Importing Libraries

```
# Import necessary libraries for data processing, visualization, and
machine learning.
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report, accuracy_score,
confusion_matrix, ConfusionMatrixDisplay
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import roc_auc_score
import warnings
warnings.filterwarnings('ignore')
```

Load the dataset

```
# Load the dataset from CSV file using the correct separator (;).
bank = pd.read_csv("bank-full.csv",sep=';')
```

Display the number of rows and columns in the dataset.

```
bank.shape
bank.info()
print (bank.head(2))
bank.describe()
```

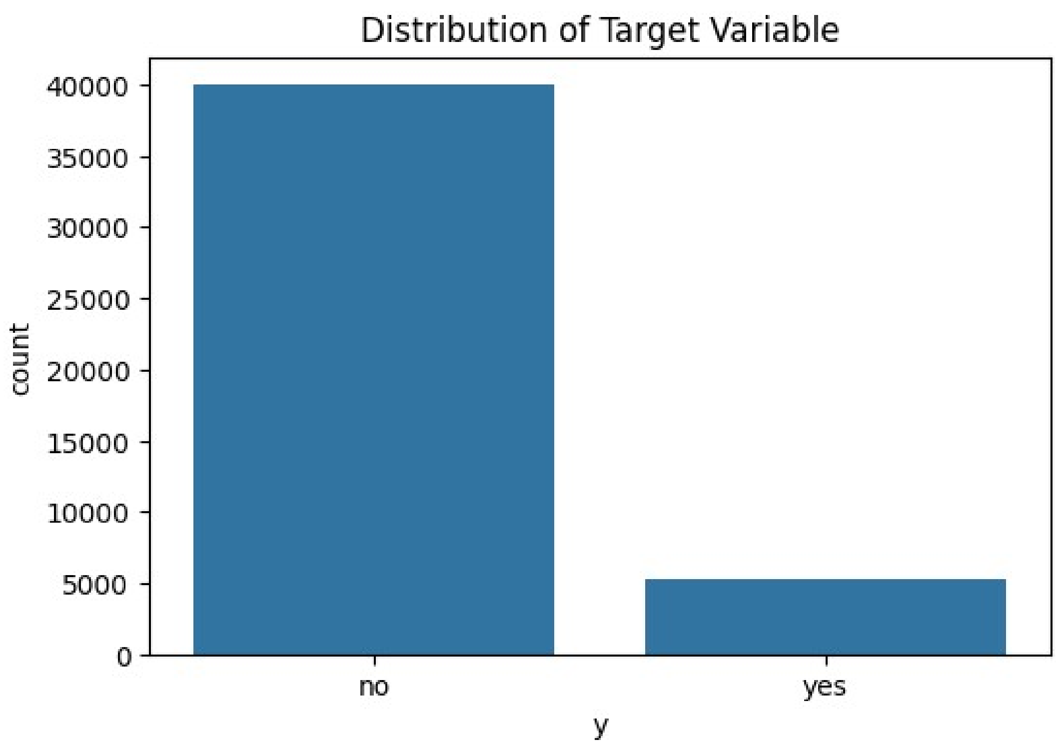
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        45211 non-null  int64
 1   job        45211 non-null  object
 2   marital    45211 non-null  object
 3   education  45211 non-null  object
```

```
 4   default    45211 non-null  object
 5   balance    45211 non-null  int64
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   contact    45211 non-null  object
 9   day        45211 non-null  int64
 10  month      45211 non-null  object
 11  duration   45211 non-null  int64
 12  campaign   45211 non-null  int64
 13  pdays      45211 non-null  int64
 14  previous   45211 non-null  int64
 15  poutcome   45211 non-null  object
 16  y          45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
   age          job  marital  education default  balance housing loan
contact  \
0   58  management  married   tertiary      no     2143     yes   no
unknown
1   44  technician   single  secondary      no       29     yes   no
unknown

   day month  duration  campaign  pdays  previous poutcome   y
0    5   may       261         1     -1         0  unknown  no
1    5   may       151         1     -1         0  unknown  no

                age        balance           day      duration
campaign  \
count  45211.000000   45211.000000  45211.000000  45211.000000
45211.000000
mean      40.936210    1362.272058     15.806419    258.163080
2.763841
std       10.618762    3044.765829      8.322476    257.527812
3.098021
min       18.000000   -8019.000000      1.000000      0.000000
1.000000
25%       33.000000      72.000000      8.000000    103.000000
1.000000
50%       39.000000     448.000000     16.000000    180.000000
2.000000
75%       48.000000    1428.000000     21.000000    319.000000
3.000000
max       95.000000  102127.000000     31.000000   4918.000000
63.000000

              pdays      previous
count  45211.000000  45211.000000
mean      40.197828      0.580323
std      100.128746      2.303441
min       -1.000000      0.000000
```

```
25%        -1.000000      0.000000
50%        -1.000000      0.000000
75%        -1.000000      0.000000
max       871.000000    275.000000
```

Distribution of Target Variable

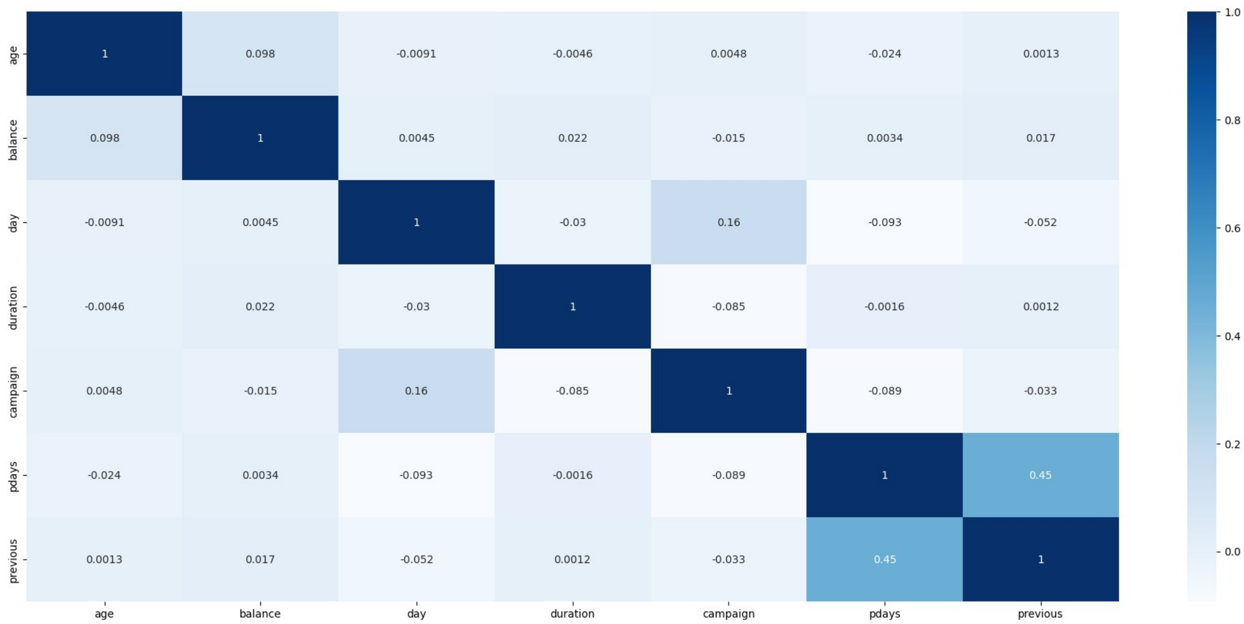
```
df=bank
plt.figure(figsize=(6, 4))
sns.countplot(x=df['y'])
plt.title("Distribution of Target Variable")
plt.show()
```



Heatmap for Numerical Feature Correlations

Visualizing the correlation matrix of numerical features using a heatmap to identify relationships between variables.

