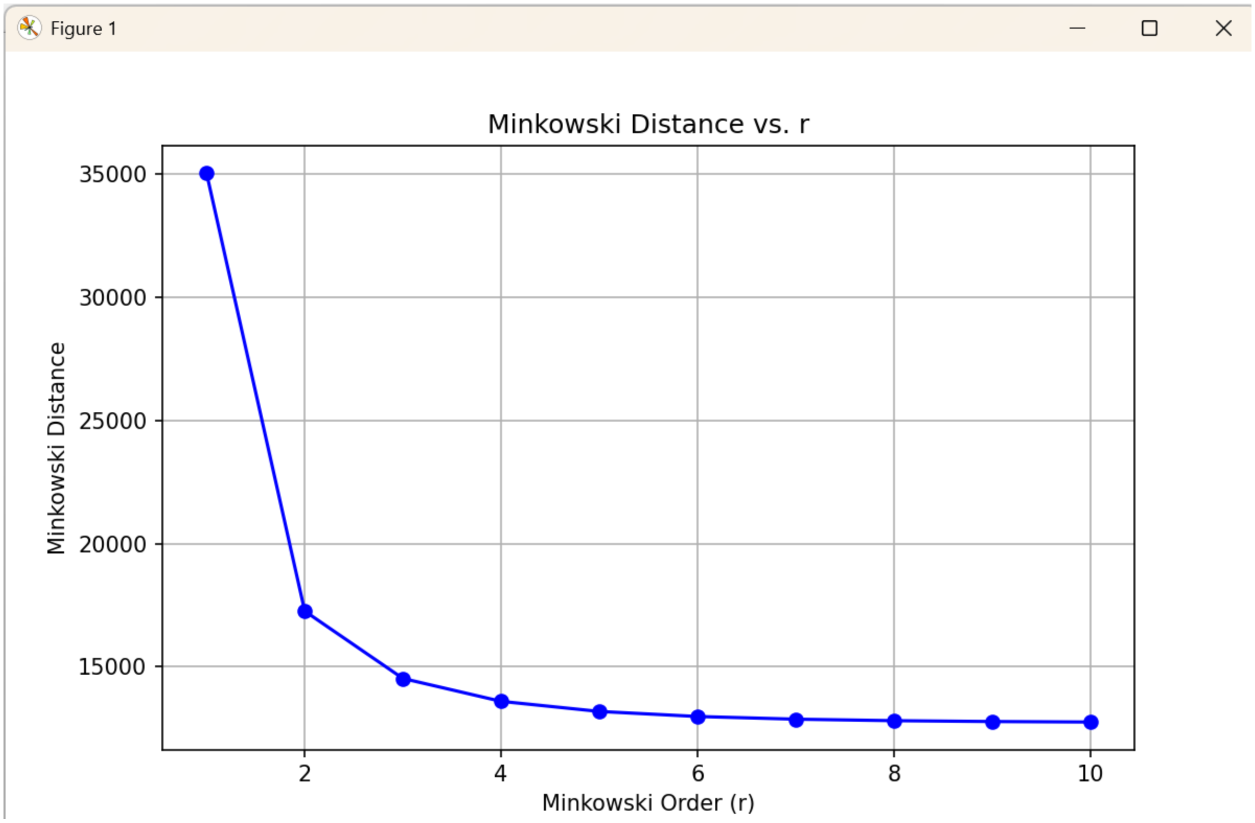
A3)

Take any two feature vectors from your dataset. Calculate the Minkwoski distance with r from 1 to 10. Make a plot of the distance and observe the nature of this graph.

