Analyzing a UK Bank Campaign for Fixed-Term Saving Accounts

Introduction

This report focuses on analyzing and predicting customer responses to a UK bank's fixed term saving account campaign. The dataset used in the analysis has been preprocessed to explore various aspects of customer demographics, engagement behaviors, and campaign effectiveness. The primary aim was to gain actionable insights and build predictive models that could optimize future campaign strategies.

In order to achieve the objective, data preprocessing and exploratory data analysis (EDA) was conducted. This was followed by development of classification models such as Logistic Regression, Decision Trees, and K-Nearest Neighbors (KNN). Results of these models and evaluations of their predictive performance based on appropriate metrics and visualizations have been discussed in this report. I have also added definitions of 'predictive performance' to support individuals unaware of terminology within the report. The findings of the report can be used to inform strategic decision making and enhance the effectiveness of future marketing efforts.

The analysis is based on two datasets:

1. **Campaign Information Dataset (all_campaign.csv)**: This dataset includes information about the bank's efforts to contact customers and the responses to the campaign.
2. **Personal Characteristics Dataset (all_personal.csv)**: This dataset contains demographic and financial information about the customers.

Objectives

The primary goal is to assess the campaign's effectiveness and predict customer responses using machine learning techniques. The analysis is structured into two key tasks:

1. Data Pre-processing and Exploratory Data Analysis (EDA)

- **Data Pre-processing**: This involves ensuring the data is clean and ready for analysis. Tasks include:
    - Handling missing or inconsistent values.
    - Merging the two datasets using the custID column as the common key.

    - Transforming or encoding categorical variables if necessary.

- **EDA**: Analyze the data to gain insights into:
    - Customer demographics and financial attributes.
    - Campaign performance, such as response rates across different segments.

2. Building Response Models

Using the pre-processed dataset, develop and compare three classification models to predict whether a customer will respond positively to the campaign:

- **Logistic Regression**: A linear model that predicts probabilities based on independent variables.
- **Decision Tree**: A non-linear model that splits the dataset into segments based on feature importance.
- **k-Nearest Neighbors (kNN)**: A distance-based method that predicts the response based on the closest data points.

The effectiveness of these models will be evaluated using:

- Metrics such as accuracy, precision, recall, and F1-score.
- The **ROC curve** (Receiver Operating Characteristic curve) to compare the models' ability to distinguish between positive and negative responses.

Data Preprocessing

[Appendix A] initializes the necessary tools for data processing, visualization, and machine learning. Libraries like Pandas help manage and manipulate data, while Matplotlib and Seaborn provide visual insights into trends and distributions. Scikit-Learn enables data splitting, preprocessing, model creation, and performance evaluation, making it the backbone for predictive analysis and campaign evaluation in the project.

1. Loading and Exploring Datasets

[Appendix B] loads the two datasets, all_campaign.csv and all_personal.csv, into Pandas DataFrames and displays their first few rows. This step provides an initial overview of the data structure, including column names and sample values, enabling a quick understanding of the information available in each dataset. It serves as a foundation for identifying potential issues like missing values or mismatched formats for further processing.

First 5 rows of Campaign Data:

	custID	contact	duration	response
0	C00002	unknown	151	no
1	C00004	unknown	92	no
2	C00005	unknown	198	no
3	C00006	unknown	139	no
4	C00007	unknown	217	no

First 5 rows of Personal Data:

	custID	age	region	job	marital	education	default	balance	housing	loan
0	C00002	44	London	technician	single	secondary	no	34	yes	no
1	C00004	47	London	others	married	NaN	no	1751	yes	no
2	C00005	33	South East	others	single	NaN	no	1	no	no
3	C00006	35	London	management	married	tertiary	no	269	yes	no
4	C00007	28	Yorkshire and the Humber	management	single	tertiary	no	520	yes	yes

2. **Inspecting Dataset Structure**

[Appendix C] inspects the structure of the datasets by displaying information about each column, including data types, non-null counts, and memory usage. It helps identify issues such as missing values or incorrect data types that may need correction during preprocessing. This step is critical for understanding the data's quality and preparing it for analysis.

```
Campaign Data:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 33909 entries, 0 to 33908
Data columns (total 4 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   custID    33909 non-null  object
 1   contact   33909 non-null  object
 2   duration  33909 non-null  int64
 3   response  33909 non-null  object
dtypes: int64(1), object(3)
memory usage: 1.0+ MB
```

```
Personal Data:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 33909 entries, 0 to 33908
Data columns (total 10 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   custID     33909 non-null  object
 1   age        33909 non-null  int64 
 2   region     33909 non-null  object
 3   job        33909 non-null  object
 4   marital    33909 non-null  object
 5   education  32518 non-null  object
 6   default    33909 non-null  object
 7   balance    33909 non-null  int64 
 8   housing    33909 non-null  object
 9   loan       33909 non-null  object
dtypes: int64(2), object(8)
memory usage: 2.6+ MB
```