```
plt.figure(figsize=(23,10))
sns.heatmap(df.select_dtypes(include=['number']).corr(), cmap='Blues',
annot=True)
plt.show()
```

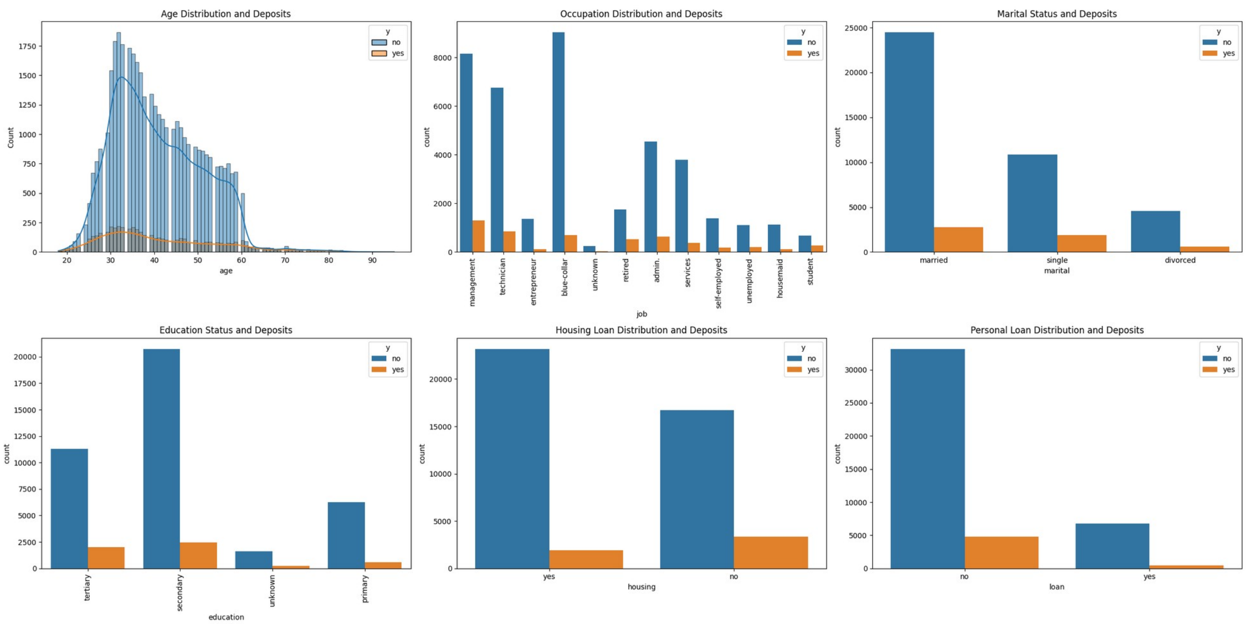


Customer Demographics and Deposit Trends

A series of visualizations analyzing the distribution of key demographic attributes (age, occupation, marital status, education, housing loan, and personal loan) and their relationship with term deposits.

```
fig, axes = plt.subplots(2, 3, figsize=(24, 12))

# Age Distribution
sns.histplot(x="age", data=bank, kde=True, hue="y", ax=axes[0, 0])
axes[0, 0].set_title("Age Distribution and Deposits")

# Occupation Distribution
sns.countplot(x="job", data=bank, hue="y", ax=axes[0, 1])
axes[0, 1].set_title("Occupation Distribution and Deposits")
axes[0, 1].tick_params(axis='x', rotation=90)

# Marital Status Distribution
sns.countplot(x="marital", data=bank, hue="y", ax=axes[0, 2])
axes[0, 2].set_title("Marital Status and Deposits")

# Education Distribution
sns.countplot(x="education", data=bank, hue="y", ax=axes[1, 0])
axes[1, 0].set_title("Education Status and Deposits")
axes[1, 0].tick_params(axis='x', rotation=90)

# Housing Loan Distribution
sns.countplot(x="housing", data=bank, hue="y", ax=axes[1, 1])
axes[1, 1].set_title("Housing Loan Distribution and Deposits")
```

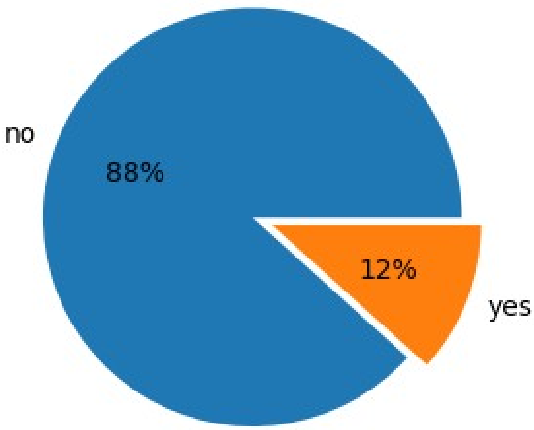
```
# Personal Loan Distribution
sns.countplot(x="loan", data=bank, hue="y", ax=axes[1, 2])
axes[1, 2].set_title("Personal Loan Distribution and Deposits")

plt.tight_layout()
plt.show()
```



Count of Deposit Subscription Outcome

A pie chart visualizing the proportion of customers who subscribed (`yes`) versus those who did not (`no`) to the term deposit.

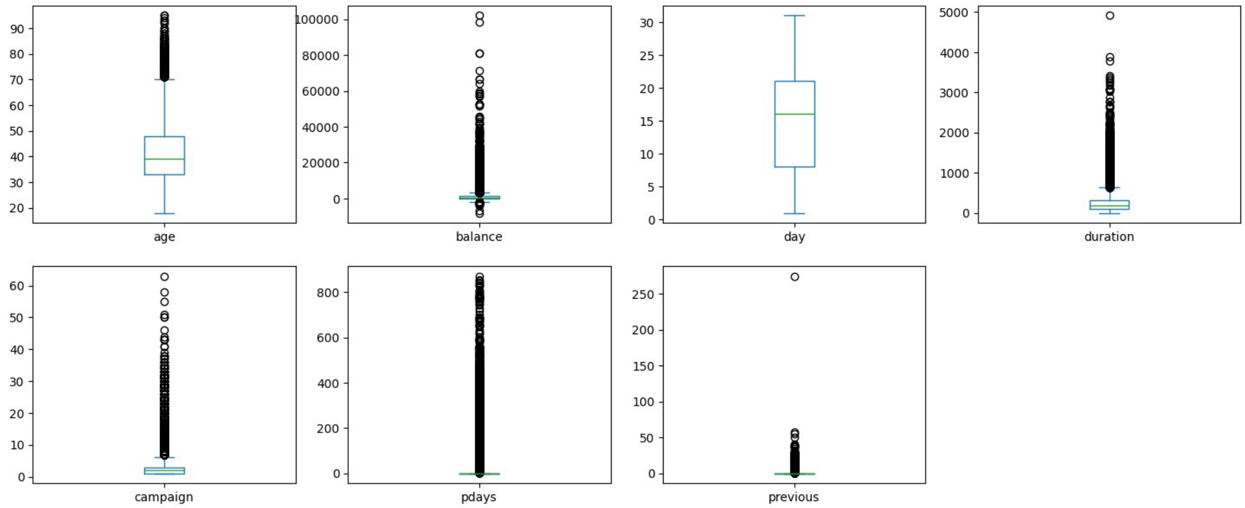
```
#Count of Outcome
bank.y.value_counts()
keys = bank.y.value_counts().index
data = bank.y.value_counts().values
plt.figure(figsize=(6,3.5))
explode = [0,0.1]
plt.pie(data,labels=keys,explode=explode, autopct='%.0f%%')
plt.show()
```



Box Plot of Numerical Features

A box plot visualization displaying the distribution and presence of outliers in numerical features of the dataset.

