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Practical 1: Data Pre-processing and Exploration

1a. Load a CSV dataset. Handle missing values, inconsistent formatting, and outliers.

1. Import Libraries

 # Import necessary libraries

import pandas as pd

import numpy as np

import seaborn as sns

import matplotlib.pyplot as plt

2. Load the Dataset

 # Load the Titanic dataset from a URL

url = "https://raw.githubusercontent.com/datasciencedojo/datasets/master/titanic.csv" data = pd.read_csv(url)

 # Display the first few rows

print(data.head())

3. Handle Missing Values

 # Check for missing values

print("Missing values in each column:")

print(data.isnull().sum())

 # Fill missing values in 'Age' with the mean

data['Age'].fillna(data['Age'].mean(), inplace=True)

 # Fill missing values in 'Embarked' with the most common value
data['Embarked'].fillna(data['Embarked'].mode()[0], inplace=True)

 # Drop rows where 'Cabin' is missing (too many NaNs)

data.drop(columns=['Cabin'], inplace=True)

 # Verify missing values are handled

print("\nAfter handling missing values:")

print(data.isnull().sum())

4. Fix Inconsistent Formatting

 # Fix inconsistent formatting in the 'Sex' column

data['Sex'] = data['Sex'].str.lower().str.strip()

 # Verify unique values

print("\nUnique values in 'Sex' column after formatting:")

print(data['Sex'].unique())

5. Detect and Handle Outliers

 # Boxplot for the 'Fare' column

sns.boxplot(data['Fare'], color='skyblue')

plt.title('Boxplot of Fare')

plt.show()

 # Detect outliers using the IQR method

Q1 = data['Fare'].quantile(0.25)

Q3 = data['Fare'].quantile(0.75)

IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR

upper_bound = Q3 + 1.5 * IQR

 # Capping outliers

data['Fare'] = np.where(data['Fare'] > upper_bound, upper_bound, np.where(data['Fare'] < lower_bound, lower_bound, data['Fare']))

Verify with an updated boxplot

sns.boxplot(data['Fare'], color='lightgreen')

plt.title('Boxplot of Fare (After Handling Outliers)')

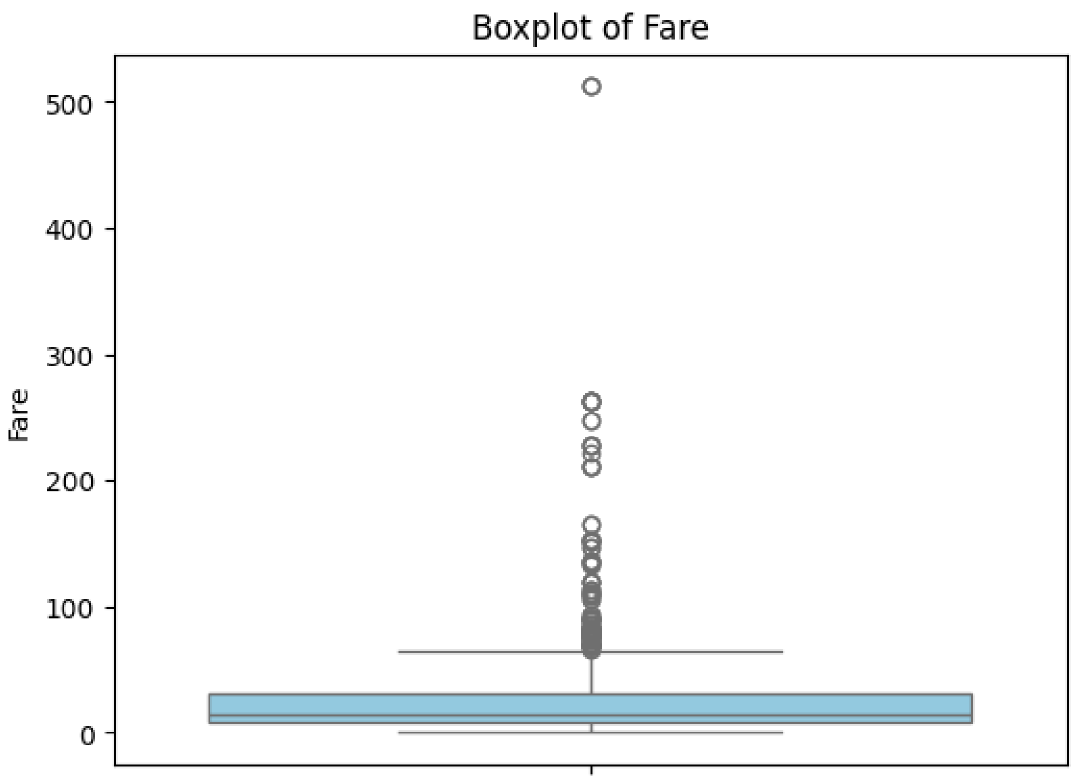
plt.show()

6. Save the Cleaned Dataset

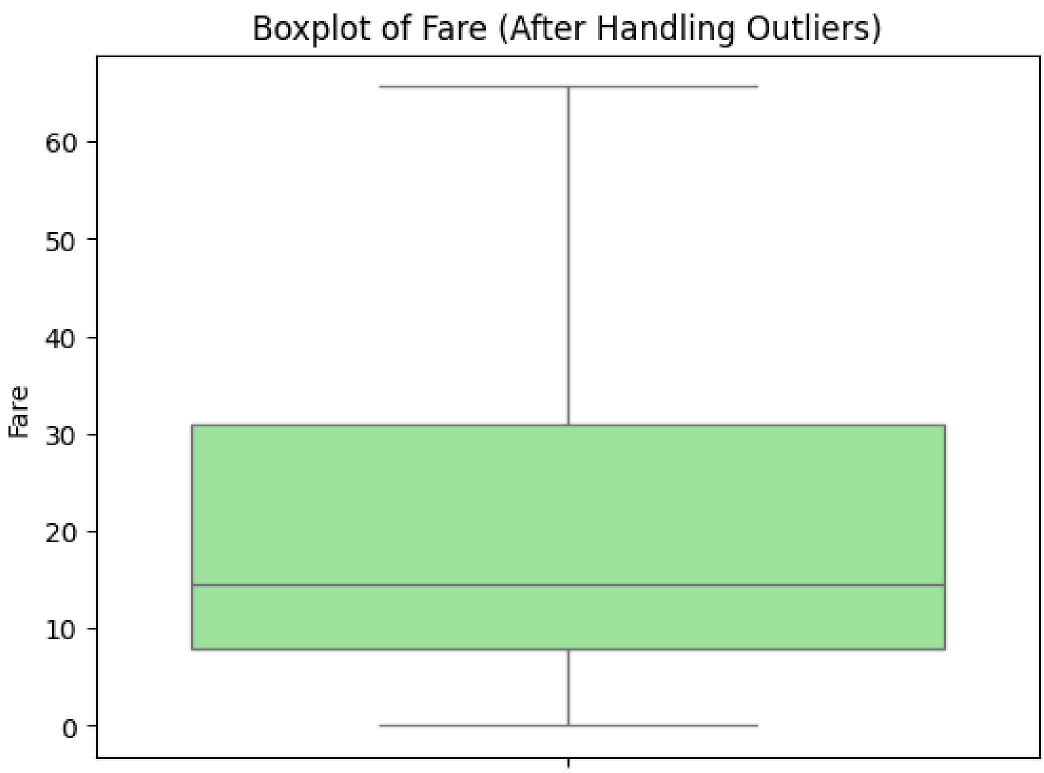
 # Save the cleaned dataset

data.to_csv('cleaned_titanic.csv', index=False)

print("\nCleaned dataset saved as 'cleaned_titanic.csv'") .



Boxplot of Fare
Fare
500
400
300
200
100
0



Boxplot of Fare (After Handling Outliers)
Fare
60
50
40
30
20
10
0

1b. Load a dataset, calculate descriptive summary statistics, create visualizations using different graphs, and identify potential features and target variables Note:
Explore Univariate and Bivariate graphs (Matplotlib) and Seaborn for visualization

1. Import Necessary Libraries

 # Import required libraries

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

2. Load the Dataset

 # Load the dataset from the URL

url = "https://raw.githubusercontent.com/mwaskom/seaborn-data/master/iris.csv" data = pd.read_csv(url)

 # Display the first few rows

print("First 5 rows of the dataset:")

print(data.head())

3. Calculate Descriptive Summary Statistics

 # Dataset information

print("\nDataset Info:")

print(data.info())

 # Summary statistics for numerical columns

print("\nDescriptive Statistics for Numerical Columns:")

print(data.describe())

 # Check unique values for categorical columns

print("\nUnique values in 'species' column:")

print(data['species'].value_counts())

4. Univariate Analysis

 # Histograms for numerical columns

data.hist(figsize=(10, 8), color='skyblue', edgecolor='black')

plt.suptitle("Histograms of Numerical Features")

plt.show()

 # Bar plot for 'species' column

sns.countplot(x='species', data=data, palette='pastel')

plt.title("Count of Each Species")

plt.show()

5. Bivariate Analysis

 # Scatter plot for two features

plt.figure(figsize=(8, 6))

plt.scatter(data['sepal_length'], data['sepal_width'], alpha=0.7, c='blue') plt.title("Sepal Length vs Sepal Width")

plt.xlabel("Sepal Length")

plt.ylabel("Sepal Width")

plt.show()

 # Pairplot to visualize relationships between features

sns.pairplot(data, hue='species', palette='husl', diag_kind='kde')

plt.suptitle("Pairplot of Features by Species", y=1.02)

plt.show()

 # Boxplot for petal_length across species

sns.boxplot(x='species', y='petal_length', data=data, palette='Set3')

plt.title("Boxplot of Petal Length by Species")

plt.show()

6. Identify Potential Features and Target Variables

 # Separate features and target

features = data.drop(columns=['species']) # Drop the target column

target = data['species'] # Target variable

print("\nFeatures:")

print(features.head())

print("\nTarget:")

print(target.head())

 # Visualize target distribution

sns.countplot(x=target, palette='viridis')

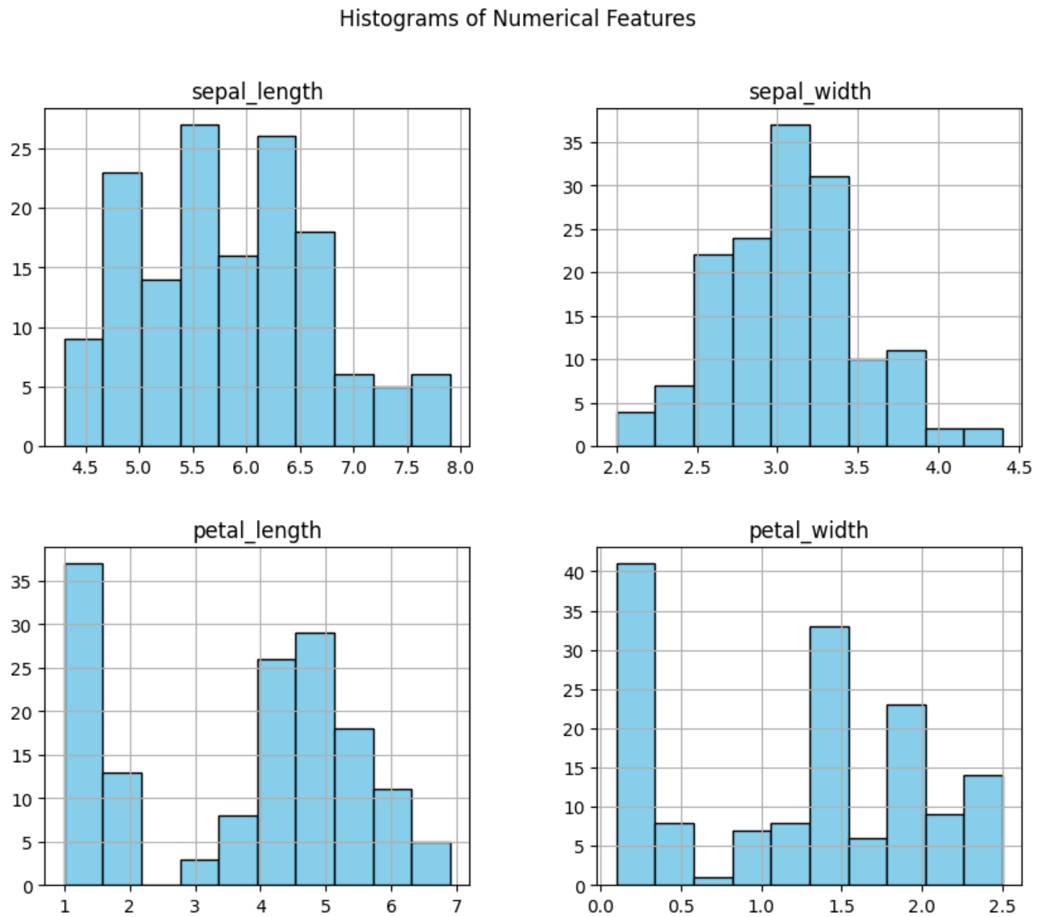
plt.title("Target Variable Distribution")

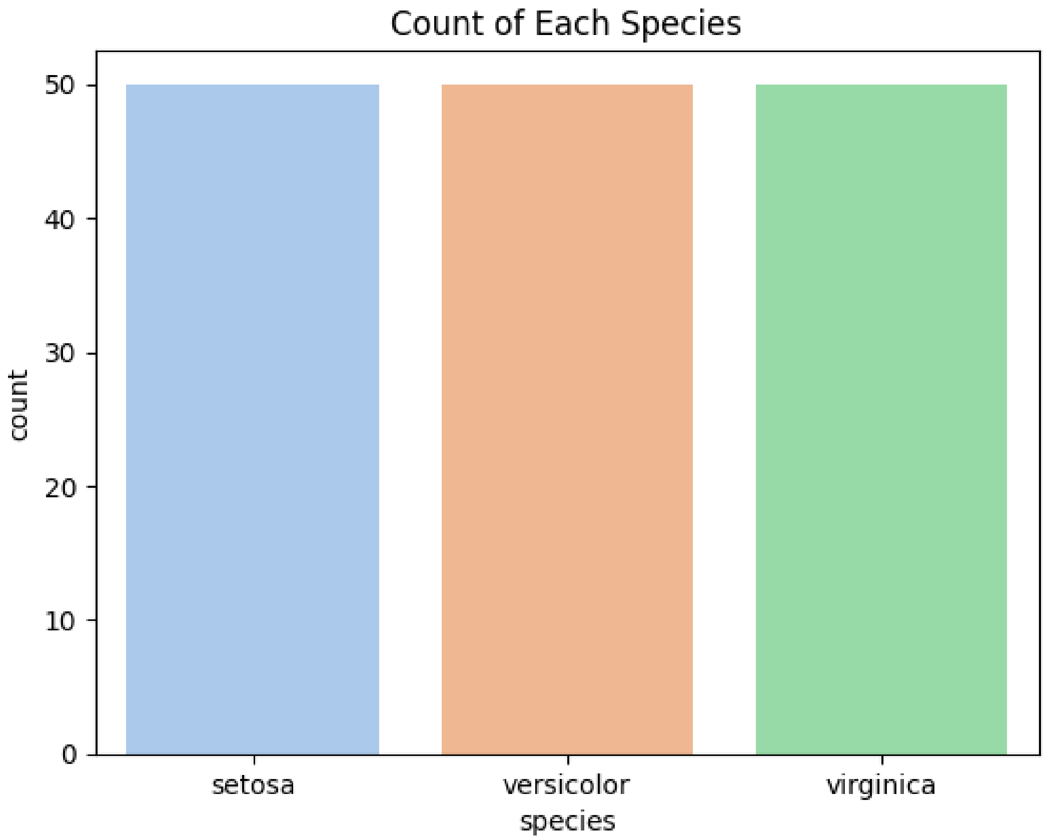
plt.show()