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

data = pd.read_csv(r"C:\Users\vanga\Downloads\archive
(10)\Agrofood_co2_emission.csv")

features =
data.select_dtypes(include=[np.number]).dropna().values

if len(features) < 2:
    raise ValueError("Not enough numerical data points to
compute Minkowski distance.")

vector_1 = features[0]
vector_2 = features[1]

r_values = np.arange(1, 11)
distances = [np.linalg.norm(vector_1 - vector_2, ord=r) for r in
r_values]

plt.figure(figsize=(8, 5))
plt.plot(r_values, distances, marker='o', linestyle='-', color='b')
plt.xlabel("Minkowski Order (r)")
plt.ylabel("Minkowski Distance")
plt.title("Minkowski Distance vs. r")
plt.grid(True)
```

plt.show()

output:



A4)

Divide dataset in your project into two parts – train & test set. To accomplish this, use the train-test_split() function available in SciKit.

import pandas as pd

import numpy as np

from sklearn.model_selection import train_test_split

```
# Load dataset

file_path = "/mnt/data/Agrofood_co2_emission.csv"

df = pd.read_csv(file_path)


# Select two classes (e.g., Afghanistan and Algeria)

selected_classes = ["Afghanistan", "Algeria"]

df_selected = df[df["Area"].isin(selected_classes)]


# Prepare features (X) and labels (y)

X = df_selected.drop(columns=["Area", "Year"])  # Remove non-numeric columns

y = df_selected["Area"]  # Target labels (classification based on country)


# Split into train (70%) and test (30%) sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

Print dataset sizes

print("Training Set Size:", X_train.shape)

print("Testing Set Size:", X_test.shape)

output:

Training set size(43,29)

Testing set size(19,29)

A5)

Train a kNN classifier (k =3) using the training set obtained from above exercise.

import pandas as pd

import numpy as np

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

from sklearn.neighbors import KNeighborsClassifier

Load dataset

file_path = "/mnt/data/Agrofood_co2_emission.csv"

df = pd.read_csv(file_path)

```
# Select two classes (e.g., Afghanistan and Algeria)

selected_classes = ["Afghanistan", "Algeria"]

df_selected = df[df["Area"].isin(selected_classes)]


# Prepare features (X) and labels (y)

X = df_selected.drop(columns=["Area", "Year"]).fillna(0)  # Remove non-numeric columns & handle NaNs

y = df_selected["Area"]  # Target labels (classification based on country)


# Split into train (70%) and test (30%) sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)


# Standardize features (Important for kNN)

scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)

X_test_scaled = scaler.transform(X_test)
```

Train kNN classifier with k=3

knn = KNeighborsClassifier(n_neighbors=3)

knn.fit(X_train_scaled, y_train)

Evaluate model

accuracy = knn.score(X_test_scaled, y_test)

print(f"kNN Model Accuracy: {accuracy * 100:.2f}%")

KNN modelaccuracy:100.00%

A6)

Evaluate the kNN model using the test set

accuracy = knn.score(X_test_scaled, y_test)

Print the accuracy

print(f"Accuracy of kNN model on the test set: {accuracy * 100:.2f}%")

output:

KNN modelaccuracy:100.00%

A7)

Use the predict() function to study the prediction behavior of the classifier for test vectors.

>>>*neigh.predict(X_test)*

Perform classification for a given vector using neigh.predict(<<test_vect>>). This shall produce the class of the test vector (test_vect is any feature vector from your test set).

```
# Predict the classes for the test set using the trained kNN model

predictions = knn.predict(X_test_scaled)



# Print the predictions for the test set

print(f"Predicted classes for the test set: {predictions}")



# Perform classification for a single test vector

test_vect = X_test_scaled[0]  # Using the first vector from the test set as an example

predicted_class = knn.predict([test_vect])



print(f"Predicted class for the first test vector: {predicted_class[0]}")
```

output:

predicted classes for test set:['Algeria',Afghanisthan']