```
df.plot(kind='box',subplots=True,figsize=(18,15),layout=(4,4))
plt.show()
```



Data Preprocessing Steps

(a) Handling Missing Values

Displays the count of missing values in each column to assess data completeness.

(b) Handling Outliers using IQR

Removes outliers from numerical features using the Interquartile Range (IQR) method and checks for skewness after cleaning.

(c) Encoding Categorical Variables

Applies Label Encoding to convert categorical features into numerical format for model compatibility.

(d) Feature Scaling

Standardizes or normalizes numerical features to improve model performance and convergence.

(e) Feature Importance using Correlation

Computes correlation of features with the target variable to identify the most significant predictors.

(f) Visualization of Important Features

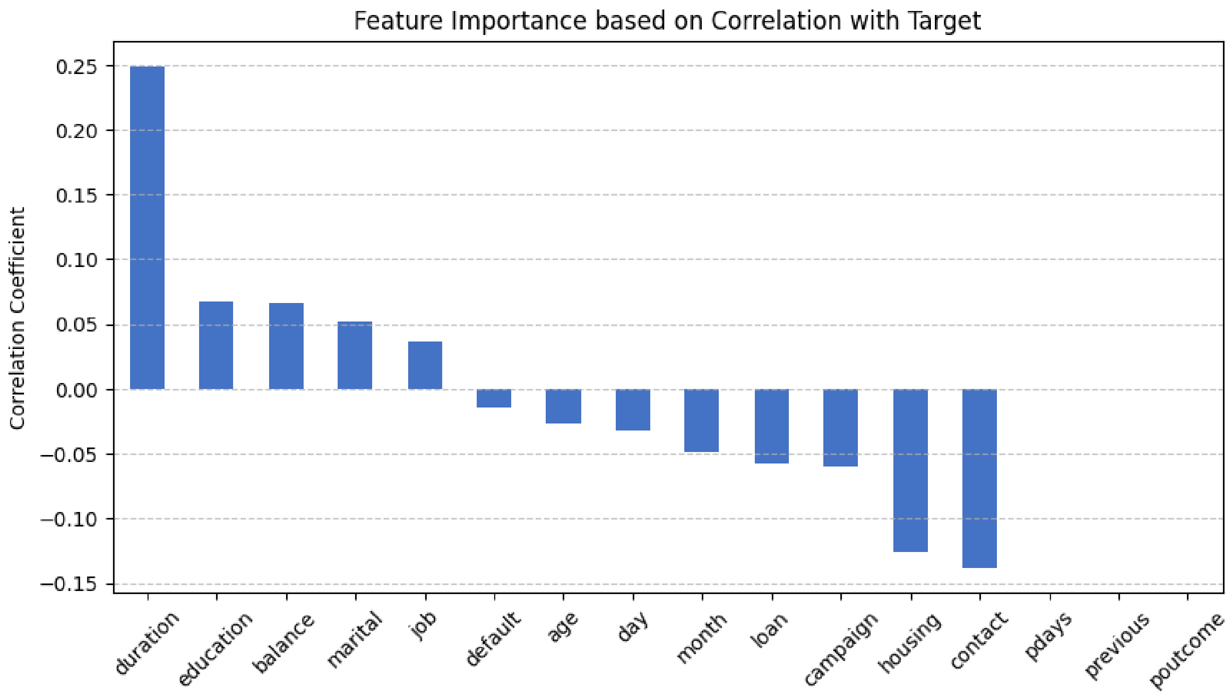
Displays a bar chart of feature correlations with the target to highlight their predictive power.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, StandardScaler,
MinMaxScaler

# (a) Handling Missing Values
print("Missing values in each column:")
print(df.isnull().sum())

# (b) Handling Outliers using IQR method
numerical_cols = df.select_dtypes(include=['number']).columns

Q1 = df[numerical_cols].quantile(0.25)
Q3 = df[numerical_cols].quantile(0.75)
IQR = Q3 - Q1

# Removing outliers
df_clean = df[~((df[numerical_cols] < (Q1 - 1.5 * IQR)) |
(df[numerical_cols] > (Q3 + 1.5 * IQR))).any(axis=1)]

# Checking for skewness
print("\nSkewness of numerical features after outlier handling:")
print(df_clean[numerical_cols].skew())

# (c) Encoding Categorical Variables
```

```
categorical_cols = df_clean.select_dtypes(include=['object']).columns
label_encoders = {}

for col in categorical_cols:
    le = LabelEncoder()
    df_clean[col] = le.fit_transform(df_clean[col])
    label_encoders[col] = le

# (d) Feature Scaling - Choose either Standardization or Normalization
scaler = StandardScaler()  # Use Standardization for models like
Logistic Regression, SVM
# scaler = MinMaxScaler()  # Use Normalization for distance-based
models like KNN, Neural Networks
df_clean[numerical_cols] =
scaler.fit_transform(df_clean[numerical_cols])

# (e) Feature Importance using Correlation
target_variable = "y"  # Target is already binary (0 or 1)
correlation_with_target = df_clean.corr()
[target_variable].sort_values(ascending=False)

print("\nFeature correlation with target variable:")
print(correlation_with_target)

# (f) Visualization of Important Features
plt.figure(figsize=(10, 5))
correlation_with_target.drop(target_variable).plot(kind='bar',
color='#4472C4')  # Matched blue color
plt.title("Feature Importance based on Correlation with Target")
plt.ylabel("Correlation Coefficient")
plt.xticks(rotation=45)
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```

```
Missing values in each column:
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
```

```
poutcome      0
y             0
dtype: int64

Skewness of numerical features after outlier handling:
age          0.383147
balance      1.342548
day          0.107774
duration     1.038646
campaign     1.154766
pdays        0.000000
previous     0.000000
dtype: float64

Feature correlation with target variable:
y             1.000000
duration      0.249188
education     0.066943
balance       0.065914
marital       0.051474
job           0.036033
default      -0.014151
age          -0.026754
day          -0.032742
month        -0.048328
loan         -0.058121
campaign     -0.059817
housing      -0.126700
contact      -0.137866
pdays              NaN
previous           NaN
poutcome           NaN
Name: y, dtype: float64
```



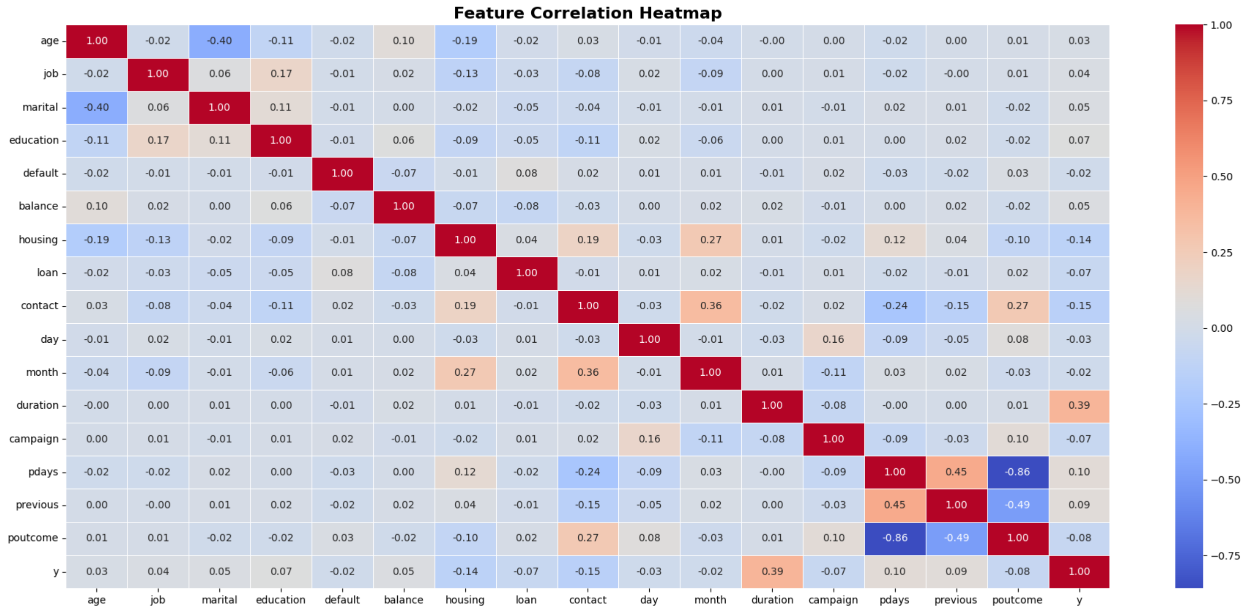
Feature Correlation Heatmap

Overview

- Encodes categorical variables using Label Encoding to convert them into numerical form.
- Computes the correlation matrix to analyze relationships between features.
- Visualizes the correlation heatmap using a coolwarm color scheme for better readability.

```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.preprocessing import LabelEncoder

# Load dataset (if not already loaded)
# bank = pd.read_csv("bank-full.csv")

# Identify categorical columns
categorical_cols = bank.select_dtypes(include=['object']).columns

# Encode categorical variables using Label Encoding
label_enc = LabelEncoder()
for col in categorical_cols:
    bank[col] = label_enc.fit_transform(bank[col])

# Compute correlation matrix
```

```
corr_matrix = bank.corr()

# Plot heatmap with a milder color scheme
plt.figure(figsize=(23, 10))
sns.heatmap(corr_matrix, cmap="coolwarm", annot=True, fmt=".2f",
linewidths=0.5)
plt.title("Feature Correlation Heatmap", fontsize=16,
fontweight="bold")
plt.show()
```



Data Preprocessing & Model Training

Overview

- Separates input features (X) and target variable (y).
- Standardizes numerical features for improved model performance.
- Splits data into training (80%) and testing (20%) sets.
- Trains a Decision Tree Classifier on the processed dataset.