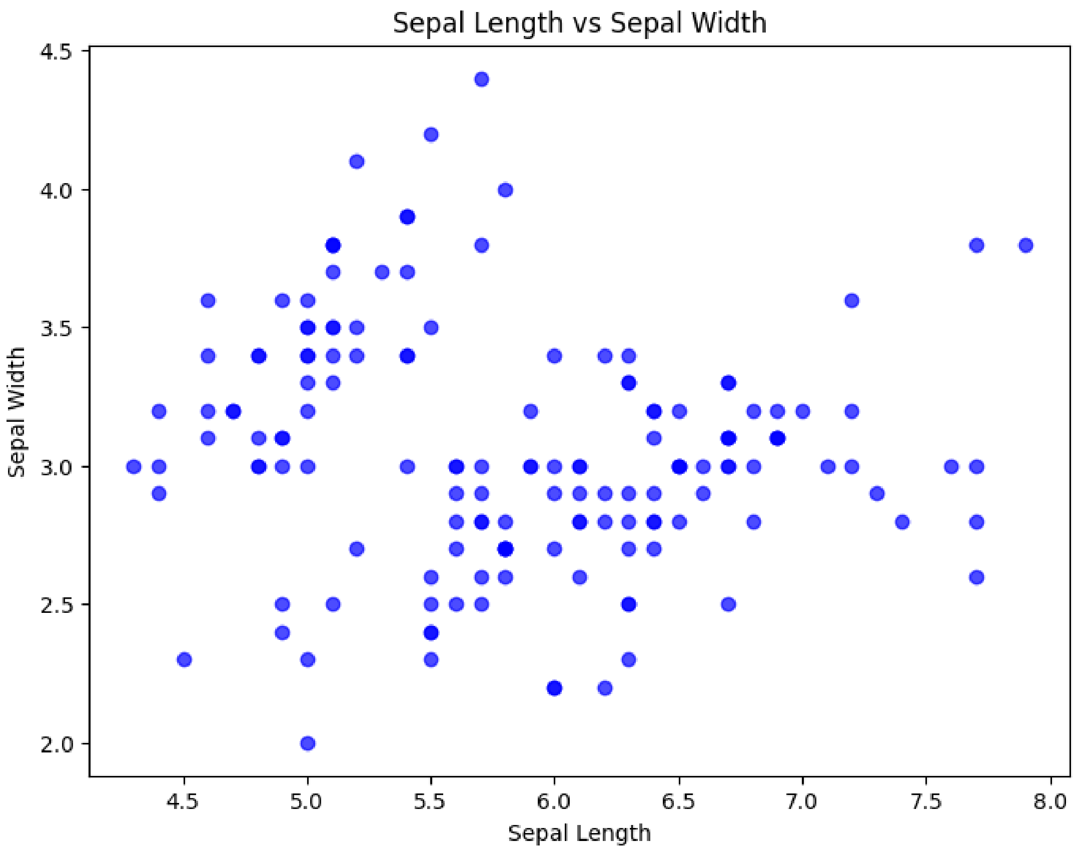
7. Save the Cleaned and Processed Dataset

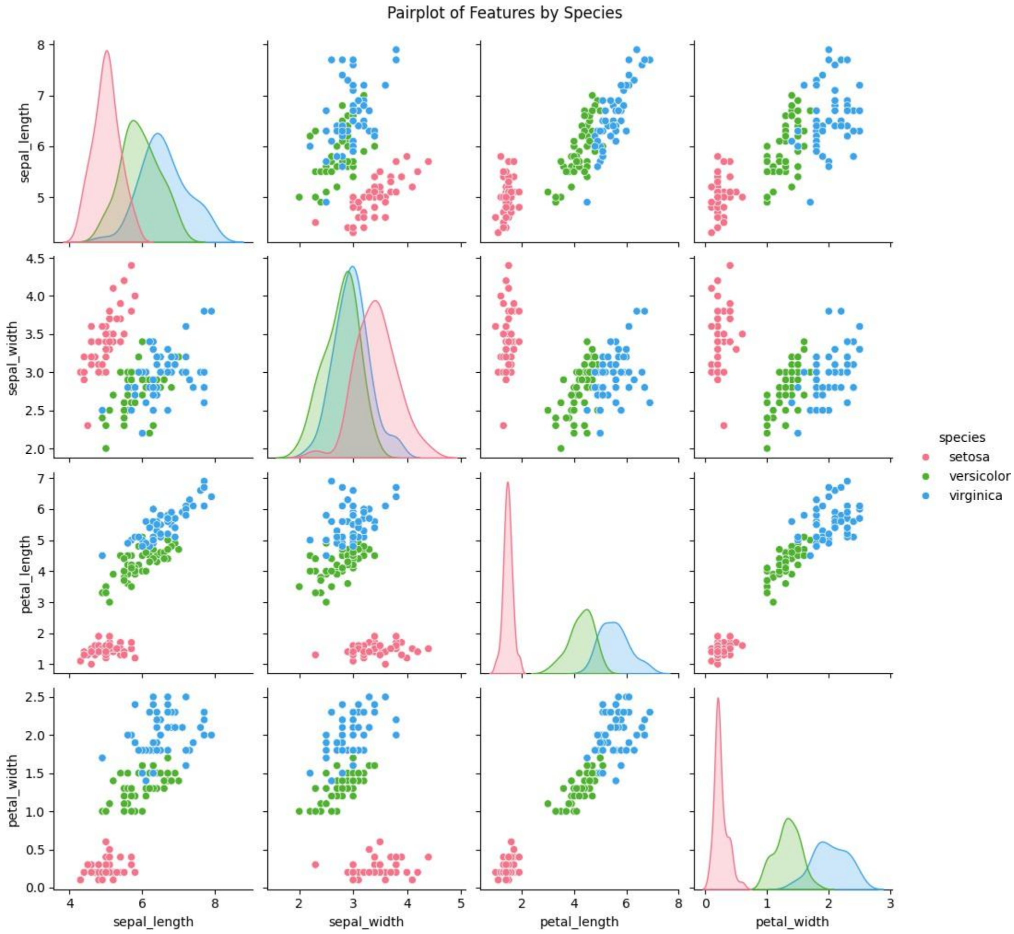
 # Save the dataset

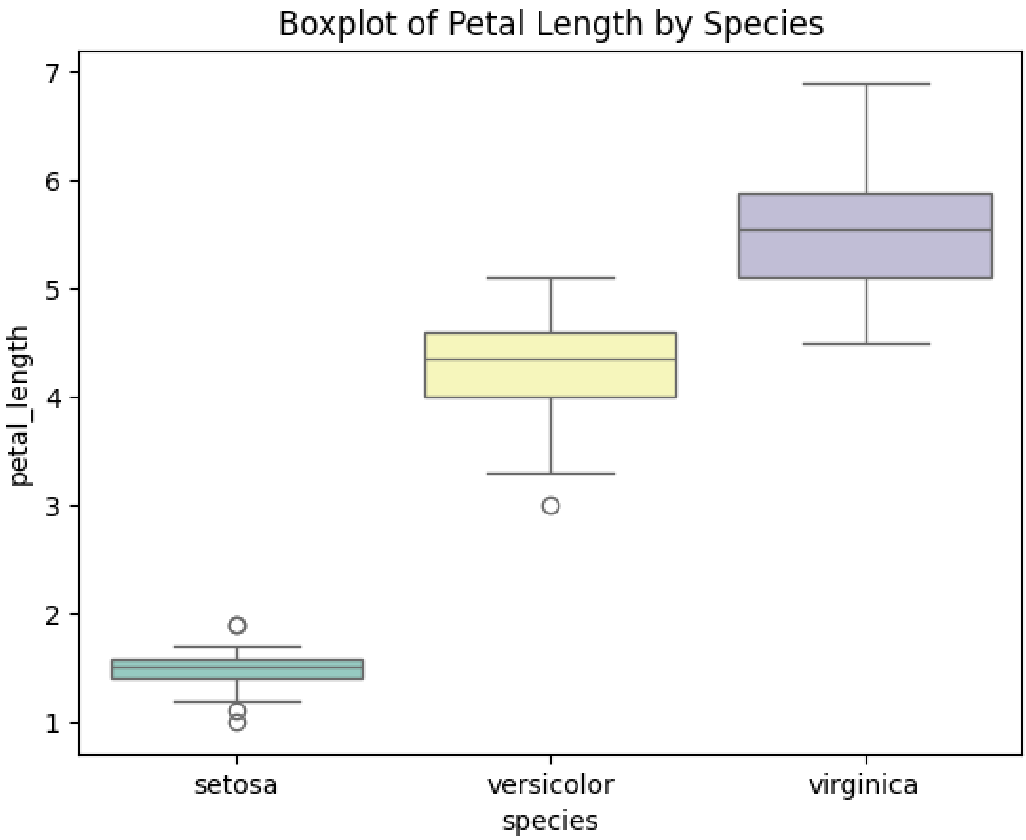
data.to_csv('processed_iris.csv', index=False) print("\nProcessed dataset saved as 'processed_iris.csv'")




Count of Each Species
50
40
30
20
10
0
count
setosa
versicolor
virginica
species


Sepal Length vs Sepal Width
4.5
4.0
3.5
3.0
2.5
2.0
Sepal Width
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
Sepal Length


Pairplot of Features by Species
sepal_length
sepal_width
petal_length
petal_width
species
setosa
versicolor
virginica


Boxplot of Petal Length by Species
petal_length
setosa
versicolor
virginica
species

1c. Create or Explore datasets to use all pre-processing routines like label encoding, scaling, and binarization.

1. Import Necessary Libraries

 # Import required libraries

import pandas as pd

import numpy as np

from sklearn.preprocessing import LabelEncoder, MinMaxScaler, StandardScaler, Binarizer

2. Create or Load a Dataset

 # Create a sample dataset

data = pd.DataFrame({

'Category': ['A', 'B', 'C', 'A', 'B', 'C'], # Categorical variable

'Age': [23, 45, 31, 22, 35, 30], # Numerical variable

'Income': [50000, 60000, 70000, 80000, 90000, 100000], # Numerical variable 'Has_Car': ['Yes', 'No', 'Yes', 'No', 'Yes', 'No'] # Binary categorical variable })

 # Display the dataset

print("Sample Dataset:")

print(data)

3. Apply Pre-Processing Routines

 # Label Encoding for 'Category' column

label_encoder = LabelEncoder()

data['Category_Encoded'] = label_encoder.fit_transform(data['Category'])

Label Encoding for binary column 'Has_Car'

data['Has_Car_Encoded'] = label_encoder.fit_transform(data['Has_Car'])

print("\nAfter Label Encoding:")

print(data)

 # Min-Max Scaling for 'Income'

min_max_scaler = MinMaxScaler()

data['Income_MinMax'] = min_max_scaler.fit_transform(data[['Income']]) # Standard Scaling for 'Age' standard_scaler = StandardScaler()

data['Age_Standardized'] = standard_scaler.fit_transform(data[['Age']])

print("\nAfter Scaling:")

print(data)

 # Binarization for 'Income' with a threshold of 75,000

binarizer = Binarizer(threshold=75000)

data['Income_Binary'] = binarizer.fit_transform(data[['Income']])

print("\nAfter Binarization:")

print(data)

4. Save the Processed Dataset

 # Save the processed dataset

data.to_csv('processed_data.csv', index=False)

print("\nProcessed dataset saved as 'processed_data.csv'")

```
Sample Dataset:
  Category  Age  Income Has_Car
0        A   23   50000     Yes
1        B   45   60000      No
2        C   31   70000     Yes
3        A   22   80000      No
4        B   35   90000     Yes
5        C   30  100000      No
```

```
After Label Encoding:
  Category  Age  Income Has_Car  Category_Encoded  Has_Car_Encoded
0        A   23   50000     Yes                 0                1
1        B   45   60000      No                 1                0
2        C   31   70000     Yes                 2                1
3        A   22   80000      No                 0                0
4        B   35   90000     Yes                 1                1
5        C   30  100000      No                 2                0
```

```
After Scaling:
  Category  Age  Income Has_Car  Category_Encoded  Has_Car_Encoded  \
0        A   23   50000     Yes                 0                1
1        B   45   60000      No                 1                0
2        C   31   70000     Yes                 2                1
3        A   22   80000      No                 0                0
4        B   35   90000     Yes                 1                1
5        C   30  100000      No                 2                0

   Income_MinMax  Age_Standardized
0            0.0         -1.035676
1            0.2          1.812434
2            0.4          0.000000
3            0.6         -1.165136
4            0.8          0.517838
5            1.0         -0.129460
```

```
After Binarization:
  Category  Age  Income Has_Car  Category_Encoded  Has_Car_Encoded  \
0        A   23   50000     Yes                 0                1
1        B   45   60000      No                 1                0
2        C   31   70000     Yes                 2                1
3        A   22   80000      No                 0                0
4        B   35   90000     Yes                 1                1
5        C   30  100000      No                 2                0

   Income_MinMax  Age_Standardized  Income_Binary
0            0.0         -1.035676              0
1            0.2          1.812434              0
2            0.4          0.000000              0
3            0.6         -1.165136              1
4            0.8          0.517838              1
5            1.0         -0.129460              1
```

2: Testing Hypothesis

AIM: Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples. Read the training data from a. CSV file and generate the final specific hypothesis. (Create your dataset)

1. Import Necessary Libraries

 # Import required libraries

```
import pandas as pd
import numpy as np
```

2. Create the Dataset and Save it as CSV

```
# Create a synthetic dataset
data = {
 'Sky': ['Sunny', 'Sunny', 'Rainy', 'Sunny', 'Rainy'],
 'Temperature': ['Warm', 'Cold', 'Warm', 'Warm', 'Cold'],
 'Humidity': ['Normal', 'High', 'High', 'Normal', 'Normal'],
 'Wind': ['Strong', 'Strong', 'Weak', 'Strong', 'Weak'],
 'Water': ['Warm', 'Warm', 'Cool', 'Warm', 'Cool'],
 'Forecast': ['Same', 'Same', 'Change', 'Same', 'Change'],
 'Condition': ['Yes', 'No', 'No', 'Yes', 'No'] # Target variable
}
# Convert the dataset to a DataFrame
df = pd.DataFrame(data)
# Save the dataset to a CSV file
df.to_csv('training_data.csv', index=False)
# Display the dataset
print("Dataset:")
print(df)
```

3. Load the Dataset

 # Load the dataset from CSV

```
dataset = pd.read_csv('training_data.csv')
```

 # Display the dataset

print("\nLoaded Dataset:")

print(dataset)

4. Define the FIND-S Algorithm

def find_s(training_data):

 # Extract the features and target

features = training_data.iloc[:, :-1].values # All columns except the last

target = training_data.iloc[:, -1].values # Last column (target variable)

Initialize the most specific hypothesis

hypothesis = ['Ø'] * features.shape[1]

 # Iterate through each example in the dataset

for i, example in enumerate(features):

if target[i] == 'Yes': # Consider only positive examples for j in range(len(hypothesis)):

if hypothesis[j] == 'Ø': # Update the hypothesis initially hypothesis[j] = example[j]

elif hypothesis[j] != example[j]: # Generalize if inconsistent hypothesis[j] = '?'

return hypothesis

5. Run the FIND-S Algorithm

 # Apply the FIND-S algorithm

final_hypothesis = find_s(dataset)