predicted class for the first test vector:Algeria

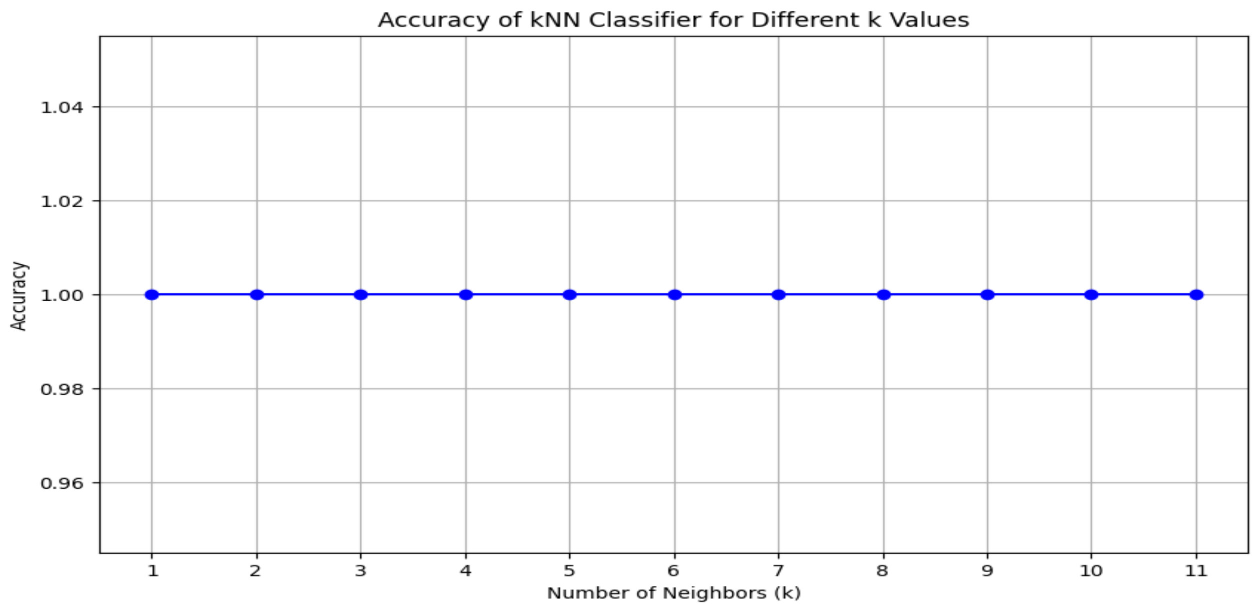
A8)

Make k = 1 to implement NN classifier and compare the results with kNN (k = 3). Vary k from 1 to 11 and make an accuracy plot

```
Import pandas as pd

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

from sklearn.neighbors import KNeighborsClassifier


# Load dataset

file_path = "/mnt/data/Agrofood_co2_emission.csv"

df = pd.read_csv(file_path)


# Select two classes (e.g., Afghanistan and Algeria)

selected_classes = ["Afghanistan", "Algeria"]

df_selected = df[df["Area"].isin(selected_classes)]
```

```
# Prepare features (X) and labels (y)

X = df_selected.drop(columns=["Area", "Year"]).fillna(0)  #
Remove non-numeric columns & handle NaNs

y = df_selected["Area"]  # Target labels (classification based on
country)


# Split into train (70%) and test (30%) sets

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)


# Standardize features (Important for kNN)

scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)

X_test_scaled = scaler.transform(X_test)


# List to store accuracy for each k value

accuracies = []

# Train and evaluate kNN models for k from 1 to 11

for k in range(1, 12):
```

```
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train_scaled, y_train)
    accuracy = knn.score(X_test_scaled, y_test)
    accuracies.append(accuracy)

# Plot the accuracy vs. k
plt.figure(figsize=(10, 6))
plt.plot(range(1, 12), accuracies, marker='o', color='b',
linestyle='-', markersize=6)
plt.title("Accuracy of kNN Classifier for Different k Values")
plt.xlabel("Number of Neighbors (k)")
plt.ylabel("Accuracy")
plt.xticks(range(1, 12))
plt.grid(True)
plt.show()
```



A9)