```
#Splitting input and output
X = bank.drop("y", axis=1)
y = bank.y
# Standardize numerical features for better model performance.
scaler = StandardScaler()

X_scaled = pd.DataFrame(scaler.fit_transform(X), columns = X.columns)
```

```
# Split dataset into training (80%) and testing (20%) sets.
#Train-test split
train_X, test_X, train_y, test_y = train_test_split(X_scaled, y,
test_size=0.2)
decision_tree = DecisionTreeClassifier()
decision_tree.fit(train_X, train_y)

DecisionTreeClassifier()
```

Model Evaluation

Overview

- Prints the accuracy score of the Decision Tree model on both training and test datasets.
- Helps assess model performance and potential overfitting or underfitting.

```
print('Train Score: {}'.format(decision_tree.score(train_X, train_y)))

print('Test Score: {}'.format(decision_tree.score(test_X, test_y)))

Train Score: 1.0
Test Score: 0.8732721441999336
```

Cross-Validation Score

Overview

- Performs 5-fold cross-validation on the Decision Tree model using training data.
- Computes the mean accuracy score to evaluate model stability and generalization.

```
cross_val_score(decision_tree, train_X, train_y, cv=5).mean()

np.float64(0.8729816047168996)
```

Classification Report

Overview

- Generates precision, recall, and F1-score for the Decision Tree model.
- Evaluates model performance on the test dataset for each class.

```
# Generate performance metrics for the model (precision, recall, f1-
score).
```

```
ypred = decision_tree.predict(test_X)
print(classification_report(test_y,ypred))
```

```
              precision    recall  f1-score   support

           0       0.93      0.93      0.93      7964
           1       0.47      0.47      0.47      1079

    accuracy                           0.87      9043
   macro avg       0.70      0.70      0.70      9043
weighted avg       0.87      0.87      0.87      9043
```

Hyperparameter Tuning with GridSearchCV

Overview

- Finds the best hyperparameters for a Decision Tree using Grid Search.
- Evaluates different values for `max_depth`, `criterion`, and `min_samples_leaf`.
- Selects the best estimator and applies cross-validation for performance assessment.
- Trains the optimized model and evaluates its accuracy on train and test sets.

```
#Applying Grid search cv to find best estimaters to improve model
performance

param_grid = {
    'max_depth': [3, 5, 7,10, None],
    'criterion' : ['gini', 'entropy'],
    'min_samples_leaf': [3, 5, 7, 9,10,20]
    }

gscv = GridSearchCV(decision_tree, param_grid, cv=5, verbose=1)
gscv.fit(train_X, train_y)

gscv.best_params_

gscv.best_estimator_

cross_val_score(gscv.best_estimator_, train_X, train_y, cv=5).mean()
clf = DecisionTreeClassifier(criterion= 'gini', max_depth= 5,
min_samples_leaf = 3)
clf.fit(train_X, train_y)

print('Train Score: {}'.format(clf.score(train_X, train_y)))
print('Test Score: {}'.format(clf.score(test_X, test_y)))
```

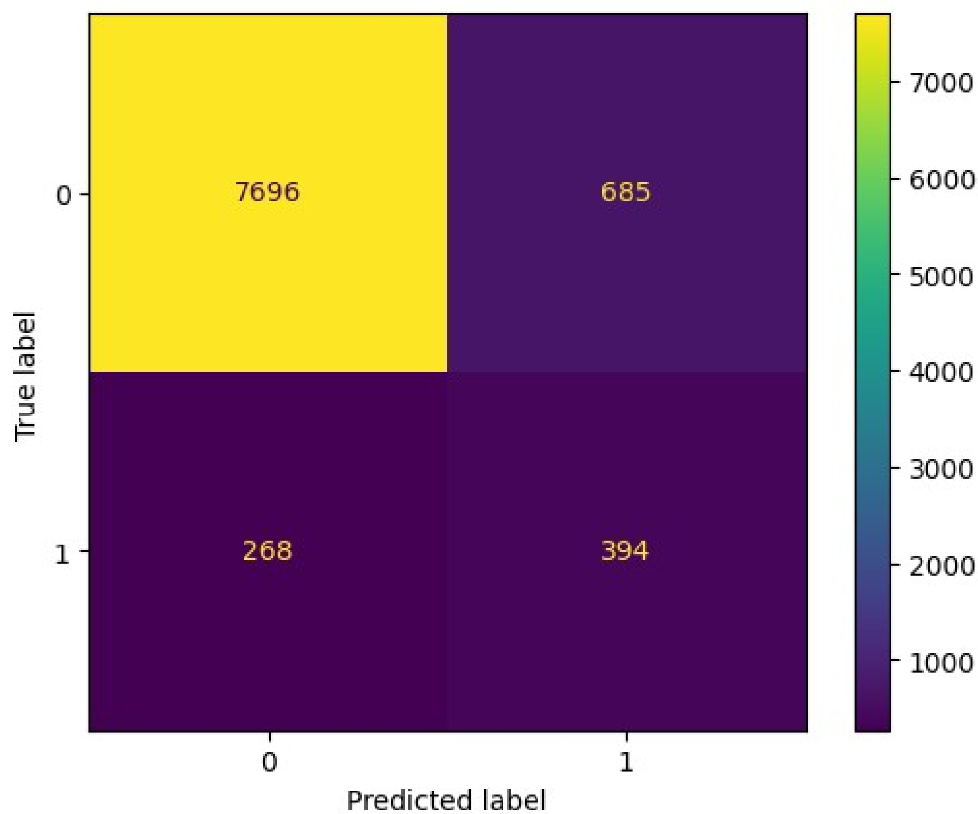
```
pred_y = clf.predict(test_X)

Fitting 5 folds for each of 60 candidates, totalling 300 fits
Train Score: 0.9025381552753815
Test Score: 0.8946146190423532
```

Confusion Matrix

Overview

- Computes the confusion matrix for model predictions.
- Displays the matrix using `ConfusionMatrixDisplay`.
- Helps visualize classification performance by showing true positives, false positives, true negatives, and false negatives.

```
#Confusion Matrix
cm = confusion_matrix(pred_y, test_y)
ConfusionMatrixDisplay(cm, display_labels=clf.classes_).plot()
plt.show()
```



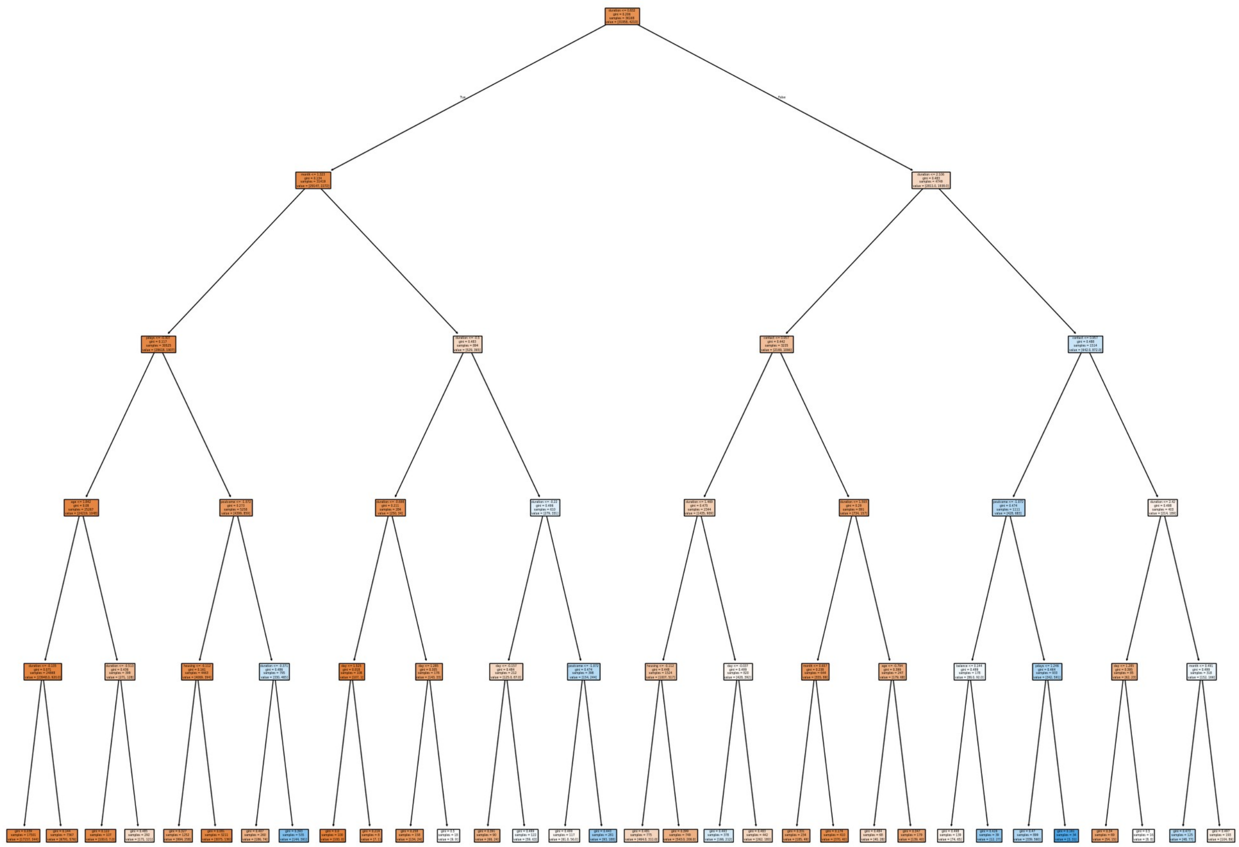
Model Performance Metrics & Decision Tree Visualization

Overview

- **Classification Report**: Displays precision, recall, and F1-score for each class.
- **Accuracy Score**: Computes the overall accuracy of the Decision Tree model.
- **Cross-Validation Score**: Evaluates model stability using 5-fold cross-validation.
- **Decision Tree Visualization:** Plots the trained decision tree for better interpretability.