 # Display the final specific hypothesis

print("\nFinal Specific Hypothesis:")

print(final_hypothesis)

```
Dataset:
     Sky Temperature Humidity    Wind Water Forecast Condition
0  Sunny        Warm   Normal  Strong  Warm     Same       Yes
1  Sunny        Cold     High  Strong  Warm     Same        No
2  Rainy        Warm     High    Weak  Cool   Change        No
3  Sunny        Warm   Normal  Strong  Warm     Same       Yes
4  Rainy        Cold   Normal    Weak  Cool   Change        No
```

```
Loaded Dataset:
     Sky Temperature Humidity    Wind Water Forecast Condition
0  Sunny        Warm   Normal  Strong  Warm     Same       Yes
1  Sunny        Cold     High  Strong  Warm     Same        No
2  Rainy        Warm     High    Weak  Cool   Change        No
3  Sunny        Warm   Normal  Strong  Warm     Same       Yes
4  Rainy        Cold   Normal    Weak  Cool   Change        No
```

```
Final Specific Hypothesis:
['Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same']
```

3. Linear Models

3a. Simple Linear Regression

Fit a linear regression model on a dataset. Interpret coefficients, make predictions, and evaluate performance using metrics like R-squared and MSE

Step 1: Import Libraries

```
# Import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

Step 2: Create a Dataset and Save as CSV

```
# Create a sample dataset
data = {
   'House_Size': [750, 800, 850, 900, 1000, 1100, 1200, 1300, 1400, 1500],
   'Price': [150000, 160000, 165000, 170000, 180000, 190000, 200000, 210000, 220000,
230000]
}
# Convert the dataset into a DataFrame
df = pd.DataFrame(data)
# Save to CSV file
df.to_csv('house_prices.csv', index=False)
# Display the dataset
print("Dataset:")
print(df)
```

Step 3: Load the Dataset

 # Load the dataset

dataset = pd.read_csv('house_prices.csv')

 # Display the first few rows

print("\nLoaded Dataset:")

print(dataset.head())

Step 4: Split the Dataset into Training and Test Sets

 # Features and target variable

X = dataset[['House_Size']] # Feature: House size

y = dataset['Price']   # Target: Price

 # Split data into training and testing sets (80% train, 20% test)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

print("\nTraining and Testing Data Sizes:")

print("Training Data Size:", X_train.shape[0])

print("Testing Data Size:", X_test.shape[0])

Step 5: Fit a Linear Regression Model

 # Initialize and fit the linear regression model

model = LinearRegression()

model.fit(X_train, y_train)

 # Display the coefficients

print("\nModel Coefficients:")

print("Slope (m):", model.coef_[0])

print("Intercept (b):", model.intercept_)

Step 6: Make Predictions

 # Predict on the test set

y_pred = model.predict(X_test)

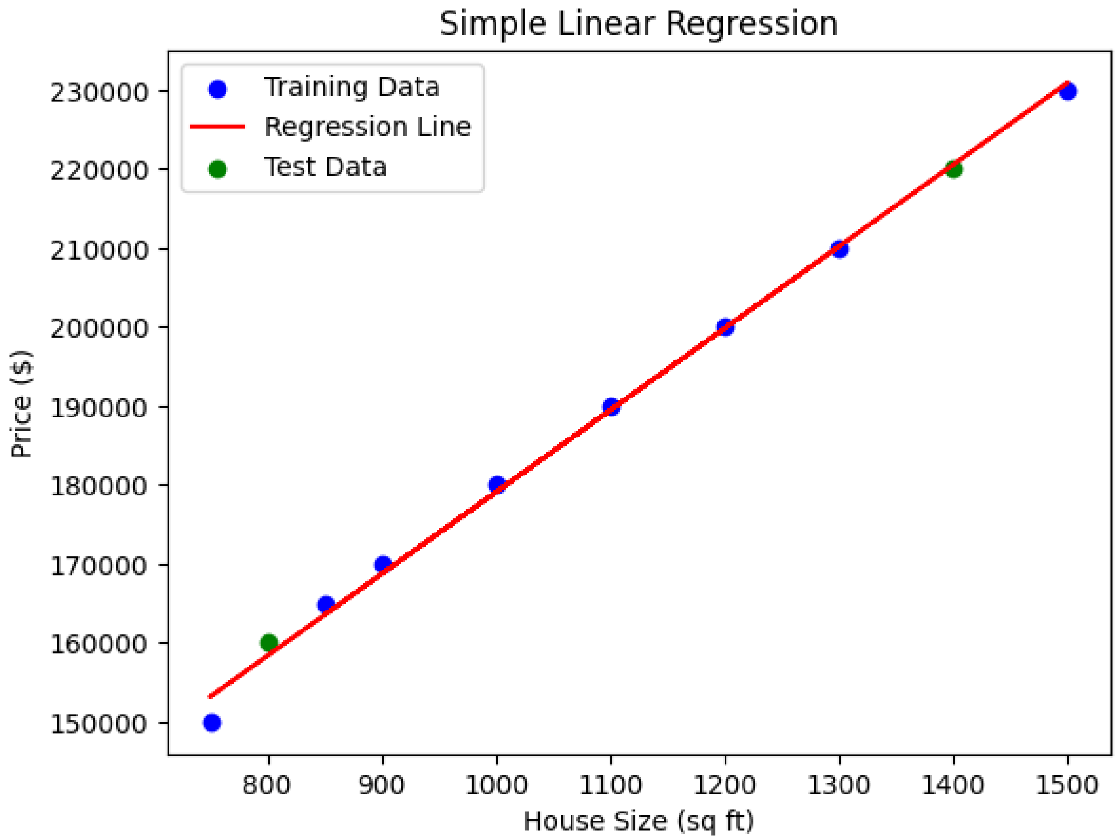
```python
# Display predictions
print("\nPredictions on Test Data:")
print("Actual Prices:", y_test.values)
print("Predicted Prices:", y_pred)
```

Step 7: Evaluate the Model

```python
# Calculate evaluation metrics
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
# Display metrics
print("\nModel Performance Metrics:")
print("Mean Squared Error (MSE):", mse)
print("R-squared (R²):", r2)
```

Step 8: Visualize the Results

```python
# Scatter plot of the training data
plt.scatter(X_train, y_train, color='blue', label='Training Data')
# Plot the regression line
plt.plot(X_train, model.predict(X_train), color='red', label='Regression Line')
# Scatter plot of the test data
plt.scatter(X_test, y_test, color='green', label='Test Data')
plt.title("Simple Linear Regression")
plt.xlabel("House Size (sq ft)")
plt.ylabel("Price ($)")
plt.legend()
plt.show()
```


Simple Linear Regression
Training Data
Regression Line
Test Data
230000
220000
210000
200000
190000
180000
170000
160000
150000
Price ($)
800
900
1000
1100
1200
1300
1400
1500
House Size (sq ft)

3b. Multiple Linear Regression

Extend linear regression to multiple feature. Handle feature selection and potential multicollinearity

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression

from sklearn.metrics import mean_squared_error, r2_score

from statsmodels.stats.outliers_influence import variance_inflation_factor

from sklearn.preprocessing import LabelEncoder  # Import LabelEncoder

from sklearn.impute import SimpleImputer
```

 # Load dataset

```
from google.colab import files

uploaded = files.upload()  # Upload your CSV file
```

 # Read the CSV file

```
data = pd.read_csv(list(uploaded.keys())[0])
```

 # Display the first few rows

```
print(data.head())
```

 # Check for null values and basic statistics

```
print(data.info())

print(data.describe())
```

 # Define a function to calculate VIF

```
def calculate_vif(df):
```

 # Select only numeric features for VIF calculation

```
 numeric_df = df.select_dtypes(include=np.number)
```

```python
    # Drop rows with infinite or missing values
    numeric_df = numeric_df.replace([np.inf, -np.inf], np.nan).dropna()
    vif_data = pd.DataFrame()
    vif_data["feature"] = numeric_df.columns
    vif_data["VIF"] = [variance_inflation_factor(numeric_df.values, i) for i in range(numeric_df.shape[1])]
    return vif_data
# Selecting features and target variable
X = data.drop("Survived", axis=1)  # Changed 'y' to 'Survived'
y = data["Survived"]
# Handle categorical features (e.g., using Label Encoding)
for col in X.select_dtypes(include=['object']).columns:
    le = LabelEncoder()
    X[col] = le.fit_transform(X[col])
# Impute missing values using the mean (you can choose other strategies)
imputer = SimpleImputer(strategy='mean') # Create an imputer instance
X = pd.DataFrame(imputer.fit_transform(X), columns=X.columns) # Impute and update X
# Calculate VIF for initial features
print("VIF before handling multicollinearity:")
print(calculate_vif(X)) # Call the modified function
# Drop features based on VIF analysis (example: drop 'X1' if VIF is high)
# Check if the column exists before dropping
if 'X1' in X.columns:
    X = X.drop("X1", axis=1)  # Replace 'X1' with the actual high VIF feature name
else:
    print("Column 'X1' not found in the DataFrame.")
# Recalculate VIF
print("VIF after handling multicollinearity:")
print(calculate_vif(X))
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

 # Initialize and fit the model =

```
LinearRegression()
model.fit(X_train, y_train)
```

 # Get coefficients and intercept

```
print("Coefficients:", model.coef_)
print("Intercept:", model.intercept_)
```

 # Predictions

```
y_pred = model.predict(X_test)
```

 # Evaluation metrics

```
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)
print(f"RMSE: {rmse}")
print(f"R^2: {r2}")
from sklearn.feature_selection import RFE
```

 # Recursive Feature Elimination

```
rfe = RFE(estimator=LinearRegression(), n_features_to_select=5) # Adjust features
rfe.fit(X_train, y_train)
```

 # Selected features

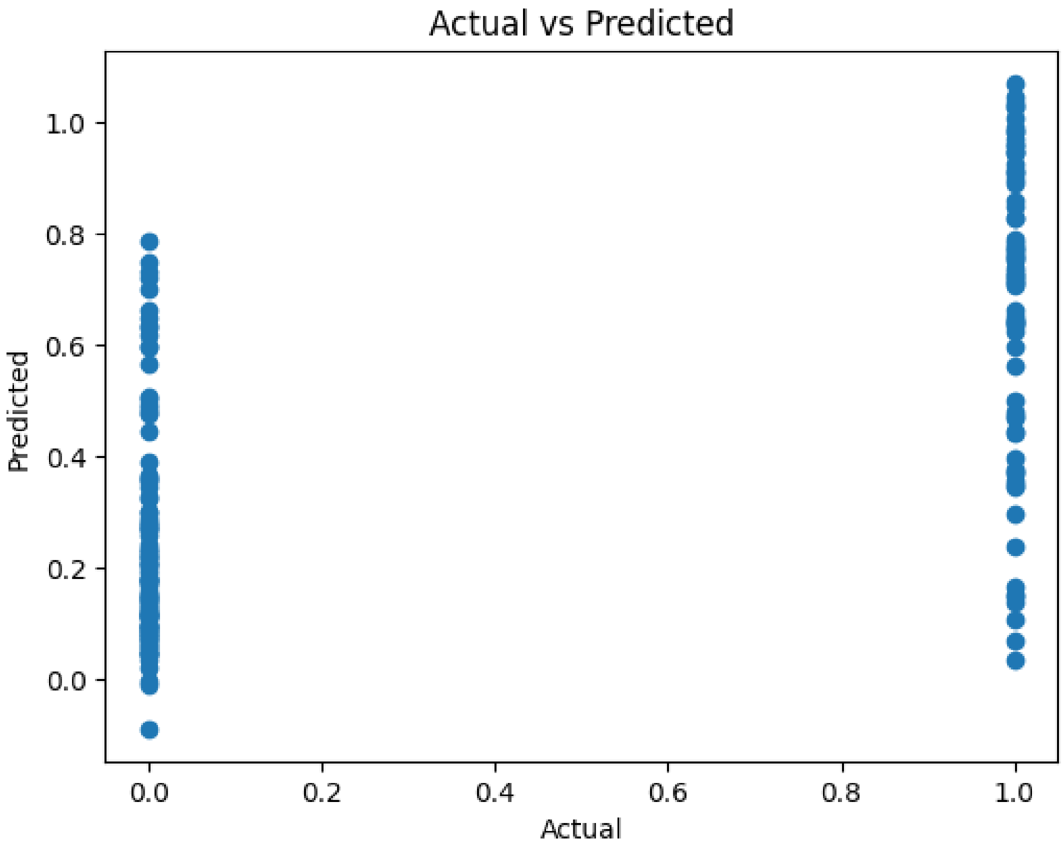
```
print("Selected Features:", X.columns[rfe.support_])
```

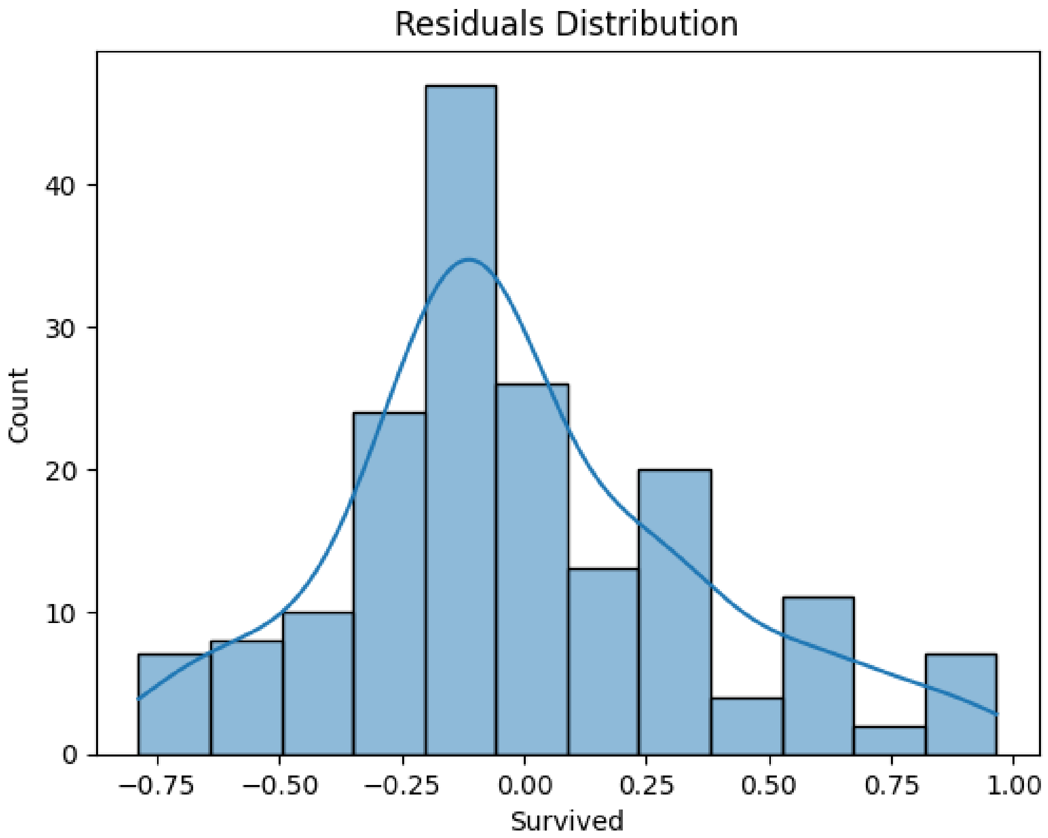
 # Scatter plot of actual vs predicted values

```
plt.scatter(y_test, y_pred)
plt.xlabel("Actual")
plt.ylabel("Predicted")
plt.title("Actual vs Predicted")
plt.show()
```

 # Residuals

```
residuals = y_test - y_pred
sns.histplot(residuals, kde=True)
plt.title("Residuals Distribution") plt.show()
```


Actual vs Predicted
Predicted
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Actual


Residuals Distribution
Count
40
30
20
10
0
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
Survived

3c. Regualarized Linear Models

Implement Regression variants like LASSO and Ridge on any generated dataset

1. Set Up the Environment