3. Checking and handling for Missing Values

[Appendix D] identifies missing values in both datasets. The output shows that the education column in the personal_data dataset has 1,391 missing values, while all other columns in both datasets are complete. This insight highlights the need to handle the missing education values through techniques like imputation or removal during data preprocessing to ensure the dataset is suitable for analysis and modeling.

```
Missing values in Campaign Data:
custID      0
contact     0
duration    0
response    0
dtype: int64

Missing values in Personal Data:
custID          0
age             0
region          0
job             0
marital         0
education    1391
default         0
balance         0
housing         0
loan            0
dtype: int64
```

[Appendix E] addresses the missing values in the education column of the personal_data dataset by filling them with the label 'unknown'. This approach preserves all rows of the dataset while ensuring consistency in the education column, which is essential for maintaining data integrity during analysis and modeling.

4. Checking for Duplicate Rows

[Appendix F] checks for duplicate rows in both datasets to ensure data quality. The output shows that neither the campaign_data nor the personal_data contains duplicate rows. This indicates that no further action is needed to address redundancy, allowing the analysis to proceed smoothly.

```
Duplicate rows in Campaign Data: 0
Duplicate rows in Personal Data: 0
```

5. Merging Datasets

[Appendix G] merges the campaign_data and personal_data datasets on the common column custID using an inner join. The result combines campaign information with personal characteristics for customers available in both datasets. The merged dataset provides a unified view of the data, enabling deeper analysis of customer responses and characteristics.

First 5 rows of Merged Data:

	custID	contact	duration	response	age	region	job	marital	education	default	balance	housing	loan
0	C00002	unknown	151	no	44	London	technician	single	secondary	no	34	yes	no
1	C00004	unknown	92	no	47	London	others	married	unknown	no	1751	yes	no
2	C00005	unknown	198	no	33	South East	others	single	unknown	no	1	no	no
3	C00006	unknown	139	no	35	London	management	married	tertiary	no	269	yes	no
4	C00007	unknown	217	no	28	Yorkshire and the Humber	management	single	tertiary	no	520	yes	yes

---

Exploratory Data Analysis (EDA)

1. Summary Statistics of Merged Data

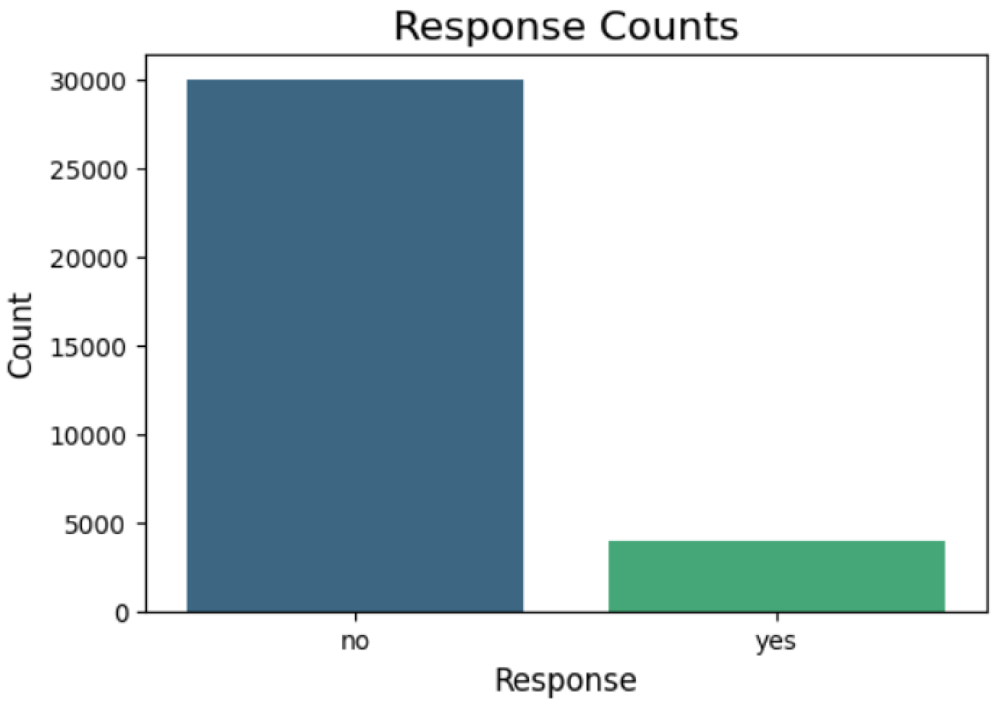
The summary statistics provide an overview of the merged dataset, including counts, unique values, frequencies, and basic statistical measures like mean, standard deviation, and range for numeric columns in [Appendix H]. Key observations include a wide range of duration values (from 0 to 4918 seconds), customer ages spanning 18 to 95 years, and a high concentration of response values as "no." This summary highlights variations in customer characteristics and campaign interactions, offering insights for deeper analysis.