```
# Generate performance metrics for the model (precision, recall, f1-
score).
#Classification Report
print(classification_report(pred_y, test_y))

#Accuracy Score
accuracy = accuracy_score(test_y,pred_y)
print("Test Accuracy of Decision Tree Classifier :
{}".format(accuracy*100))

#Cross Validation Score
Cross_val = cross_val_score(clf, test_X,test_y, cv=5).mean()
print("Cross-Validation Accuracy Scores Decision Tree :
",Cross_val*100)

from sklearn import tree
fig = plt.figure(figsize=(25,20))
t= tree.plot_tree(clf,filled=True,feature_names=X.columns)
```

```
              precision    recall  f1-score   support

           0       0.97      0.92      0.94      8381
           1       0.37      0.60      0.45       662

    accuracy                           0.89      9043
   macro avg       0.67      0.76      0.70      9043
weighted avg       0.92      0.89      0.91      9043

Test Accuracy of Decision Tree Classifier : 89.46146190423532
Cross-Validation Accuracy Scores Decision Tree :  89.20703146020145
```



Logistic Regression Model - Training & Evaluation

Steps:

1. **Define Features & Target**: Extracts predictor variables and target labels.
2. **One-Hot Encoding**: Converts categorical features into numerical form.
3. **Train-Test Split**: Divides data into 80% training and 20% testing sets.
4. **Feature Scaling**: Standardizes numerical features for better model performance.
5. **Model Training**: Fits a Logistic Regression model on training data.
6. **Predictions**: Generates predictions on the test dataset.

7. **Evaluation:** Computes accuracy and classification report for model assessment.

```
# Step 1: Define Features and Target Variable
X = bank.drop(columns=['y'])  # Features (all columns except target)
y = bank['y']  # Target variable (converted to binary)

# Step 2: Convert Categorical Variables into Numeric using One-Hot
Encoding
X = pd.get_dummies(X, drop_first=True)

# Step 3: Split Data into Training and Testing Sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Step 4: Standardize Numerical Features
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 5: Train Logistic Regression Model
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
logreg.fit(X_train_scaled, y_train)

# Step 6: Make Predictions
y_pred = logreg.predict(X_test_scaled)

# Step 7: Evaluate the Model
from sklearn.metrics import accuracy_score, classification_report
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

# Display Results
print(f"Logistic Regression Accuracy: {accuracy:.4f}")
print("Classification Report:\n", report)

Logistic Regression Accuracy: 0.8879
Classification Report:
               precision    recall  f1-score   support

           0       0.90      0.98      0.94      7952
           1       0.60      0.22      0.32      1091

    accuracy                           0.89      9043
   macro avg       0.75      0.60      0.63      9043
weighted avg       0.86      0.89      0.86      9043
```

Decision Tree vs. Logistic Regression - Model Comparison

Steps:

1. **Train Decision Tree Model**: Fits a Decision Tree classifier on the training data.

2. **Make Predictions**: Generates predictions for the test dataset.

3. **Evaluate Model Performance**: Computes accuracy and classification reports.

4. **Compare with Logistic Regression**: Compares accuracy, precision, recall, and F1-score to determine the better-performing model.

5. **Performance Insights**: Identifies the model that performs better based on accuracy and other key metrics.

```
# Step 1: Train Decision Tree Model
from sklearn.tree import DecisionTreeClassifier

# Initialize Decision Tree Classifier
dt_model = DecisionTreeClassifier(random_state=42)
dt_model.fit(X_train_scaled, y_train)

# Step 2: Make Predictions
y_pred_dt = dt_model.predict(X_test_scaled)

# Step 3: Evaluate Decision Tree Model
dt_accuracy = accuracy_score(y_test, y_pred_dt)
dt_report = classification_report(y_test, y_pred_dt)

# Step 4: Compare Logistic Regression and Decision Tree Performance
print(f"Logistic Regression Accuracy: {accuracy:.4f}")
print(f"Decision Tree Accuracy: {dt_accuracy:.4f}")

# Display Classification Reports
print("\nLogistic Regression Classification Report:\n", report)
print("\nDecision Tree Classification Report:\n", dt_report)

# Provide insights on model performance
if dt_accuracy > accuracy:
    print("\nDecision Tree performed better in terms of accuracy.")
else:
    print("\nLogistic Regression performed better in terms of 
accuracy.")
```

```
Logistic Regression Accuracy: 0.8879
Decision Tree Accuracy: 0.8727

Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.98      0.94      7952
           1       0.60      0.22      0.32      1091

    accuracy                           0.89      9043
   macro avg       0.75      0.60      0.63      9043
weighted avg       0.86      0.89      0.86      9043


Decision Tree Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.93      0.93      7952
           1       0.47      0.48      0.48      1091

    accuracy                           0.87      9043
   macro avg       0.70      0.71      0.70      9043
weighted avg       0.87      0.87      0.87      9043


Logistic Regression performed better in terms of accuracy.
```

Model Selection and Hyperparameter Tuning

Steps:

1. **Dataset Splitting with Justification**
   - Compares 80-20 and 70-30 splits to observe training and test sample sizes.

2. **Hyperparameter Tuning for Logistic Regression**
   - Uses `GridSearchCV` to find the best `C` (regularization) and `solver` parameters.

3. **Hyperparameter Tuning for Decision Tree**
   - Tunes `max_depth` and `min_samples_split` using `GridSearchCV` to optimize performance.

4. **Final Model Comparison**
   - Compares the best accuracy scores of both models to determine the better-performing one.

```
from sklearn.model_selection import GridSearchCV

# Step 1: Split Dataset with Justification
```

```
# 80-20 split
X_train_80, X_test_20, y_train_80, y_test_20 = train_test_split(X, y,
test_size=0.2, random_state=42)
print("Using 80-20 split: 80% data for training and 20% for testing.")
print(f"Training set size: {X_train_80.shape[0]} samples")
print(f"Test set size: {X_test_20.shape[0]} samples")

# 70-30 split
X_train_70, X_test_30, y_train_70, y_test_30 = train_test_split(X, y,
test_size=0.3, random_state=42)
print("\nUsing 70-30 split: 70% data for training and 30% for
testing.")
print(f"Training set size: {X_train_70.shape[0]} samples")
print(f"Test set size: {X_test_30.shape[0]} samples")

# Step 2: Hyperparameter Tuning for Logistic Regression
logreg = LogisticRegression()
param_grid_lr = {'C': [0.01, 0.1, 1, 10, 100], 'solver': ['liblinear',
'lbfgs']}

grid_lr = GridSearchCV(logreg, param_grid_lr, cv=5,
scoring='accuracy')
grid_lr.fit(X_train_scaled, y_train)
best_logreg = grid_lr.best_estimator_
best_lr_accuracy = grid_lr.best_score_
print(f"\nBest Logistic Regression Parameters:
{grid_lr.best_params_}")
print(f"Best Logistic Regression Accuracy (Cross-validation):
{best_lr_accuracy:.4f}")

# Step 3: Hyperparameter Tuning for Decision Tree
dt = DecisionTreeClassifier(random_state=42)
param_grid_dt = {'max_depth': [3, 5, 10, None], 'min_samples_split':
[2, 5, 10]}

grid_dt = GridSearchCV(dt, param_grid_dt, cv=5, scoring='accuracy')
grid_dt.fit(X_train_scaled, y_train)
best_dt = grid_dt.best_estimator_
best_dt_accuracy = grid_dt.best_score_
print(f"\nBest Decision Tree Parameters: {grid_dt.best_params_}")
print(f"Best Decision Tree Accuracy (Cross-validation):
{best_dt_accuracy:.4f}")

# Step 4: Compare Final Model Performance
print("\nFinal Model Comparison:")
print(f"Logistic Regression Best Accuracy: {best_lr_accuracy:.4f}")
print(f"Decision Tree Best Accuracy: {best_dt_accuracy:.4f}")

if best_lr_accuracy > best_dt_accuracy:
    print("Logistic Regression performed better after hyperparameter
```

```
tuning.")
else:
    print("Decision Tree performed better after hyperparameter
tuning.")