```
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.linear_model import Ridge, Lasso, ElasticNet

from sklearn.metrics import mean_squared_error, r2_score

from sklearn.datasets import make_regression

# Set random seed for reproducibility

np.random.seed(42)
```

2. Generate a Synthetic Dataset

```
# Generate synthetic data

X, y = make_regression(

    n_samples=1000,  # Number of samples

    n_features=10,   # Number of features

    noise=15,        # Add some noise

    random_state=42

)

# Convert to DataFrame for exploration

data = pd.DataFrame(X, columns=[f"X{i}" for i in range(1, 11)])

data["y"] = y

# Display the first few rows

print(data.head())
```

3. Split the Dataset

```
# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    data.drop("y", axis=1),  # Features
    data["y"],              # Target variable
    test_size=0.2,          # 20% for testing
    random_state=42
)
```

4. Train and Evaluate Ridge Regression

```
# Initialize Ridge Regression with a regularization parameter (alpha)
ridge = Ridge(alpha=1.0)
# Train the model
ridge.fit(X_train, y_train)
# Predictions
ridge_pred = ridge.predict(X_test)
# Evaluate Ridge Regression
ridge_rmse = np.sqrt(mean_squared_error(y_test, ridge_pred))
ridge_r2 = r2_score(y_test, ridge_pred)
print(f"Ridge RMSE: {ridge_rmse}")
print(f"Ridge R^2: {ridge_r2}")
```

5. Train and Evaluate Lasso Regression

```
# Initialize Lasso Regression
lasso = Lasso(alpha=0.1)
# Train the model
lasso.fit(X_train, y_train)
# Predictions
lasso_pred = lasso.predict(X_test)
# Evaluate Lasso Regression
```

lasso_rmse = np.sqrt(mean_squared_error(y_test, lasso_pred))

lasso_r2 = r2_score(y_test, lasso_pred)

print(f"Lasso RMSE: {lasso_rmse}")

print(f"Lasso R^2: {lasso_r2}")

 # Features shrunk to zero

print("Lasso Coefficients:", lasso.coef_)

6. Train and Evaluate ElasticNet Regression

 # Initialize ElasticNet

elastic_net = ElasticNet(alpha=0.1, l1_ratio=0.5) # l1_ratio balances L1 and L2 penalties

 # Train the model

elastic_net.fit(X_train, y_train)

 # Predictions

elastic_net_pred = elastic_net.predict(X_test)

 # Evaluate ElasticNet Regression

elastic_net_rmse = np.sqrt(mean_squared_error(y_test, elastic_net_pred))

elastic_net_r2 = r2_score(y_test, elastic_net_pred)

print(f"ElasticNet RMSE: {elastic_net_rmse}")

print(f"ElasticNet R^2: {elastic_net_r2}")

7. Compare Results

 # Collect metrics

metrics = pd.DataFrame({

    "Model": ["Ridge", "Lasso", "ElasticNet"],

    "RMSE": [ridge_rmse, lasso_rmse, elastic_net_rmse],

    "R^2": [ridge_r2, lasso_r2, elastic_net_r2]

})

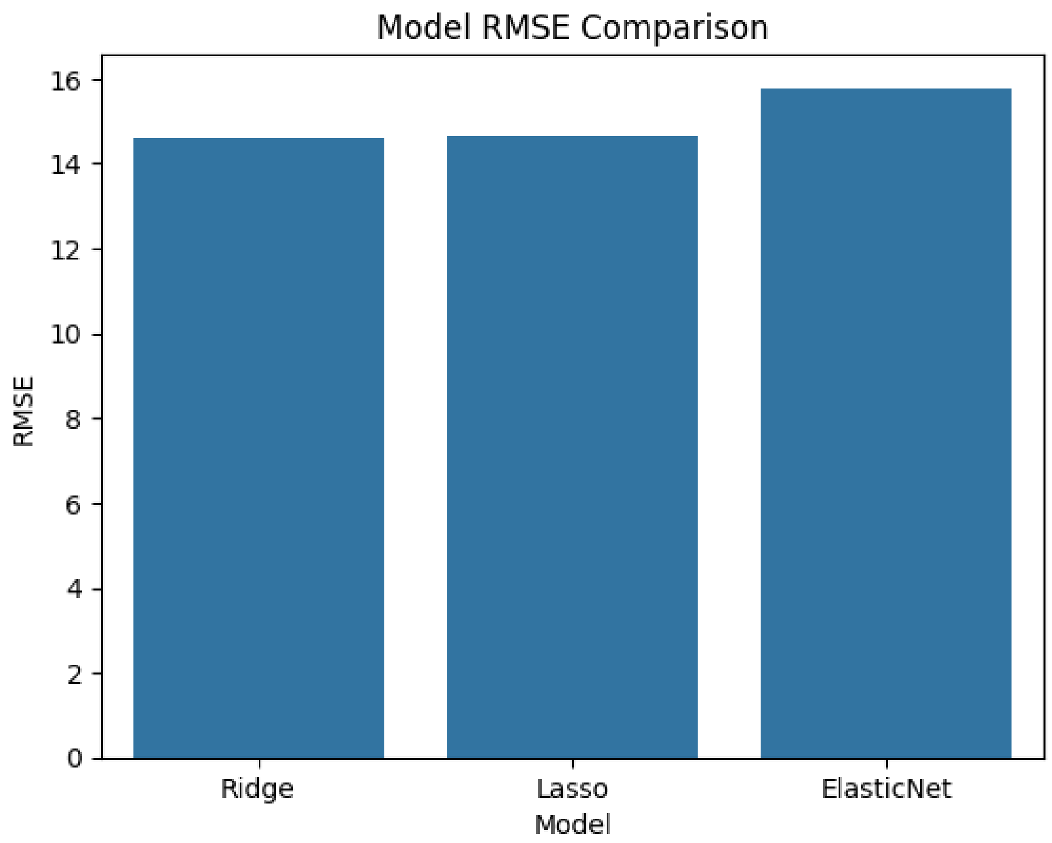
print(metrics)

 # Plot RMSE comparison

sns.barplot(data=metrics, x="Model", y="RMSE")

plt.title("Model RMSE Comparison")

plt.show()



4. Discriminative Models

4a. Logistic Regression : Perform binary classification using logistic regression. Calculate accuracy, precision, recall, and understand the ROC curve."

Step 1: Import Required Libraries

```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score, roc_curve, auc
import matplotlib.pyplot as plt
```

Step 2: Prepare the Dataset

```
from sklearn.datasets import make_classification
# Create a synthetic dataset
X, y = make_classification(n_samples=1000, n_features=10, n_classes=2, random_state=42)
# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

Step 3: Train the Logistic Regression Model

```
# Initialize the logistic regression model
logreg = LogisticRegression()
# Train the model on the training data
logreg.fit(X_train, y_train)
```

Step 4: Make Predictions

```
# Predict labels for the test set
y_pred = logreg.predict(X_test)
# Predict probabilities for the ROC curve
y_prob = logreg.predict_proba(X_test)[:, 1]
```

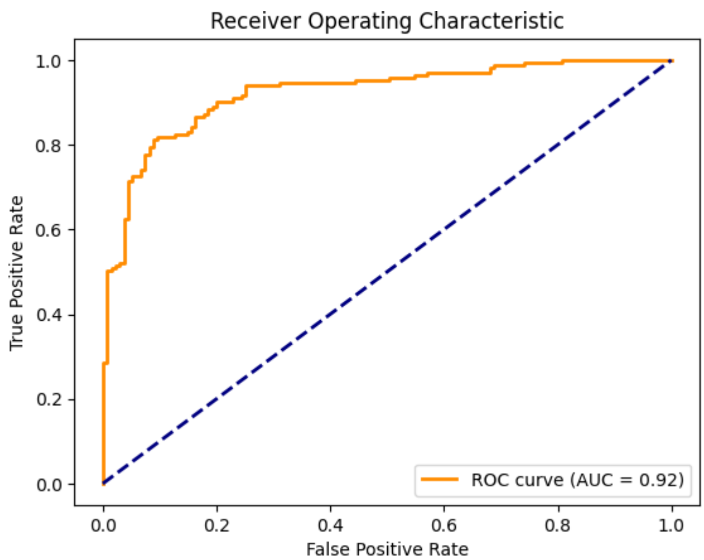
Step 5: Evaluate the Model

```
# Calculate metrics
```

```
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
```

Step 6: Plot the ROC Curve

```
# Compute ROC curve and AUC
fpr, tpr, _ = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr)
# Plot the ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f"ROC curve (AUC = {roc_auc:.2f})")
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```



4b .Implement and demonstrate k-nearest Neighbor algorithm. Read the training data from a .CSV file and build the model to classify a test sample. Print both correct and wrong predictions.

Step 1: Import Required Libraries

```
# Import necessary libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from google.colab import files
```

Step 2: Create or Upload the CSV File

```
# Check if the user wants to create a dataset or upload one
print("Do you have a CSV file to upload? (yes/no)")
response = input().lower()
if response == "yes":
    uploaded = files.upload()
    filename = list(uploaded.keys())[0]
else:
    # Create a synthetic dataset
    from sklearn.datasets import make_classification
    # Generate synthetic data
    X, y = make_classification(
        n_samples=200, n_features=5, n_classes=2, random_state=42
    )
    # Combine features and target into a single DataFrame
    data = pd.DataFrame(X, columns=[f"Feature_{i}" for i in range(X.shape[1])])
    data['Target'] = y
```

Save the dataset to a CSV file

filename = "synthetic_data.csv"

data.to_csv(filename, index=False)

print(f"Synthetic dataset saved as {filename}.")

Step 3: Load the CSV File into a DataFrame

 # Load the dataset into a DataFrame

data = pd.read_csv(filename)

 # Display the first few rows of the dataset

print("Loaded Dataset:")

print(data.head())

Step 4: Preprocess the Data

 # Separate features (X) and labels (y)

X = data.iloc[:, :-1].values # All columns except the last one

y = data.iloc[:, -1].values # Last column as the target

 # Split the dataset into training and testing sets (80% train, 20% test)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

Step 5: Train the k-NN Model

 # Initialize the k-NN model with k=3

knn = KNeighborsClassifier(n_neighbors=3)

 # Train the model on the training data

knn.fit(X_train, y_train)

Step 6: Predict Test Samples

 # Predict the labels for the test set

y_pred = knn.predict(X_test)

Step 7: Evaluate and Print Predictions

 # Calculate and display the accuracy

```
accuracy = accuracy_score(y_test, y_pred)

print(f"\nModel Accuracy: {accuracy:.2f}\n")
```

 # Display correct and incorrect predictions

```
print("Correct Predictions:")

for i in range(len(y_test)):

    if y_pred[i] == y_test[i]:

        print(f"Sample {i}: Predicted={y_pred[i]}, Actual={y_test[i]}")

print("\nIncorrect Predictions:")

for i in range(len(y_test)):

    if y_pred[i] != y_test[i]:

        print(f"Sample {i}: Predicted={y_pred[i]}, Actual={y_test[i]}")
```

Output :

```
[ ]
    Model Accuracy: 0.88

    Correct Predictions:
    Sample 0: Predicted=0, Actual=0
    Sample 1: Predicted=1, Actual=1
    Sample 2: Predicted=1, Actual=1
    Sample 3: Predicted=0, Actual=0
    Sample 4: Predicted=1, Actual=1
    Sample 5: Predicted=1, Actual=1
    Sample 6: Predicted=0, Actual=0
    Sample 7: Predicted=0, Actual=0
    Sample 9: Predicted=1, Actual=1
    Sample 10: Predicted=1, Actual=1
    Sample 11: Predicted=1, Actual=1
    Sample 12: Predicted=0, Actual=0
    Sample 13: Predicted=0, Actual=0
    Sample 14: Predicted=0, Actual=0
    Sample 15: Predicted=0, Actual=0
    Sample 16: Predicted=0, Actual=0
    Sample 17: Predicted=1, Actual=1
    Sample 18: Predicted=1, Actual=1
    Sample 19: Predicted=0, Actual=0
    Sample 20: Predicted=0, Actual=0
    Sample 22: Predicted=1, Actual=1
    Sample 23: Predicted=1, Actual=1
    Sample 24: Predicted=1, Actual=1
    Sample 25: Predicted=1, Actual=1
    Sample 26: Predicted=1, Actual=1
    Sample 27: Predicted=0, Actual=0
    Sample 28: Predicted=0, Actual=0
    Sample 30: Predicted=1, Actual=1
    Sample 31: Predicted=1, Actual=1
    Sample 32: Predicted=1, Actual=1
    Sample 34: Predicted=0, Actual=0
    Sample 35: Predicted=1, Actual=1
    Sample 36: Predicted=1, Actual=1
    Sample 38: Predicted=1, Actual=1
    Sample 39: Predicted=1, Actual=1
```

```
Incorrect Predictions:
Sample 8: Predicted=1, Actual=0
Sample 21: Predicted=1, Actual=0
Sample 29: Predicted=0, Actual=1
Sample 33: Predicted=1, Actual=0
Sample 37: Predicted=1, Actual=0
```

4c. Build a decision tree classifier or regressor. Control hyperparameters like tree depth to avoid overfitting. Visualize the tree.

Step 1: Import Required Libraries

 # Import necessary libraries

```
import pandas as pd

import numpy as np

from sklearn.model_selection import train_test_split

from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor, plot_tree

from sklearn.metrics import accuracy_score, mean_squared_error

import matplotlib.pyplot as plt

from google.colab import files
```

Step 2: Create or Upload the CSV File

 # Check if the user wants to upload a file or generate one

```
print("Do you have a CSV file to upload? (yes/no)")

response = input().lower()

if response == "yes":

  # Upload the CSV file

  uploaded = files.upload()

  filename = list(uploaded.keys())[0]

else:

  # Generate synthetic data (classification or regression)

  from sklearn.datasets import make_classification, make_regression

  print("Choose a task: (1) Classification (2) Regression")

  task = int(input())

  if task == 1:

  # Generate synthetic classification data

    X, y = make_classification(n_samples=200, n_features=5, random_state=42)

    task_type = "classification"
```

```
else:
    # Generate synthetic regression data
    X, y = make_regression(n_samples=200, n_features=5, random_state=42)
    task_type = "regression"
# Combine features and target into a single DataFrame
data = pd.DataFrame(X, columns=[f"Feature_{i}" for i in range(X.shape[1])])
data['Target'] = y
# Save the dataset to a CSV file
filename = "synthetic_data.csv"
data.to_csv(filename, index=False)
print(f"Synthetic {task_type} dataset saved as {filename}.")
```

Step 3: Load the Dataset

```
# Load the dataset
data = pd.read_csv(filename)
# Display the first few rows of the dataset
print("Dataset Preview:")
print(data.head())
```

Step 4: Preprocess the Data

```
# Separate features and target
X = data.iloc[:, :-1].values  # All columns except the last one
y = data.iloc[:, -1].values  # Last column as the target
# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Step 5: Build the Decision Tree

```
# Define the tree depth to avoid overfitting
max_depth = 3
```

 # Initialize the model

```
if task_type == "classification":
    model = DecisionTreeClassifier(max_depth=max_depth, random_state=42)
else:
    model = DecisionTreeRegressor(max_depth=max_depth, random_state=42)
```