Summary Statistics:

	custID	contact	duration	response	age	region	job	marital	education	default	balance	housing	loan
count	33909	33909	33909.000000	33909	33909.000000	33909	33909	33909	33909	33909	33909.000000	33909	33909
unique	33909	3	NaN	2	NaN	10	11	3	4	2	NaN	2	2
top	C00002	virtual assistant	NaN	no	NaN	South East	others	married	secondary	no	NaN	yes	no
freq	1	22044	NaN	29942	NaN	9092	7520	20464	17431	33313	NaN	18911	28458
mean	NaN	NaN	257.605356	NaN	40.970362	NaN	NaN	NaN	NaN	NaN	1569.568286	NaN	NaN
std	NaN	NaN	256.434874	NaN	10.628341	NaN	NaN	NaN	NaN	NaN	3420.725486	NaN	NaN
min	NaN	NaN	0.000000	NaN	18.000000	NaN	NaN	NaN	NaN	NaN	-7962.000000	NaN	NaN
25%	NaN	NaN	103.000000	NaN	33.000000	NaN	NaN	NaN	NaN	NaN	83.000000	NaN	NaN
50%	NaN	NaN	180.000000	NaN	39.000000	NaN	NaN	NaN	NaN	NaN	520.000000	NaN	NaN
75%	NaN	NaN	318.000000	NaN	48.000000	NaN	NaN	NaN	NaN	NaN	1655.000000	NaN	NaN
max	NaN	NaN	4918.000000	NaN	95.000000	NaN	NaN	NaN	NaN	NaN	114438.000000	NaN	NaN

2. Analyzing Campaign Performance

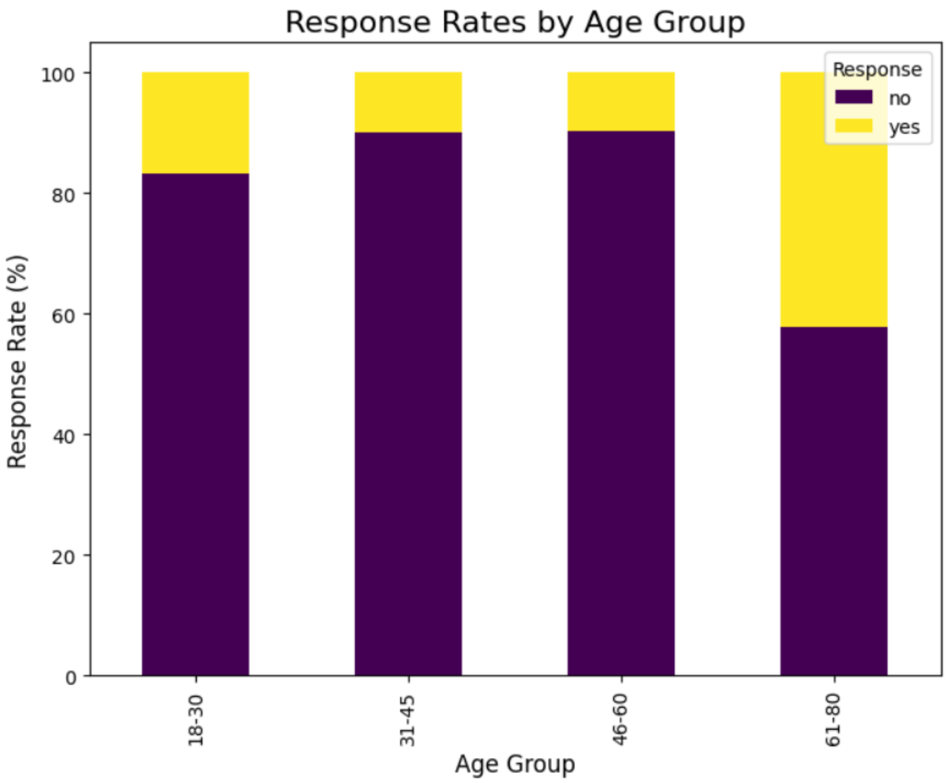
[Appendix I] calculates and visualizes the response rates to the bank's campaign. The output shows that 88.3% of customers did not respond positively, while 11.7% responded affirmatively. The bar plot visualizes the distribution of these responses, with a dominant "no" response, which indicates the need for further investigation into factors that could improve customer engagement.