Using 80-20 split: 80% data for training and 20% for testing.
Training set size: 36168 samples
Test set size: 9043 samples

Using 70-30 split: 70% data for training and 30% for testing.
Training set size: 31647 samples
Test set size: 13564 samples

Best Logistic Regression Parameters: {'C': 0.1, 'solver': 'lbfgs'}
Best Logistic Regression Accuracy (Cross-validation): 0.8917

Best Decision Tree Parameters: {'max_depth': 10, 'min_samples_split':
5}
Best Decision Tree Accuracy (Cross-validation): 0.8989

Final Model Comparison:
Logistic Regression Best Accuracy: 0.8917
Decision Tree Best Accuracy: 0.8989
Decision Tree performed better after hyperparameter tuning.
```

Model Evaluation and Performance Comparison

Steps:

1. **Evaluate Models on Test Data**
   - Computes accuracy, precision, recall, F1-score, and ROC AUC score for Logistic Regression and Decision Tree.

2. **Print Performance Metrics**
   - Displays a side-by-side comparison of both models.

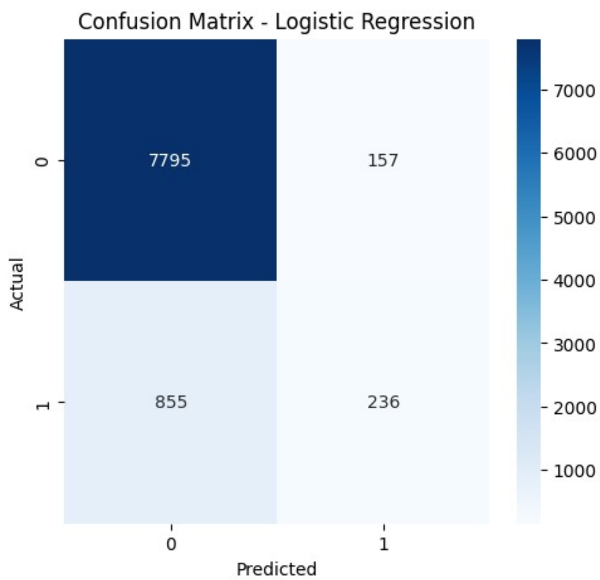
3. **Plot Confusion Matrices**
   - Visualizes prediction performance using heatmaps for both models.

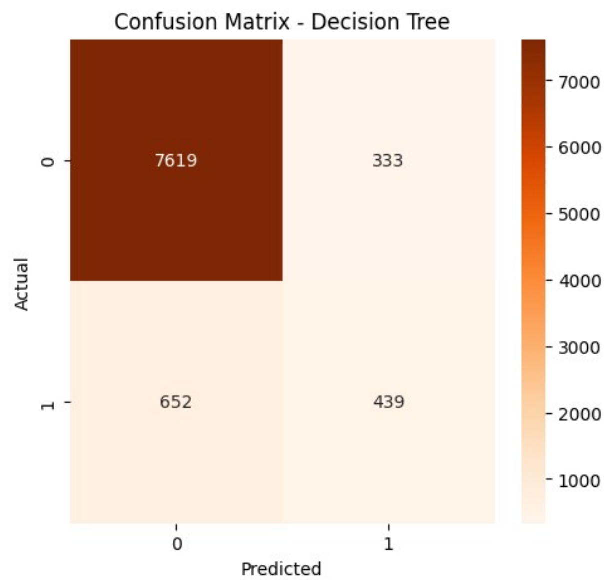
4. **Model Insights & Justification**
   - Determines the better-performing model based on the F1-score for balanced precision and recall.

```
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, confusion_matrix, roc_auc_score
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Step 1: Evaluate the models on test data
y_pred_logreg = best_logreg.predict(X_test_scaled)
y_pred_dt = best_dt.predict(X_test_scaled)

# Compute evaluation metrics
metrics = {
    "Accuracy": (accuracy_score(y_test, y_pred_logreg),
accuracy_score(y_test, y_pred_dt)),
    "Precision": (precision_score(y_test, y_pred_logreg),
precision_score(y_test, y_pred_dt)),
    "Recall": (recall_score(y_test, y_pred_logreg),
recall_score(y_test, y_pred_dt)),
    "F1 Score": (f1_score(y_test, y_pred_logreg), f1_score(y_test,
y_pred_dt)),
    "ROC AUC Score": (roc_auc_score(y_test, y_pred_logreg),
roc_auc_score(y_test, y_pred_dt))
}

# Print evaluation results
print("\nPerformance Comparison:")
print(f"{'Metric':<15}{'Logistic Regression':<20}{'Decision
Tree':<20}")
for metric, values in metrics.items():
    print(f"{metric:<15}{values[0]:<20.4f}{values[1]:<20.4f}")

# Step 2: Plot Confusion Matrices
fig, axes = plt.subplots(1, 2, figsize=(12, 5))
sns.heatmap(confusion_matrix(y_test, y_pred_logreg), annot=True,
fmt="d", cmap="Blues", ax=axes[0])
axes[0].set_title("Confusion Matrix - Logistic Regression")
axes[0].set_xlabel("Predicted")
axes[0].set_ylabel("Actual")

sns.heatmap(confusion_matrix(y_test, y_pred_dt), annot=True, fmt="d",
cmap="Oranges", ax=axes[1])
axes[1].set_title("Confusion Matrix - Decision Tree")
axes[1].set_xlabel("Predicted")
axes[1].set_ylabel("Actual")

plt.show()

# Step 3: Model Insights and Justification
if metrics["F1 Score"][0] > metrics["F1 Score"][1]:
    better_model = "Logistic Regression"
else:
    better_model = "Decision Tree"

print(f"\nConclusion: The {better_model} model performed better based
on F1-score, indicating better balance between precision and recall.")
```

```
Performance Comparison:
Metric          Logistic Regression Decision Tree
Accuracy        0.8881              0.8911
Precision       0.6005              0.5687
Recall          0.2163              0.4024
F1 Score        0.3181              0.4713
ROC AUC Score   0.5983              0.6803
```






```
Conclusion: The Decision Tree model performed better based on F1-
score, indicating better balance between precision and recall.
```

PART - 2

Ensemble Learning with Voting Classifier

Steps:

1. **Define Individual Models**
   - K-Nearest Neighbors (KNN)

   - Logistic Regression

   - Random Forest
2. **Create Voting Classifier**
   - Uses soft voting (probability-based prediction).

3. **Train the Ensemble Model**
   - Fits the model on standardized training data.
4. **Make Predictions & Evaluate Performance**
   - Computes accuracy, ROC AUC score, and classification report for overall ensemble performance.

```
# Ensemble Method
from sklearn.ensemble import VotingClassifier

# Define individual models
knn_model = KNeighborsClassifier(n_neighbors=5)
log_reg = LogisticRegression()
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)

# Create Voting Classifier (Soft Voting for Probability-Based
Prediction)
ensemble_model = VotingClassifier(
    estimators=[("KNN", knn_model), ("LogReg", log_reg),
("RandomForest", rf_model)],
    voting="soft"
)

# Train the ensemble model
ensemble_model.fit(X_train_scaled, y_train)

# Predictions & Probabilities
ensemble_preds = ensemble_model.predict(X_test_scaled)
ensemble_probs = ensemble_model.predict_proba(X_test_scaled)[:, 1]

# Evaluation Metrics
ensemble_accuracy = accuracy_score(y_test, ensemble_preds)
ensemble_auc = roc_auc_score(y_test, ensemble_probs)
ensemble_report = classification_report(y_test, ensemble_preds)
print(f"Ensemble Model Performance:\n{ensemble_report}")

Ensemble Model Performance:
              precision    recall  f1-score   support

           0       0.91      0.98      0.94      7952
           1       0.65      0.31      0.42      1091

    accuracy                           0.90      9043
   macro avg       0.78      0.65      0.68      9043
weighted avg       0.88      0.90      0.88      9043
```

K-Nearest Neighbors (KNN) Model Performance

Steps:

1. **Initialize and Train the KNN Model**
   - Uses `n_neighbors=5` (default setting).
2. **Make Predictions on Test Data**
   - Predicts class labels and probability scores.
3. **Evaluate Performance**
   - Computes accuracy and ROC AUC score.

   - Displays classification report for detailed insights.