 # Train the model

```
model.fit(X_train, y_train)
```

Step 6: Make Predictions

 # Predict on the test set

```
y_pred = model.predict(X_test)
```

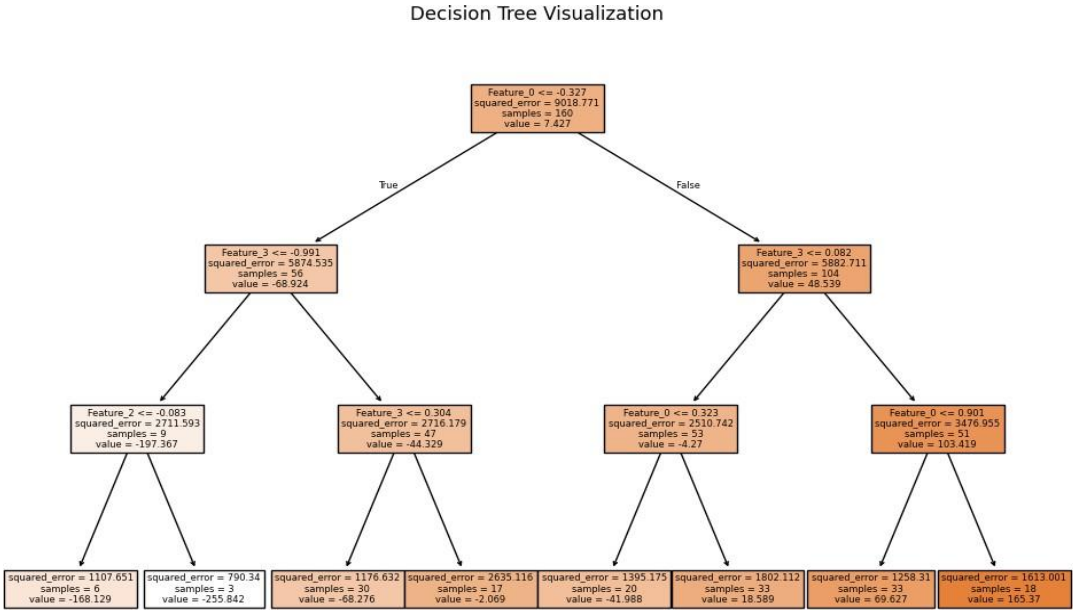
 # Evaluate the model

```
if task_type == "classification":
    accuracy = accuracy_score(y_test, y_pred)
    print(f"Accuracy: {accuracy:.2f}")
else:
    mse = mean_squared_error(y_test, y_pred)
    print(f"Mean Squared Error: {mse:.2f}")
```

Step 7: Visualize the Tree

 # Visualize the decision tree

```
plt.figure(figsize=(12, 8))
plot_tree(model, feature_names=data.columns[:-1], class_names=str(np.unique(y)) if task_type == "classification" else None, filled=True)
plt.title("Decision Tree Visualization")
plt.show()
```


Decision Tree Visualization
Feature_0 <= -0.327
squared_error = 9018.771
samples = 160
value = 7.427
True
False
Feature_3 <= -0.991
squared_error = 5874.535
samples = 56
value = -68.924
Feature_3 <= 0.082
squared_error = 5882.711
samples = 104
value = 48.539
Feature_2 <= -0.083
squared_error = 2711.593
samples = 9
value = -197.367
Feature_3 <= 0.304
squared_error = 2716.179
samples = 47
value = -44.329
Feature_0 <= 0.323
squared_error = 2510.742
samples = 53
value = -4.27
Feature_0 <= 0.901
squared_error = 3476.955
samples = 51
value = 103.419
squared_error = 1107.651
samples = 6
value = -168.129
squared_error = 790.34
samples = 3
value = -255.842
squared_error = 1176.632
samples = 30
value = -68.276
squared_error = 2635.116
samples = 17
value = -2.069
squared_error = 1395.175
samples = 20
value = -41.988
squared_error = 1802.112
samples = 33
value = 18.589
squared_error = 1258.31
samples = 33
value = 69.627
squared_error = 1613.001
samples = 18
value = 165.37

4d. Implement a Support Vector Machine for any relevant dataset.

Step 1: Import Required Libraries

```
# Import necessary libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report
from google.colab import files
```

Step 2: Create or Upload a Dataset

```
# Check if the user wants to upload a file or generate one
print("Do you have a CSV file to upload? (yes/no)")
response = input().lower()
if response == "yes":
    # Upload the CSV file
    uploaded = files.upload()
    filename = list(uploaded.keys())[0]
else:
    # Generate synthetic classification data
    from sklearn.datasets import make_classification
    X, y = make_classification(n_samples=200, n_features=5, n_classes=2, random_state=42)

    # Combine features and target into a DataFrame
    data = pd.DataFrame(X, columns=[f"Feature_{i}" for i in range(X.shape[1])])
    data['Target'] = y
    # Save the synthetic dataset to a CSV file
    filename = "synthetic_data.csv"
```

```
    data.to_csv(filename, index=False)
    print(f"Synthetic dataset saved as {filename}.")
```

Step 3: Load the Dataset

 # Load the dataset into a DataFrame

```
data = pd.read_csv(filename)
```

 # Display the first few rows of the dataset

```
print("Dataset Preview:")
print(data.head())
```

Step 4: Preprocess the Data

 # Separate features (X) and target (y)

```
X = data.iloc[:, :-1].values  # All columns except the last one
y = data.iloc[:, -1].values  # Last column as the target
```

 # Split the dataset into training (80%) and testing (20%) sets

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Step 5: Train the Support Vector Machine

 # Initialize the SVM model (use RBF kernel as default)

```
svm_model = SVC(kernel='rbf', C=1.0, gamma='scale', random_state=42)
```

 # Train the SVM model on the training data

```
svm_model.fit(X_train, y_train)
```

Step 6: Make Predictions

 # Predict the labels for the test set

```
y_pred = svm_model.predict(X_test)
```

Step 7: Evaluate the Model

 # Calculate and print the accuracy

accuracy = accuracy_score(y_test, y_pred)

print(f"Model Accuracy: {accuracy:.2f}")

 # Print a detailed classification report

print("\nClassification Report:")

print(classification_report(y_test, y_pred))

Step 8: Visualize the Decision Boundary (Optional for 2D Data)

import matplotlib.pyplot as plt

 # Generate 2D synthetic data

from sklearn.datasets import make_blobs

X, y = make_blobs(n_samples=100, centers=2, random_state=42, cluster_std=1.5)

 # Fit the SVM on this data

svm_model.fit(X, y)

 # Plot the decision boundary

plt.figure(figsize=(8, 6))

plt.scatter(X[:, 0], X[:, 1], c=y, cmap='coolwarm', edgecolor='k')

 # Create a grid to evaluate the model

xx, yy = np.meshgrid(np.linspace(X[:, 0].min(), X[:, 0].max(), 100),

              np.linspace(X[:, 1].min(), X[:, 1].max(), 100))

Z = svm_model.decision_function(np.c_[xx.ravel(), yy.ravel()])

Z = Z.reshape(xx.shape)

 # Plot the decision boundary and margins

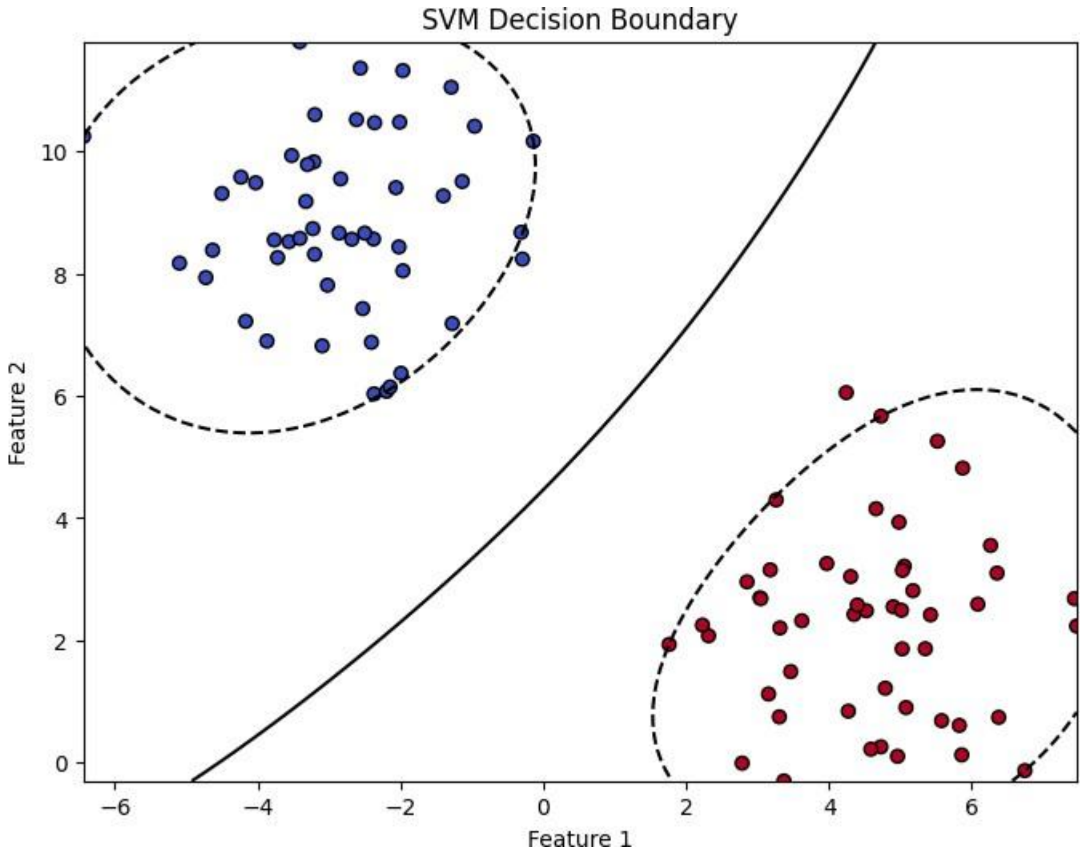
plt.contour(xx, yy, Z, levels=[-1, 0, 1], linestyles=['--', '-', '--'], colors='k')

plt.title("SVM Decision Boundary")

plt.xlabel("Feature 1")

plt.ylabel("Feature 2")

plt.show()


SVM Decision Boundary
Feature 1
Feature 2
−6
−4
−2
0
2
4
6
0
2
4
6
8
10

4e. Train a random forest ensemble. Experiment with the number of trees and feature sampling. Compare performance to a single decision tree.

Step 1: Import Required Libraries

```
# Import necessary libraries

import pandas as pd

import numpy as np

from sklearn.model_selection import train_test_split

from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import accuracy_score, classification_report

from google.colab import files
```

Step 2: Create or Upload a Dataset

```
# Check if the user wants to upload a file or generate one

print("Do you have a CSV file to upload? (yes/no)")

response = input().lower()

if response == "yes":

   # Upload the CSV file

   uploaded = files.upload()

   filename = list(uploaded.keys())[0]

else:

   # Generate synthetic classification data

   from sklearn.datasets import make_classification

   X, y = make_classification(n_samples=300, n_features=10, n_classes=2, random_state=42)

   # Combine features and target into a DataFrame

   data = pd.DataFrame(X, columns=[f"Feature_{i}" for i in range(X.shape[1])])

   data['Target'] = y

   # Save the synthetic dataset to a CSV file

   filename = "synthetic_data.csv"

   data.to_csv(filename, index=False)
```

    print(f"Synthetic dataset saved as {filename}.")

Step 3: Load the Dataset

 # Load the dataset

data = pd.read_csv(filename)

 # Display the first few rows of the dataset

print("Dataset Preview:")

print(data.head())

Step 4: Preprocess the Data

 # Separate features (X) and target (y)

X = data.iloc[:, :-1].values # All columns except the last one

y = data.iloc[:, -1].values # Last column as the target

 # Split the dataset into training (80%) and testing (20%) sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

Step 5: Train a Single Decision Tree Classifier

 # Initialize and train the Decision Tree model

decision_tree = DecisionTreeClassifier(random_state=42)

decision_tree.fit(X_train, y_train)

 # Predict and evaluate

y_pred_tree = decision_tree.predict(X_test)

accuracy_tree = accuracy_score(y_test, y_pred_tree)

print(f"Decision Tree Accuracy: {accuracy_tree:.2f}")

Step 6: Train a Random Forest Classifier

 # Initialize the Random Forest model with hyperparameter tuning

random_forest = RandomForestClassifier(n_estimators=100, max_features='sqrt', random_state=42)

 # Train the model

random_forest.fit(X_train, y_train)

 # Predict and evaluate

y_pred_rf = random_forest.predict(X_test)

accuracy_rf = accuracy_score(y_test, y_pred_rf)

print(f"Random Forest Accuracy (100 trees, sqrt features): {accuracy_rf:.2f}")

Step 7: Experiment with Random Forest Hyperparameters

 # Experiment with fewer trees and different feature sampling

rf_experiment = RandomForestClassifier(n_estimators=50, max_features=3, random_state=42)

rf_experiment.fit(X_train, y_train)

 # Predict and evaluate

y_pred_rf_exp = rf_experiment.predict(X_test)

accuracy_rf_exp = accuracy_score(y_test, y_pred_rf_exp)

print(f"Random Forest Accuracy (50 trees, max_features=3): {accuracy_rf_exp:.2f}")

Step 8: Compare the Models

print("\nModel Comparison:")

print(f"Decision Tree Accuracy: {accuracy_tree:.2f}")

print(f"Random Forest Accuracy (100 trees): {accuracy_rf:.2f}")

print(f"Random Forest Accuracy (50 trees, max_features=3): {accuracy_rf_exp:.2f}")

Step 9: Visualize Feature Importance (Optional)

import matplotlib.pyplot as plt

 # Extract feature importance from the Random Forest model

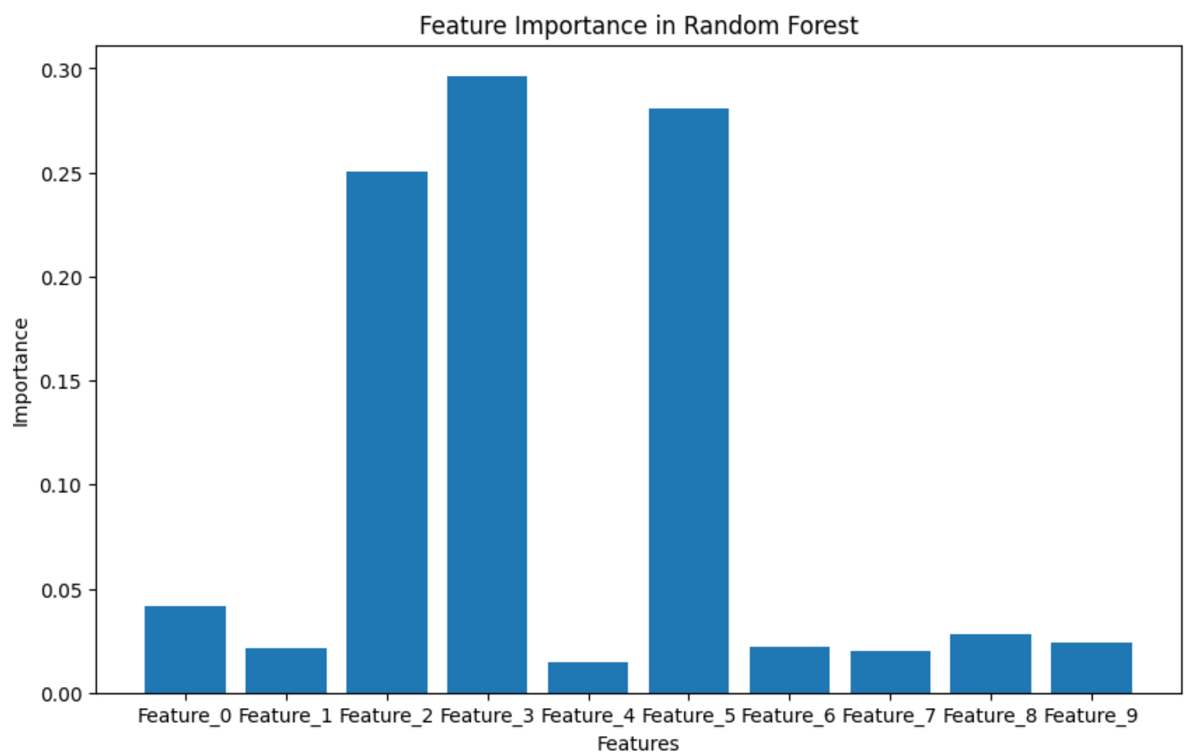
feature_importances = random_forest.feature_importances_

 # Plot the feature importance

plt.figure(figsize=(10, 6))

plt.bar(range(len(feature_importances)), feature_importances, tick_label=data.columns[:-1])

```
plt.title("Feature Importance in Random Forest")
plt.xlabel("Features")
plt.ylabel("Importance")
plt.show()
```



4f. Implement a gradient boosting machine (e.g., XGBoost). Tune hyperparameters and explore feature importance.