The campaign data shows an imbalance in response rates, with 88.3% of customers responding negatively and only 11.7% responding positively. This imbalance suggests that the dataset is skewed, which could affect the performance of machine learning models. In imbalanced datasets, models tend to be biased toward the majority class (in this case, "no" responses), potentially leading to poor predictive performance for the minority class ("yes"). Addressing this imbalance through techniques like resampling or using weighted algorithms is essential for building effective models.

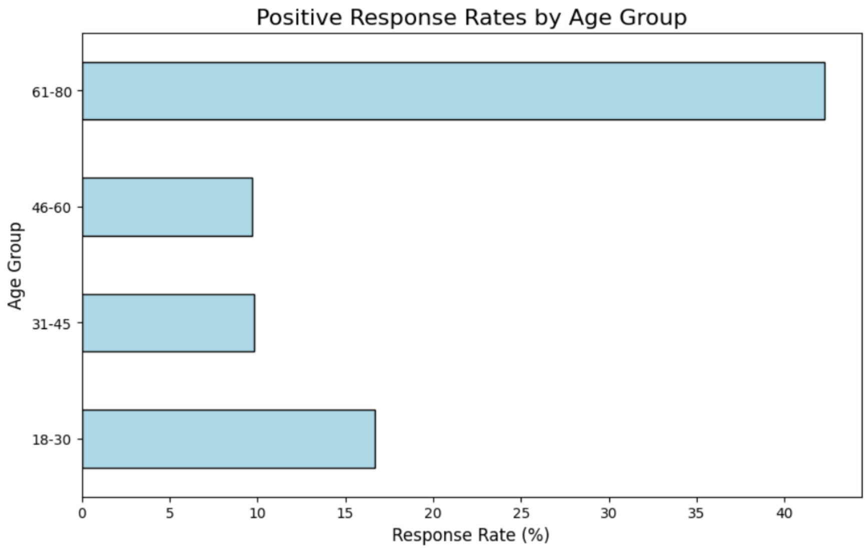
3. **Response Rates by Age Group**

[Appendix J] analysis groups customers into age categories and calculates the response rates within each group. The results show that younger customers (18-30) have a higher positive response rate (16.66%) compared to older groups, where the response rate drops. Interestingly, customers in the 61-80 age group have a much higher positive response rate (42.25%), suggesting that this demographic is more engaged with the campaign. The bar plot visualizes these trends, highlighting the varying levels of campaign effectiveness across different age groups.