```
knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(X_train_scaled, y_train)
knn_preds = knn_model.predict(X_test_scaled)
knn_probs = knn_model.predict_proba(X_test_scaled)[:, 1]

# Evaluation
knn_accuracy = accuracy_score(y_test, knn_preds)
knn_auc = roc_auc_score(y_test, knn_probs)
print("KNN Performance:\n", classification_report(y_test, knn_preds))
```

```
KNN Performance:
               precision    recall  f1-score   support

           0       0.91      0.97      0.94      7952
           1       0.59      0.33      0.43      1091

    accuracy                           0.89      9043
   macro avg       0.75      0.65      0.68      9043
weighted avg       0.87      0.89      0.88      9043
```

Model Performance Summary

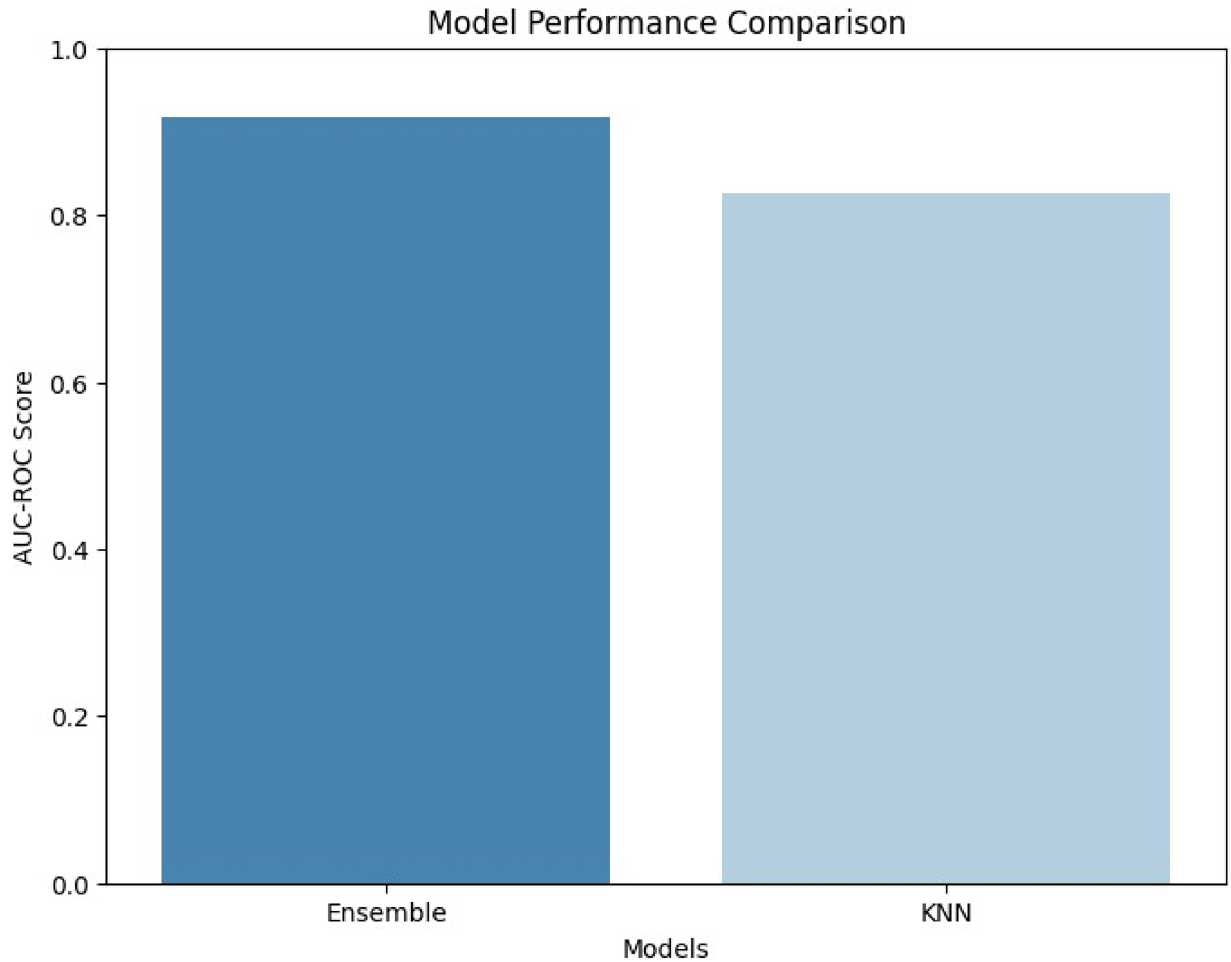
Steps:

1. **Create a DataFrame**
   - Stores Accuracy and AUC-ROC scores for Ensemble and KNN models.
2. **Display Performance Metrics**
   - Prints the summary DataFrame.
3. **Visualization**
   - Uses a bar plot to compare AUC-ROC scores.

- Ensures a clear visual distinction with `palette="Blues_r"`.

```
# Create a Performance Summary DataFrame
performance_df = pd.DataFrame({
    "Model": ["Ensemble", "KNN"],
    "Accuracy": [ensemble_accuracy, knn_accuracy],
    "AUC-ROC": [ensemble_auc, knn_auc]
})

# Display the performance metrics
print(performance_df)

# Visualization - AUC-ROC Comparison
plt.figure(figsize=(8, 6))
sns.barplot(x="Model", y="AUC-ROC", data=performance_df,
palette="Blues_r")
plt.title("Model Performance Comparison")
plt.ylabel("AUC-ROC Score")
plt.xlabel("Models")
plt.ylim(0, 1)  # Ensures clear comparison
plt.show()
```