Step 1: Import Required Libraries

```
# Import necessary libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, classification_report
from xgboost import XGBClassifier, plot_importance
import matplotlib.pyplot as plt
from google.colab import files
```

Step 2: Create or Upload a Dataset

```
# Check if the user wants to upload a file or generate one
print("Do you have a CSV file to upload? (yes/no)")
response = input().lower()
if response == "yes":
    # Upload the CSV file
    uploaded = files.upload()
    filename = list(uploaded.keys())[0]
else:
    # Generate synthetic classification data
    from sklearn.datasets import make_classification
    X, y = make_classification(n_samples=300, n_features=10, n_classes=2, random_state=42)
    # Combine features and target into a DataFrame
    data = pd.DataFrame(X, columns=[f"Feature_{i}" for i in range(X.shape[1])])
    data['Target'] = y
    # Save the synthetic dataset to a CSV file
    filename = "synthetic_data.csv"
```

data.to_csv(filename, index=False)

print(f"Synthetic dataset saved as {filename}.")

Step 3: Load the Dataset

 # Load the dataset

data = pd.read_csv(filename)

 # Display the first few rows of the dataset

print("Dataset Preview:")

print(data.head())

Step 4: Preprocess the Data

 # Separate features (X) and target (y)

X = data.iloc[:, :-1].values # All columns except the last one

y = data.iloc[:, -1].values # Last column as the target

 # Split the dataset into training (80%) and testing (20%) sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

Step 5: Train a Basic XGBoost Model

 # Initialize and train the XGBoost model with default parameters

xgb = XGBClassifier(random_state=42)

xgb.fit(X_train, y_train)

 # Predict and evaluate the model

y_pred = xgb.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)

print(f"XGBoost Accuracy (Default Parameters): {accuracy:.2f}")

Step 6: Tune Hyperparameters with GridSearchCV

 # Define a grid of hyperparameters

param_grid = {

```python
    'n_estimators': [50, 100, 150],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 5, 7]
}
# Initialize GridSearchCV
grid_search = GridSearchCV(estimator=XGBClassifier(random_state=42),
                           param_grid=param_grid,
                           scoring='accuracy',
                           cv=3,
                           verbose=1)
# Fit the model with grid search
grid_search.fit(X_train, y_train)
# Best parameters from GridSearch
print(f"Best Parameters: {grid_search.best_params_}")
# Train the final model with the best parameters
best_xgb = grid_search.best_estimator_
# Predict and evaluate
y_pred_best = best_xgb.predict(X_test)
accuracy_best = accuracy_score(y_test, y_pred_best)
print(f"XGBoost Accuracy (Tuned Parameters): {accuracy_best:.2f}")
```

Step 7: Explore Feature Importance

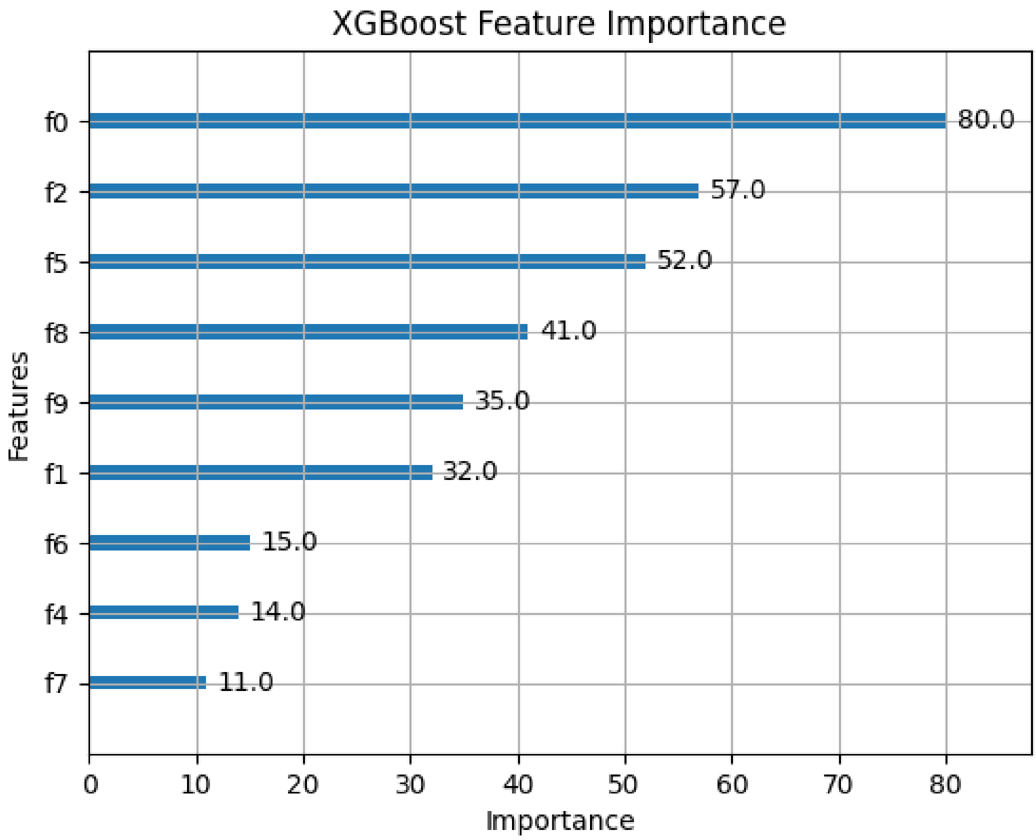
```python
# Plot feature importance for the tuned model
plt.figure(figsize=(10, 6))
plot_importance(best_xgb, importance_type='weight', xlabel="Importance",
ylabel="Features")
plt.title("XGBoost Feature Importance")
plt.show()
```

Step 8: Evaluate the Model

 # Print a detailed classification report

print("Classification Report:")

print(classification_report(y_test, y_pred_best))



5a. Implement and demonstrate the working of a Naive Bayesian classifier using a sample data set. Build the model to classify a test sample.

Step 1: Import Required Libraries

```
# Import necessary libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
from sklearn.naive_bayes import GaussianNB
from google.colab import files
```

Step 2: Create or Upload a Dataset

```
# Ask if the user wants to upload a file or generate one
print("Do you have a CSV file to upload? (yes/no)")
response = input().lower()
if response == "yes":
    # Upload the CSV file
    uploaded = files.upload()
    filename = list(uploaded.keys())[0]
else:
    # Generate synthetic classification data
    from sklearn.datasets import make_classification
    X, y = make_classification(n_samples=300, n_features=8, n_classes=2, random_state=42)
    # Combine features and target into a DataFrame
    data = pd.DataFrame(X, columns=[f"Feature_{i}" for i in range(X.shape[1])])
    data['Target'] = y
    # Save the synthetic dataset to a CSV file
    filename = "synthetic_naive_bayes_data.csv"
    data.to_csv(filename, index=False)
```

print(f"Synthetic dataset saved as {filename}.")

Step 3: Load the Dataset

 # Load the dataset

data = pd.read_csv(filename)

 # Display the first few rows of the dataset

print("Dataset Preview:")

print(data.head())

Step 4: Preprocess the Data

 # Separate features (X) and target (y)

X = data.iloc[:, :-1].values # All columns except the last one

y = data.iloc[:, -1].values # Last column as the target

 # Split the dataset into training (80%) and testing (20%) sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

Step 5: Train a Naive Bayes Classifier

 # Initialize the Gaussian Naive Bayes classifier

naive_bayes = GaussianNB()

 # Train the model

naive_bayes.fit(X_train, y_train)

Step 6: Make Predictions and Evaluate

 # Predict on the test set

y_pred = naive_bayes.predict(X_test)

 # Evaluate the model

accuracy = accuracy_score(y_test, y_pred)

print(f"Naive Bayes Accuracy: {accuracy:.2f}")

 # Detailed classification report

print("Classification Report:")

print(classification_report(y_test, y_pred))

Step 7: Test the Model with a Custom Sample

 # Define a sample test input (replace with meaningful values based on your dataset)

test_sample = [X_test[0]] # Taking the first test sample for demonstration

 # Predict the class for the test sample

predicted_class = naive_bayes.predict(test_sample)

print(f"Test Sample: {test_sample}")

print(f"Predicted Class: {predicted_class[0]}")

```
Dataset Preview:
   Feature_0  Feature_1  Feature_2  Feature_3  Feature_4  Feature_5  \
0  -1.274158   1.317988  -2.423879   0.906946  -1.583903  -0.331811
1   1.607963  -1.649959   0.299293  -0.891720   1.301741   1.508502
2  -0.154167   0.161033   2.210523   0.139400  -0.557492   0.087713
3  -0.920991   0.949136  -1.613561   0.588410   1.471170  -0.529287
4   1.013304  -1.038578  -0.305225  -0.539334  -0.609512   1.048078

   Feature_6  Feature_7  Target
0  -0.452306   0.760415       1
1   0.742095   1.561511       0
2   0.963879  -1.369803       0
3  -1.371901  -0.209324       0
4  -1.065114  -0.186971       0
```

```
Test Sample: [array([-0.90320608,  0.9220511 , -1.32308979,  0.41081065,  1.64201516,
       -1.23559176, -0.63896175,  1.00981709])]
Predicted Class: 1
```

5b. Implement Hidden Markov Models using hmmlearn

Step 1: Install Required Libraries

 # Install hmmlearn

!pip install hmmlearn

Step 2: Import Required Libraries

 # Import necessary libraries

import numpy as np

import pandas as pd

from hmmlearn import hmm

import matplotlib.pyplot as plt

Step 3: Create or Load a Dataset

 # Generate synthetic observable data

np.random.seed(42)

 # Create a sequence of observations and hidden states

observations = np.random.choice(['A', 'B', 'C'], size=100, p=[0.5, 0.3, 0.2])

hidden_states = np.random.choice(['X', 'Y'], size=100, p=[0.6, 0.**4])**

 # Save the data in a DataFrame for analysis

data = pd.DataFrame({'Observations': observations, 'Hidden States': hidden_states})

print("Generated Data:")

print(data.head())

Step 4: Encode Observations

 # Encode the observations into integers

observation_mapping = {obs: idx for idx, obs in enumerate(np.unique(observations))}

encoded_observations = np.array([observation_mapping[obs] for obs in observations])

```
# Print the mapping
print("Observation Encoding:")
print(observation_mapping)
```

Step 5: Initialize and Configure the HMM

```
# Initialize the HMM model
n_states = 2  # Number of hidden states
n_observations = len(observation_mapping)  # Number of unique observations
model = hmm.MultinomialHMM(n_components=n_states, random_state=42, n_iter=100,
tol=0.01)
# Define start probabilities (initial distribution of states)
start_probs = np.array([0.6, 0.4])  # Assumed probabilities
model.startprob_ = start_probs
# Define transition probabilities between states
trans_probs = np.array([
    [0.7, 0.3],  # From state X
    [0.4, 0.6],  # From state Y
])
model.transmat_ = trans_probs
# Define emission probabilities (probability of observations given states)
emission_probs = np.array([
    [0.5, 0.4, 0.1],  # State X emits A, B, C
    [0.2, 0.3, 0.5],  # State Y emits A, B, C
])
model.emissionprob_ = emission_probs
# Print the configured model parameters
print("Start Probabilities:", model.startprob_)
print("Transition Matrix:", model.transmat_)
print("Emission Probabilities:", model.emissionprob_)
```

Step 6: Train the Model

 # Reshape the data for HMM (requires 2D array)

encoded_observations = encoded_observations.reshape(-1, 1)

 # Fit the model

model.fit(encoded_observations)

 # Predict hidden states for the observations

predicted_states = model.predict(encoded_observations)

 # Print the predicted states

print("Predicted States:")

print(predicted_states)

Step 7: Visualize the Results

 # Map predicted states back to their original labels

state_mapping = {0: 'X', 1: 'Y'}

predicted_state_labels = [state_mapping[state] for state in predicted_states]

 # Add predicted states to the DataFrame

data['Predicted States'] = predicted_state_labels

 # Display the first few rows with predicted states

print("Data with Predicted States:")

print(data.head())

 # Plot the observations and predicted states

plt.figure(figsize=(12, 6))

plt.plot(data['Observations'], label='Observations', marker='o', linestyle='-', alpha=0.7)

plt.plot(data['Predicted States'], label='Predicted States', marker='x', linestyle='--', alpha=0.7)

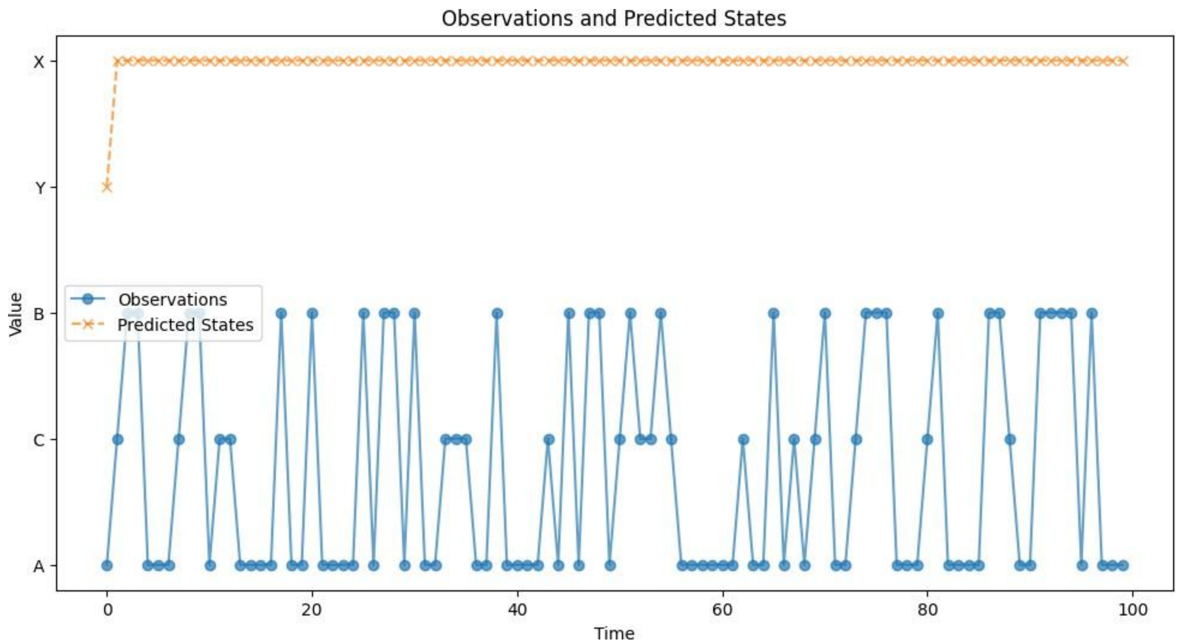
plt.legend()

plt.title("Observations and Predicted States")

plt.xlabel("Time")

plt.ylabel("Value")

plt.show()



Observations and Predicted States
X
Y
B
C
A
Value
Observations
Predicted States
0
20
40
60
80
100
Time

6. Probabilistic Models

6a. Implement Bayesian Linear Regression to explore prior and posterior distribution.