Please evaluate confusion matrix for your classification problem. From confusion matrix, the other performance metrics such as precision, recall and F1-Score measures for both training and test data. Based on your observations, infer the models learning outcome (underfit / regularfit / overfit)

output:

import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

```
from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score, accuracy_score


# Load dataset

file_path = "dataset.csv"

df = pd.read_csv(file_path)


# Select two classes (e.g., Afghanistan and Algeria)

selected_classes = ["Afghanistan", "Algeria"]

df_selected = df[df["Area"].isin(selected_classes)]


# Prepare features (X) and labels (y)

X = df_selected.drop(columns=["Area", "Year"]).fillna(0)  # Remove non-numeric columns & handle NaNs

y = df_selected["Area"]  # Target labels (classification based on country)


# Split into train (70%) and test (30%) sets
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

# Standardize features (Important for kNN)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train kNN classifier with k=3
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train_scaled, y_train)

# Predict on both training and test data
y_train_pred = knn.predict(X_train_scaled)
y_test_pred = knn.predict(X_test_scaled)

# Compute confusion matrix for training and test data
conf_matrix_train = confusion_matrix(y_train, y_train_pred)
conf_matrix_test = confusion_matrix(y_test, y_test_pred)
```

```python
# Print confusion matrices
print("Confusion Matrix (Training Set):")
print(conf_matrix_train)

print("\nConfusion Matrix (Test Set):")
print(conf_matrix_test)

# Calculate precision, recall, and F1-score for both training and test data
precision_train = precision_score(y_train, y_train_pred, average='macro')  # Changed from 'binary' to 'macro'
recall_train = recall_score(y_train, y_train_pred, average='macro')
f1_train = f1_score(y_train, y_train_pred, average='macro')

precision_test = precision_score(y_test, y_test_pred, average='macro')  # Changed from 'binary' to 'macro'
recall_test = recall_score(y_test, y_test_pred, average='macro')
```

```
f1_test = f1_score(y_test, y_test_pred, average='macro')

# Print precision, recall, and F1-score for training and test data
print("\nTraining Set Metrics:")
print(f"Precision: {precision_train:.2f}")
print(f"Recall: {recall_train:.2f}")
print(f"F1-Score: {f1_train:.2f}")

print("\nTest Set Metrics:")
print(f"Precision: {precision_test:.2f}")
print(f"Recall: {recall_test:.2f}")
print(f"F1-Score: {f1_test:.2f}")

# Plot confusion matrix using seaborn heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix_test, annot=True, fmt="d",
cmap="Blues",
            xticklabels=selected_classes,
yticklabels=selected_classes)
```

```
plt.title("Confusion Matrix (Test Set)")
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()

# ---------------------- Accuracy Plot for Different k Values -----------
-------------

k_values = range(1, 12)  # k from 1 to 11
train_accuracies = []
test_accuracies = []

for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train_scaled, y_train)

    train_accuracy = accuracy_score(y_train,
knn.predict(X_train_scaled))
```

```
    test_accuracy = accuracy_score(y_test,
knn.predict(X_test_scaled))

    train_accuracies.append(train_accuracy)
    test_accuracies.append(test_accuracy)

# Plot the accuracy vs k values
plt.figure(figsize=(10, 5))
plt.plot(k_values, train_accuracies, label="Training Accuracy",
marker="o")
plt.plot(k_values, test_accuracies, label="Test Accuracy",
marker="s")
plt.xticks(k_values)
plt.xlabel("Number of Neighbors (k)")
plt.ylabel("Accuracy")
plt.title("kNN Accuracy for Different k Values")
plt.legend()
plt.grid()
plt.show()
```

Confusion Matrix (Training Set):

[[21 0]

 [0 22]]

Confusion Matrix (Test Set):

[[10 0]

 [0 9]]

Training Set Metrics:

Precision: 1.00

Recall: 1.00

F1-Score: 1.00

Test Set Metrics:

Precision: 1.00 Recall: 1.00 F1-Score: 1.00