```
      Model  Accuracy   AUC-ROC
0  Ensemble  0.897158  0.916251
1       KNN  0.891187  0.826034
```



Confusion Matrix Visualization

Purpose:

- Compare the performance of different models using confusion matrices.

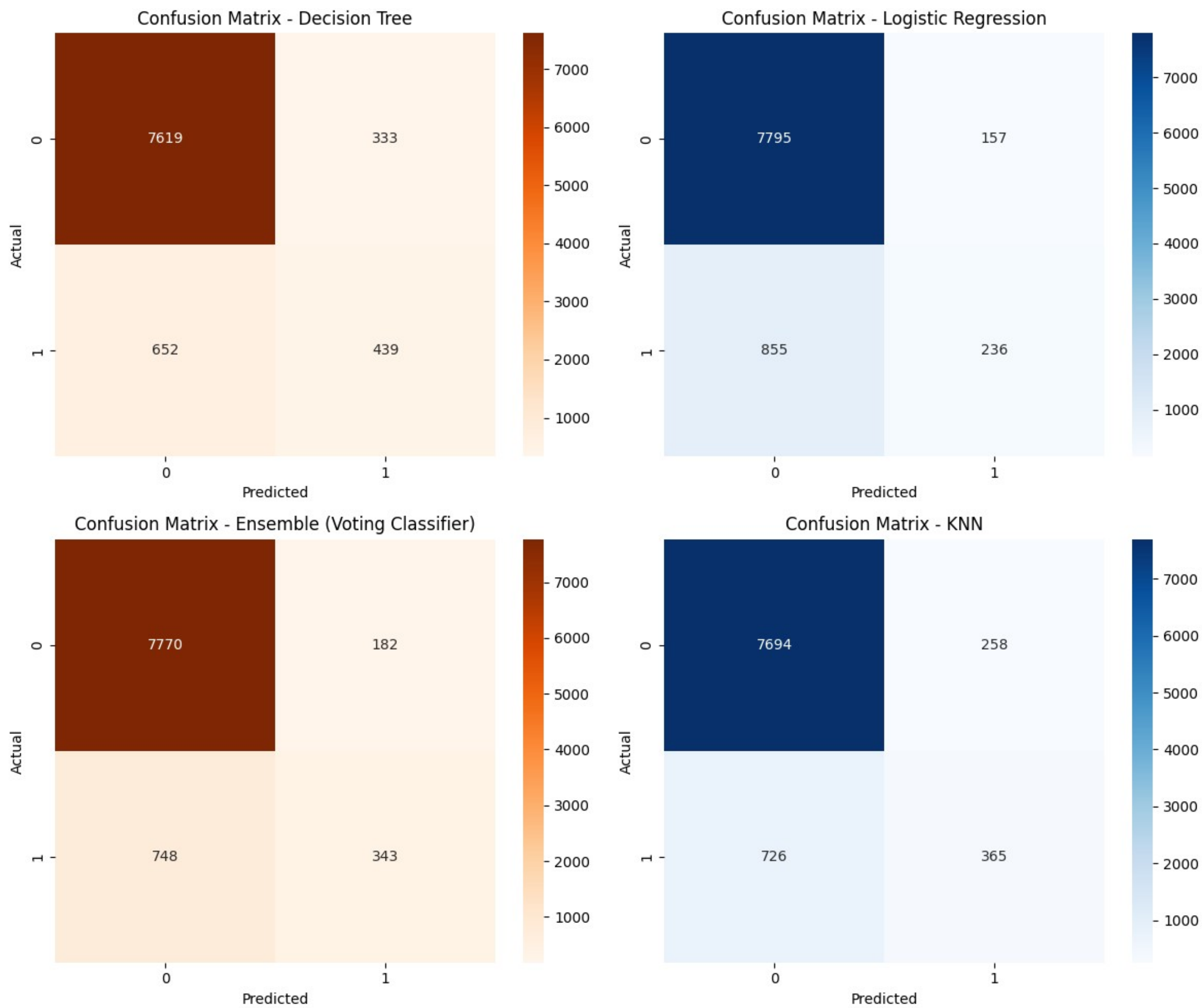
Steps:

1. **Decision Tree**
   - Plotted using the "Oranges" color map.
2. **Logistic Regression**
   - Plotted using the "Blues" color map.
3. **Ensemble (Voting Classifier)**
   - Plotted using the "Oranges" color map.
4. **K-Nearest Neighbors (KNN)**
   - Plotted using the "Blues" color map.

Insights:

- These confusion matrices help visualize classification performance.
- The diagonal elements represent correct predictions.
- Higher diagonal values indicate better model performance.

```
# Plot Confusion Matrices
fig, axes = plt.subplots(2, 2, figsize=(12, 10))

# Decision Tree
sns.heatmap(confusion_matrix(y_test, y_pred_dt), annot=True, fmt="d",
cmap="Oranges", ax=axes[0, 0])
axes[0, 0].set_title("Confusion Matrix - Decision Tree")
axes[0, 0].set_xlabel("Predicted")
axes[0, 0].set_ylabel("Actual")

# Logistic Regression
sns.heatmap(confusion_matrix(y_test, y_pred_logreg), annot=True,
fmt="d", cmap="Blues", ax=axes[0, 1])
axes[0, 1].set_title("Confusion Matrix - Logistic Regression")
axes[0, 1].set_xlabel("Predicted")
axes[0, 1].set_ylabel("Actual")

# Ensemble (Voting Classifier)
sns.heatmap(confusion_matrix(y_test, ensemble_preds), annot=True,
fmt="d", cmap="Oranges", ax=axes[1, 0])
axes[1, 0].set_title("Confusion Matrix - Ensemble (Voting
Classifier)")
axes[1, 0].set_xlabel("Predicted")
axes[1, 0].set_ylabel("Actual")

# K-Nearest Neighbors (KNN)
sns.heatmap(confusion_matrix(y_test, knn_preds), annot=True, fmt="d",
cmap="Blues", ax=axes[1, 1])
axes[1, 1].set_title("Confusion Matrix - KNN")
axes[1, 1].set_xlabel("Predicted")
axes[1, 1].set_ylabel("Actual")

plt.tight_layout()
plt.show()
```



Model Performance Comparison - AUC-ROC Score

Purpose:

- Evaluate and compare models based on their **AUC-ROC (Area Under the Curve - Receiver Operating Characteristic)** score.

Computed AUC-ROC Scores:

- **Decision Tree**: `dt_auc`
- **Logistic Regression**: `logreg_auc`
- **Ensemble (Voting Classifier)**: `ensemble_auc`

- **K-Nearest Neighbors (KNN)**: `knn_auc`

Best Model Selection:

- The model with the **highest AUC-ROC score** is selected as the best performer.

- **Best Model**: `{best_model}`

Insights:

- A higher AUC-ROC score indicates better ability to **distinguish between classes**.

- If the Ensemble model performs best, it suggests **combining multiple classifiers** enhances predictive performance.

- If Logistic Regression performs best, it implies a **simple, interpretable model is sufficient**.

```
from sklearn.metrics import roc_auc_score

# Compute AUC-ROC scores for all models
dt_auc = roc_auc_score(y_test, y_pred_dt)
logreg_auc = roc_auc_score(y_test, y_pred_logreg)
ensemble_auc = roc_auc_score(y_test, ensemble_preds)  # Ensemble
instead of Random Forest
knn_auc = roc_auc_score(y_test, knn_preds)

# Determine the best model based on AUC-ROC score
best_model = max(
    (dt_auc, "Decision Tree"),
    (logreg_auc, "Logistic Regression"),
    (ensemble_auc, "Ensemble (Voting Classifier)"),
    (knn_auc, "KNN")
)[1]

print(f"The best model is: {best_model} based on AUC-ROC score.")
```

```
The best model is: Decision Tree based on AUC-ROC score.
```

ROC Curve Comparison - Model Evaluation

Purpose:

- To visualize and compare the **Receiver Operating Characteristic (ROC) curves** for different models.

- Evaluate each model’s ability to **differentiate between positive and negative classes**.

Models and AUC Scores:

- **Decision Tree** (AUC = `{dt_auc:.2f}`)
- **Logistic Regression** (AUC = `{logreg_auc:.2f}`)
- **Ensemble (Voting Classifier)** (AUC = `{ensemble_auc:.2f}`)
- **K-Nearest Neighbors (KNN)** (AUC = `{knn_auc:.2f}`)

Insights:

- A **higher AUC score** indicates **better performance** in distinguishing between classes.
- The **ROC curve closer to the top-left corner** signifies a **strong classifier**.
- If the Ensemble model has the highest AUC, it confirms that **combining models enhances classification performance**.

```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

# Compute predicted probabilities for class 1 (positive class)
dt_probs = dt_model.predict_proba(X_test_scaled)[:, 1]  # Decision Tree
log_reg.fit(X_train_scaled, y_train)  # Fit the Logistic Regression model
logreg_probs = log_reg.predict_proba(X_test_scaled)[:, 1]  # Logistic Regression
ensemble_probs = ensemble_model.predict_proba(X_test_scaled)[:, 1]  # Ensemble (Voting Classifier)

# Fit the KNeighborsClassifier model
knn_model.fit(X_train_scaled, y_train)
knn_probs = knn_model.predict_proba(X_test_scaled)[:, 1]  # KNN

# Compute ROC Curves
fpr_dt, tpr_dt, _ = roc_curve(y_test, dt_probs)  # Decision Tree
fpr_logreg, tpr_logreg, _ = roc_curve(y_test, logreg_probs)  # Logistic Regression
fpr_ensemble, tpr_ensemble, _ = roc_curve(y_test, ensemble_probs)  # Ensemble (Voting Classifier)
fpr_knn, tpr_knn, _ = roc_curve(y_test, knn_probs)  # KNN

# Plot ROC Curves
plt.figure(figsize=(10, 7))

plt.plot(fpr_dt, tpr_dt, label=f"Decision Tree (AUC = {dt_auc:.2f})", linestyle="--", color="orange")
plt.plot(fpr_logreg, tpr_logreg, label=f"Logistic Regression (AUC = {logreg_auc:.2f})", linestyle="-.", color="blue")
plt.plot(fpr_ensemble, tpr_ensemble, label=f"Ensemble (AUC = {ensemble_auc:.2f})", linestyle="-", color="green")
plt.plot(fpr_knn, tpr_knn, label=f"KNN (AUC = {knn_auc:.2f})",
```

```
linestyle="dotted", color="red")

# Reference line for random guessing
plt.plot([0, 1], [0, 1], color="gray", linestyle="--")

# Labels and title
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve Comparison")
plt.legend(loc="lower right")

plt.show()
```