Bayesian Linear Regression is a probabilistic approach to linear regression that incorporates uncertainty in the model parameters. Instead of estimating point values for parameters (as in traditional linear regression), we estimate distributions over the parameters.

Step 1: Install Required Libraries

```
# Install necessary libraries
!pip install matplotlib seaborn scikit-learn
```

Step 2: Import Required Libraries

```
# Import necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import BayesianRidge
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from google.colab import files
```

Step 3: Create or Upload a Dataset

```
# Upload a CSV file if you have one
print("Do you have a CSV file to upload? (yes/no)")
response = input().lower()
if response == "yes":
    # Upload the CSV file
    uploaded = files.upload()
```

```
    filename = list(uploaded.keys())[0]
else:
    # Generate synthetic data for demonstration
    np.random.seed(42)
    X = np.random.rand(100, 1) * 10  # Random data between 0 and 10
    y = 2 * X + 1 + np.random.randn(100, 1) * 2  # y = 2x + 1 with some noise
    # Convert to a DataFrame
    data = pd.DataFrame(np.hstack((X, y)), columns=["X", "y"])
    # Save to CSV for convenience
    filename = "synthetic_data.csv"
    data.to_csv(filename, index=False)
    print(f"Synthetic dataset saved as {filename}.")
```

Step 4: Load and Explore the Data

 # Load the dataset (for CSV file)

```
data = pd.read_csv(filename)
```

 # Display first few rows

```
print("Dataset Preview:")
print(data.head())
```

Step 5: Preprocess the Data

 # Separate features (X) and target (y)

```
X = data["X"].values.reshape(-1, 1)  # Feature matrix
y = data["y"].values  # Target vector
```

 # Split the dataset into training (80%) and testing (20%) sets

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Step 6: Implement Bayesian Linear Regression Model

 # Initialize the BayesianRidge model (which implements Bayesian Linear Regression)

bayesian_regressor = BayesianRidge()

 # Fit the model on the training data

bayesian_regressor.fit(X_train, y_train)

 # Predict on the test data

y_pred = bayesian_regressor.predict(X_test)

Step 7: Visualize the Prior and Posterior Distributions

 # Plot the prior and posterior distributions of the parameters

fig, ax = plt.subplots(1, 2, figsize=(12, 6))

 # Plot prior distribution (assuming the model starts with a standard prior)

ax[0].set_title("Prior Distribution (Assumed)")

ax[0].hist(np.random.normal(0, 1, 1000), bins=50, alpha=0.7, color='blue', label="Prior")

ax[0].legend()

 # Plot posterior distribution (after model fitting)

ax[1].set_title("Posterior Distribution (After Fitting)")

ax[1].hist(bayesian_regressor.coef_, bins=50, alpha=0.7, color='green', label="Posterior")

ax[1].legend()

plt.show()

Step 8: Evaluate the Model Performance

 # Calculate the Mean Squared Error (MSE)

mse = mean_squared_error(y_test, y_pred)

print(f"Mean Squared Error (MSE): {mse:.2f}")

Step 9: Visualize the Fit of the Model

 # Plot the true values and the predicted values

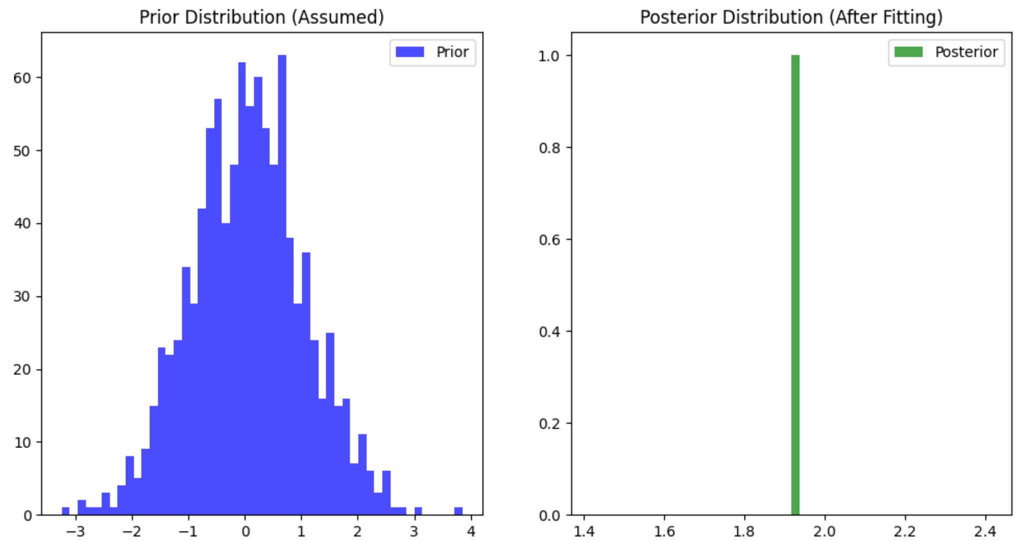
plt.figure(figsize=(8, 6))

plt.scatter(X_test, y_test, color="blue", label="True values")

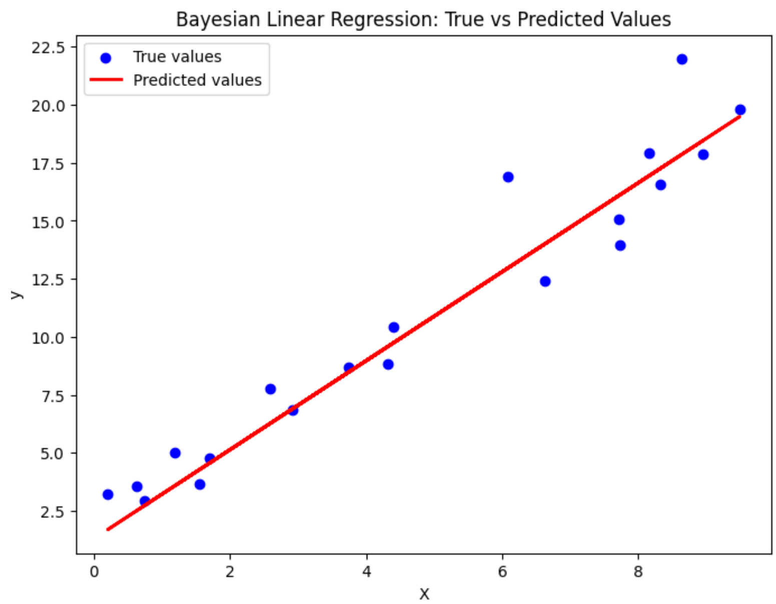
plt.plot(X_test, y_pred, color="red", label="Predicted values", linewidth=2)

```
plt.title("Bayesian Linear Regression: True vs Predicted Values")
plt.xlabel("X")
plt.ylabel("y")
plt.legend()
plt.show()
```

Mean Squared Error (MSE): 3.9



2



6b. Implement Gaussian Mixture Models for density estimation and unsupervised clustering.

Step 1: Install Required Libraries

 # Install required libraries

!pip install matplotlib seaborn scikit-learn

Step 2: Import Required Libraries

 # Import necessary libraries

import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.mixture import GaussianMixture

from sklearn.model_selection import train_test_split

from google.colab import files

Step 3: Create or Upload a Dataset

 # Ask if the user has a CSV file to upload

```
print("Do you have a CSV file to upload? (yes/no)")

response = input().lower()

if response == "yes":

    # Upload the CSV file

    uploaded = files.upload()

    filename = list(uploaded.keys())[0]

else:

    # Generate synthetic 2D data with two clusters for demonstration

    np.random.seed(42)
```

 # Generate data for two Gaussian distributions

```
    X1 = np.random.normal(loc=0, scale=1, size=(300, 2))  # Cluster 1: mean = 0, std = 1

    X2 = np.random.normal(loc=5, scale=1, size=(300, 2))  # Cluster 2: mean = 5, std = 1
```

 # Stack the data to create a dataset

X = np.vstack([X1, X2])

 # Create DataFrame to simulate the CSV file for consistency

data = pd.DataFrame(X, columns=["Feature_1", "Feature_2"])

filename = "synthetic_data.csv"

data.to_csv(filename, index=False)

print(f"Synthetic dataset saved as {filename}.")

Step 4: Load and Explore the Dataset

 # Load the dataset (if CSV file is uploaded)

data = pd.read_csv(filename)

 # Display the first few rows

print("Dataset Preview:")

print(data.head())

 # Plot the data to visualize its structure

sns.scatterplot(data=data, x="Feature_1", y="Feature_2")

plt.title("Synthetic Data")

plt.xlabel("Feature 1")

plt.ylabel("Feature 2")

plt.show()

Step 5: Fit a Gaussian Mixture Model (GMM)

 # Define the GMM model

n_components = 2 # Number of Gaussian distributions (clusters)

gmm = GaussianMixture(n_components=n_components, covariance_type='full', random_state=42)

 # Fit the GMM model to the data

gmm.fit(data)

 # Predict the cluster labels for each data point

```python
labels = gmm.predict(data)

# Add the cluster labels to the dataset for visualization

data['Cluster'] = labels

# Plot the clustered data

sns.scatterplot(data=data, x="Feature_1", y="Feature_2", hue="Cluster", palette="viridis", marker="o")

plt.title("Gaussian Mixture Model Clustering")

plt.xlabel("Feature 1")

plt.ylabel("Feature 2")

plt.legend()

plt.show()
```

Step 6: Visualize the Gaussian Mixture Model (GMM) Components

```python
# Extract the means and covariances of the Gaussian components

means = gmm.means_

covariances = gmm.covariances_

# Plot the GMM components on top of the data

plt.figure(figsize=(8, 6))

# Plot data points

sns.scatterplot(data=data, x="Feature_1", y="Feature_2", hue="Cluster", palette="viridis", marker="o", s=60, alpha=0.7)

# Plot the GMM ellipses

for mean, covar in zip(means, covariances):

    # Plot the Gaussian components as ellipses

    v, w = np.linalg.eigh(covar)

    v = 2.0 * np.sqrt(2.0) * np.sqrt(v)  # Scaling factor for the ellipse

    u = w[0] / np.linalg.norm(w[0])  # Normalize the eigenvector

    angle = np.arctan(u[1] / u[0])

    # Create the ellipse

    angle = angle * 180.0 / np.pi  # Convert to degrees
```

```
    ellipse = plt.matplotlib.patches.Ellipse(mean, v[0], v[1], angle=angle, color='red',
alpha=0.3)
    plt.gca().add_patch(ellipse)

plt.title("GMM Clustering with Gaussian Components")
plt.xlabel("Feature 1")
plt.ylabel("Feature 2")
plt.legend()
plt.show()
```

Step 7: Model Evaluation (Optional)

 # Compute the log-likelihood of the data under the fitted GMM model

```
log_likelihood = gmm.score(data)
print(f"Log-Likelihood of the data: {log_likelihood:.2f}")
```

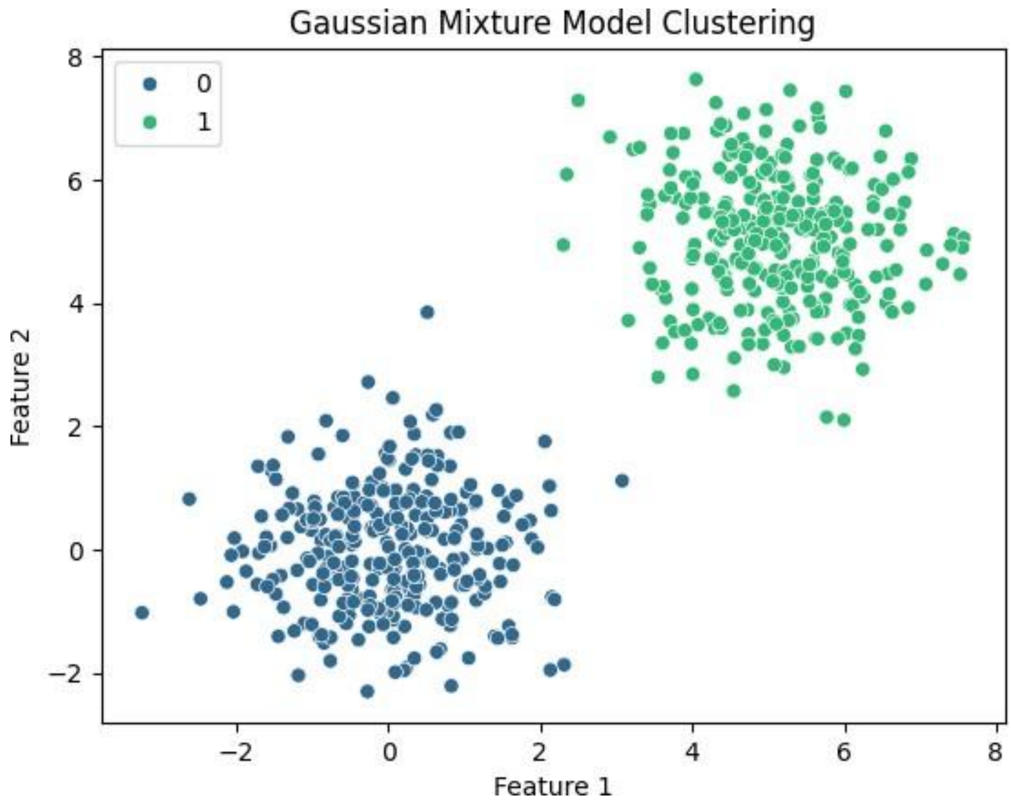
Step 8: Predict New Data Points

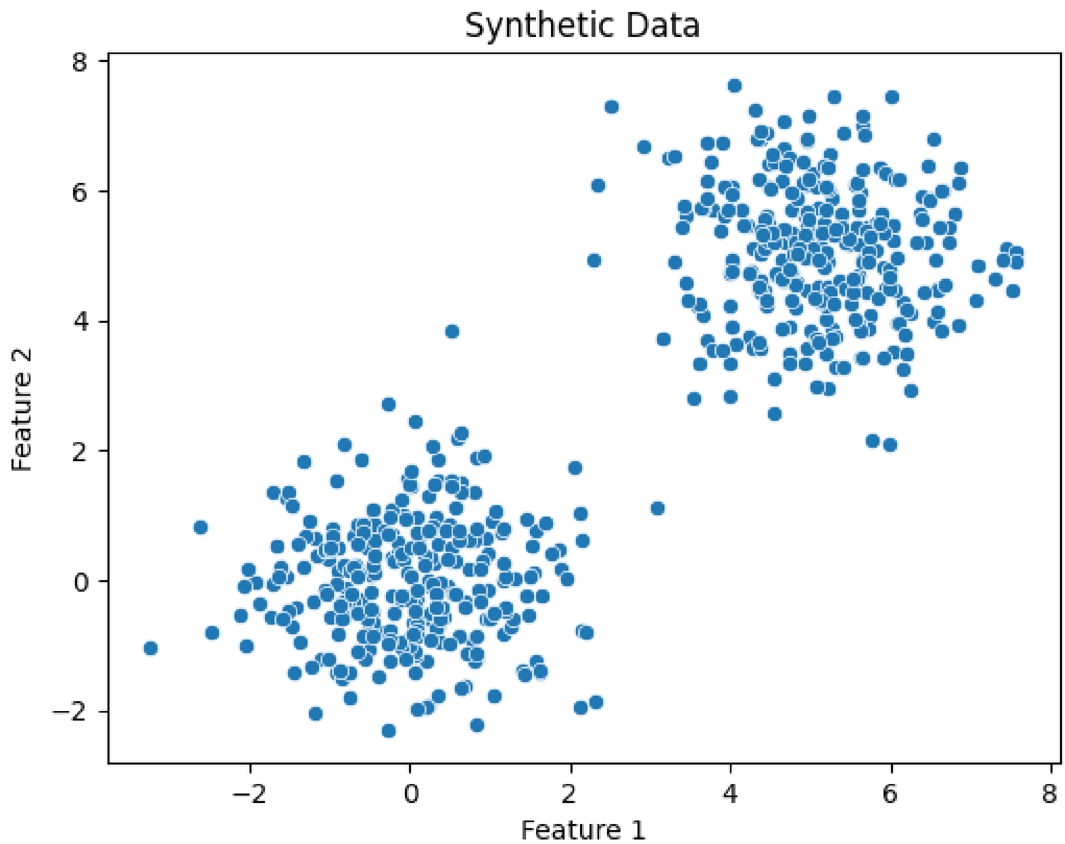
 # Example of predicting the cluster for new data points

```
new_data = np.array([[1.5, 2.5], [4.5, 5.5], [7.0, 8.0]])
new_labels = gmm.predict(new_data)
```

 # Print the predicted clusters for the new data points

```
print("Predicted Clusters for New Data Points:")
for i, label in enumerate(new_labels):
    print(f"Data point {new_data[i]} is in Cluster {label}")
```


Gaussian Mixture Model Clustering
0
1
Feature 2
Feature 1
8
6
4
2
0
−2
−2
0
2
4
6
8


Synthetic Data
Feature 2
Feature 1
8
6
4
2
0
−2
−2
0
2
4
6
8

7. Model Evaluation and Hyperparameter Tuning

a. Implement cross-validation techniques (k-fold, stratified, etc.) for robust model evaluation

1. Import Necessary Libraries

```
import numpy as np
import pandas as pd
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split, KFold, StratifiedKFold, GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
```

2. Generate a Synthetic Dataset

```
# Create a synthetic dataset with 2 classes
X, y = make_classification(
    n_samples=1000, n_features=10, n_informative=8, n_redundant=2,
    n_clusters_per_class=1, random_state=42
)
# Convert to a DataFrame for visualization
df = pd.DataFrame(X, columns=[f'Feature_{i}' for i in range(1, 11)])
df['Target'] = y
# Display the first few rows
print(df.head())
```

3. Split Data into Train and Test Sets

```
# Split data into 80% training and 20% testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42,
stratify=y)
```

4. Define k-Fold Cross-Validation

```
kf = KFold(n_splits=5, shuffle=True, random_state=42)
print("k-Fold Cross-Validation:")
for train_index, val_index in kf.split(X_train):
    print("TRAIN:", train_index, "VALIDATION:", val_index)
```

5. Define Stratified k-Fold Cross-Validation

```
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
print("\nStratified k-Fold Cross-Validation:")
for train_index, val_index in skf.split(X_train, y_train):
    print("TRAIN:", train_index, "VALIDATION:", val_index)
```

6. Train and Evaluate Using k-Fold Cross-Validation

```
# Initialize model
model = RandomForestClassifier(random_state=42)

# Perform k-Fold Cross-Validation
```

```
accuracies = []
for train_index, val_index in kf.split(X_train):
    X_kf_train, X_kf_val = X_train[train_index], X_train[val_index]
    y_kf_train, y_kf_val = y_train[train_index], y_train[val_index]

    # Train model
    model.fit(X_kf_train, y_kf_train)

    # Validate model
    y_pred = model.predict(X_kf_val)
    accuracy = accuracy_score(y_kf_val, y_pred)
    accuracies.append(accuracy)
print(f"Average Accuracy from k-Fold: {np.mean(accuracies):.2f}")
```

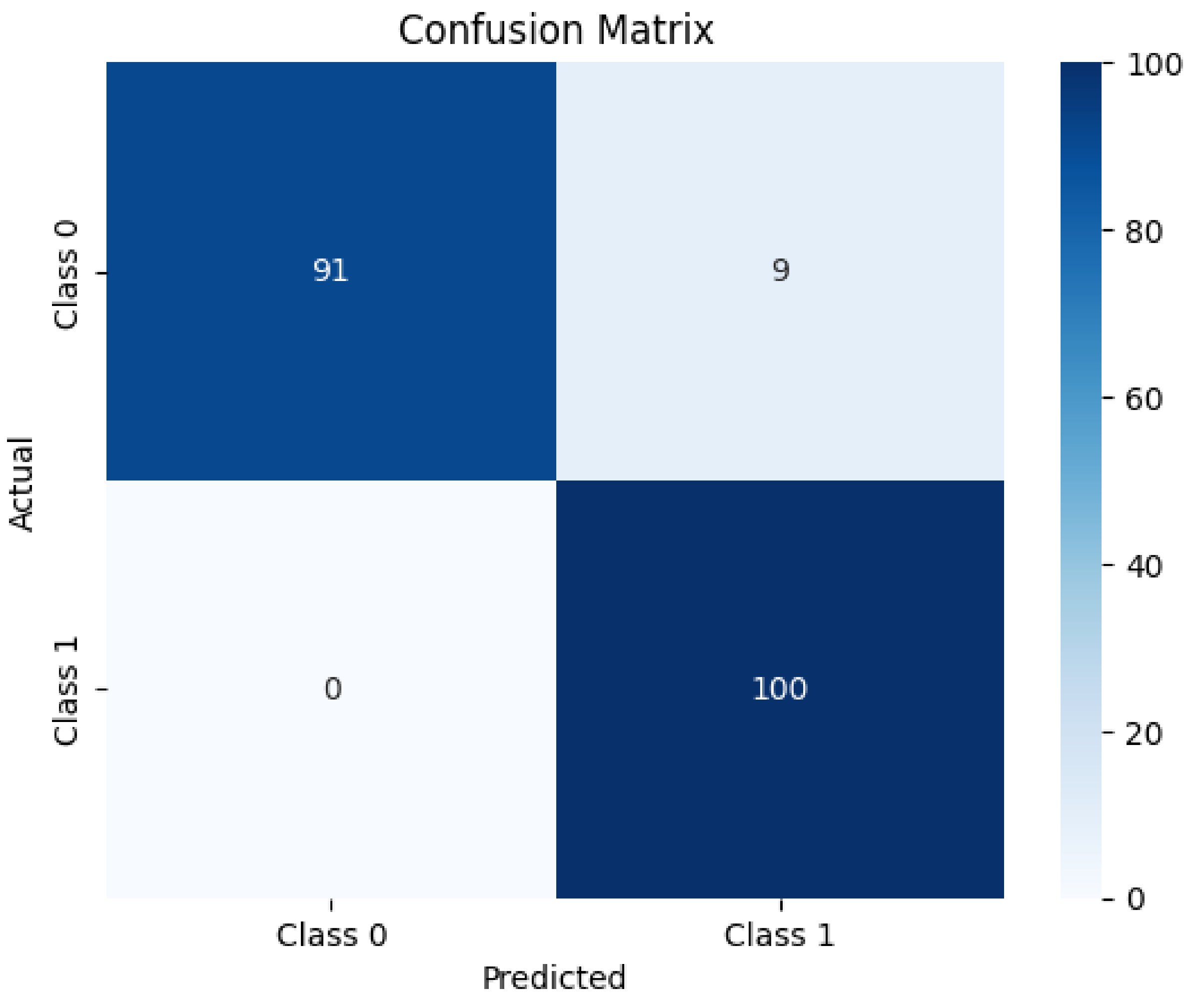
7. Hyperparameter Tuning Using GridSearchCV

```
# Define parameter grid
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
}

# Perform GridSearchCV with Stratified k-Fold
grid_search = GridSearchCV(
    estimator=RandomForestClassifier(random_state=42),
    param_grid=param_grid,
    cv=StratifiedKFold(n_splits=5, shuffle=True, random_state=42),
    scoring='accuracy',
    n_jobs=-1,
    verbose=1
)

# Fit to training data
grid_search.fit(X_train, y_train)
print("Best Parameters:", grid_search.best_params_)
print("Best Cross-Validation Accuracy:", grid_search.best_score_)
```

8. Evaluate the Final Model

```
# Use the best model for evaluation
best_model = grid_search.best_estimator_
# Predict on test data
y_test_pred = best_model.predict(X_test)
# Evaluate performance
print("\nTest Accuracy:", accuracy_score(y_test, y_test_pred))
print("\nClassification Report:\n", classification_report(y_test, y_test_pred))
# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_test_pred)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Class 0', 'Class 1'],
yticklabels=['Class 0', 'Class 1'])
plt.xlabel('Predicted')
```

```
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



7b. Systematically explore combinations of hyperparameters to optimize model performance.(use grid and randomized search)

1. Import Necessary Libraries

```
import numpy as np
import pandas as pd
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearchCV,
StratifiedKFold
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
```

2. Generate a Synthetic Dataset

```
# Generate a binary classification dataset
X, y = make_classification(
    n_samples=1000, n_features=12, n_informative=8, n_redundant=2,
    n_clusters_per_class=1, flip_y=0.03, random_state=42
)
# Convert to a DataFrame for visualization
df = pd.DataFrame(X, columns=[f'Feature_{i}' for i in range(1, 13)])
df['Target'] = y
# Display the first few rows
print(df.head())
```

3. Split Data into Train and Test Sets

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42,
stratify=y)
```

4. Define the Model

```
# Initialize a Random Forest classifier
model = RandomForestClassifier(random_state=42)
```

5. Hyperparameter Tuning Using Grid Search

```
# Define a parameter grid for Grid Search
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
# GridSearchCV with 5-fold cross-validation
grid_search = GridSearchCV(
    estimator=model,
    param_grid=param_grid,
    scoring='accuracy',
```

```
    cv=StratifiedKFold(n_splits=5, shuffle=True, random_state=42),
    verbose=1,
    n_jobs=-1
)
# Fit the model
grid_search.fit(X_train, y_train)

# Best parameters and score from Grid Search
print("Best Parameters from Grid Search:", grid_search.best_params_)
print("Best Cross-Validation Accuracy from Grid Search:", grid_search.best_score_)
```

6. Hyperparameter Tuning Using Randomized Search

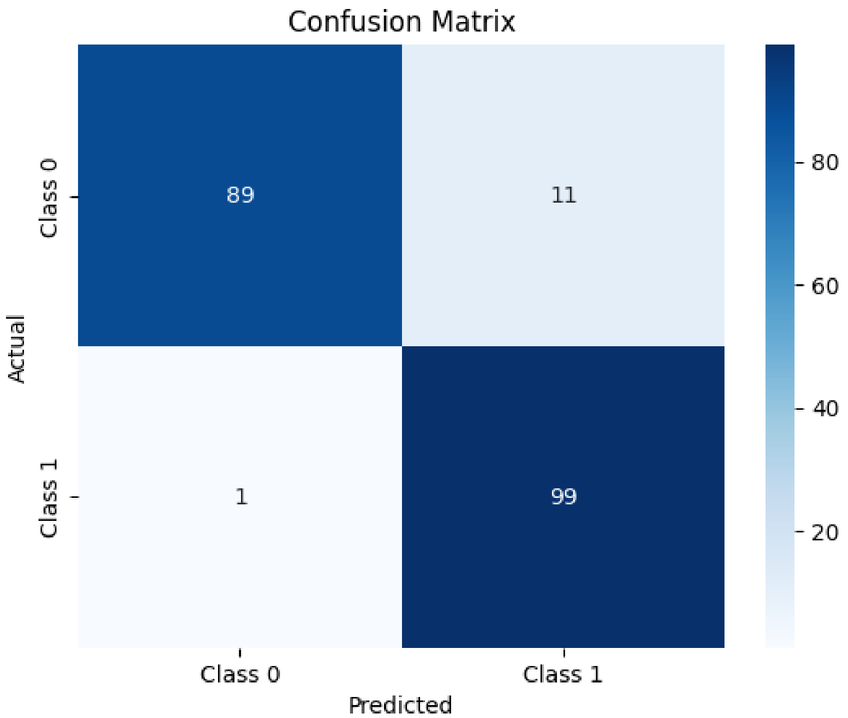
```
from scipy.stats import randint
# Define a parameter distribution for Randomized Search
param_dist = {
    'n_estimators': randint(50, 300),
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': randint(2, 15),
    'min_samples_leaf': randint(1, 10)
}
# RandomizedSearchCV with 5-fold cross-validation
random_search = RandomizedSearchCV(
    estimator=model,
    param_distributions=param_dist,
    n_iter=50,  # Number of random combinations to try
    scoring='accuracy',
    cv=StratifiedKFold(n_splits=5, shuffle=True, random_state=42),
    verbose=1,
    n_jobs=-1,
    random_state=42
)
# Fit the model
random_search.fit(X_train, y_train)

# Best parameters and score from Randomized Search
print("Best Parameters from Randomized Search:", random_search.best_params_)
print("Best Cross-Validation Accuracy from Randomized Search:",
random_search.best_score_)
```

7. Evaluate the Best Model

```
# Select the best model from Grid Search and Randomized Search
best_model = random_search.best_estimator_  # Or use grid_search.best_estimator_

# Predict on test data
y_test_pred = best_model.predict(X_test)

# Evaluate the performance
print("\nTest Accuracy:", accuracy_score(y_test, y_test_pred))
print("\nClassification Report:\n", classification_report(y_test, y_test_pred))
```

```
# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_test_pred)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Class 0', 'Class 1'],
yticklabels=['Class 0', 'Class 1'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```

```
Test Accuracy: 0.94

Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.89      0.94       100
           1       0.90      0.99      0.94       100

    accuracy                           0.94       200
   macro avg       0.94      0.94      0.94       200
weighted avg       0.94      0.94      0.94       200
```



8. Implement Bayesian Learning using inferences

1. Import Necessary Libraries

```
import numpy as np
import pandas as pd
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
```

2. Generate a Synthetic Dataset

```
# Generate a dataset with 2 classes
X, y = make_classification(
    n_samples=1000, n_features=8, n_informative=6, n_redundant=2,
    n_classes=2, random_state=42
)
# Convert to DataFrame for visualization
df = pd.DataFrame(X, columns=[f'Feature_{i}' for i in range(1, 9)])
df['Target'] = y

# Display the first few rows
print(df.head())
```

3. Split the Dataset

```
# Split data into 80% training and 20% testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42,
stratify=y)
```

4. Bayesian Learning with Naive Bayes

```
# Initialize the Gaussian Naive Bayes model
model = GaussianNB()

# Fit the model to the training data
model.fit(X_train, y_train)

# Predict on the test data
y_pred = model.predict(X_test)
```

5. Evaluate the Model

```
# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Test Accuracy: {accuracy:.2f}")

# Print classification report
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
# Generate and plot confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Class 0', 'Class 1'],
yticklabels=['Class 0', 'Class 1'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```

6. Understanding Bayesian Inference

In Bayesian Learning, the model predicts based on the probabilities:

- Prior Probability (P(C)P(C)P(C)): The likelihood of each class based on historical data.
- Likelihood (P(X|C)P(X∣C)P(X|C)): The probability of the data given a class.
- Posterior Probability (P(C|X)P(C∣X)P(C|X)): Calculated using Bayes' theorem: P(C|X)=P(X|C)·P(C)P(X)P(C∣X) = \frac{P(X∣C) \cdot P(C)}{P(X)}P(C|X)=P(X)P(X|C)·P(C)

```
# Example: Compute posterior probabilities for the first test sample
sample = X_test[0].reshape(1, -1)
posterior_probs = model.predict_proba(sample)

print(f"Sample Features: {sample}")
print(f"Posterior Probabilities: {posterior_probs}")
print(f"Predicted Class: {model.predict(sample)}")
```

```
Test Accuracy: 0.84

Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.80      0.84        99
           1       0.82      0.89      0.85       101

    accuracy                           0.84       200
   macro avg       0.85      0.84      0.84       200
weighted avg       0.85      0.84      0.84       200
```