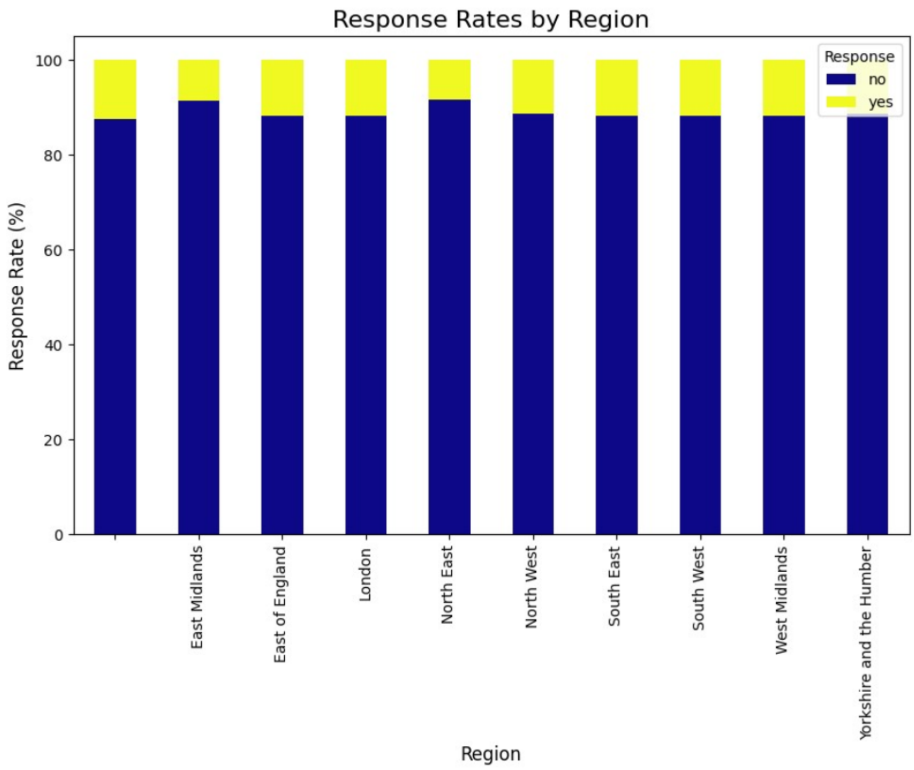
4. **Visualizing Positive Response Rates by Age Group**

[Appendix K] calculates the positive response rates for each age group and visualizes them using a horizontal bar chart. The results show that the 61-80 age group has the highest positive response rate (42.25%), while younger groups, such as 18-30, have a significantly lower rate (16.66%). The horizontal bar chart provides a clear, comparative view of these rates, making it easier to interpret the effectiveness of the campaign across different age groups. Finally, the temporary age_group column is removed to clean the dataset for further analysis.



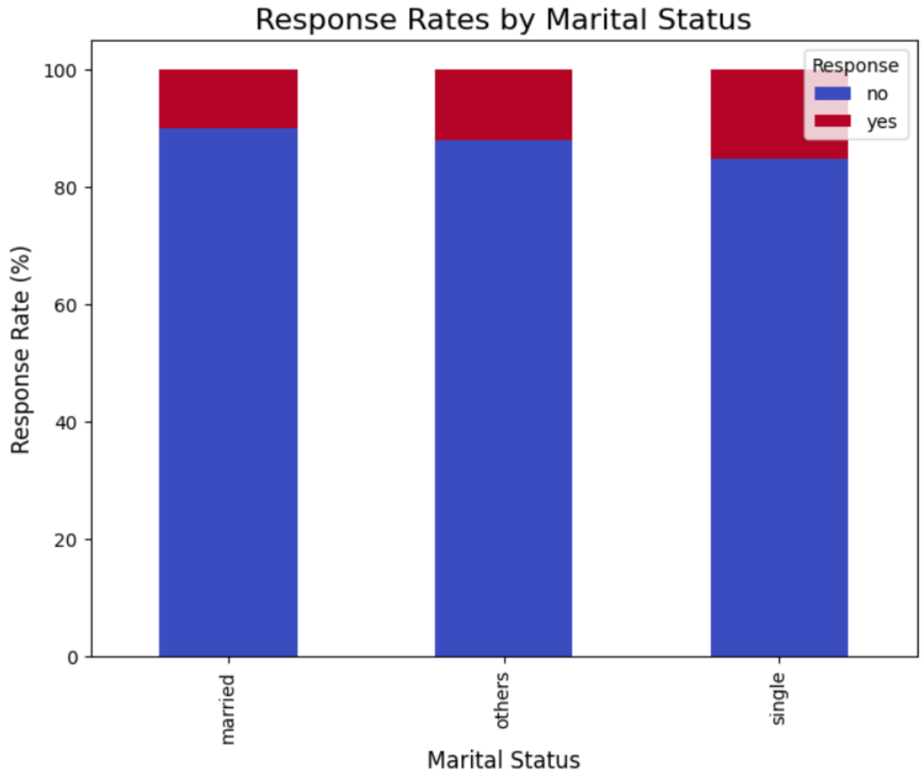
5. **Response Rates by Region**

This analysis calculates the response rates for each region, showing the percentage of positive and negative responses in [Appendix L]. While the overall response rates across regions are fairly consistent, with most regions having around 88% "no" responses and 11-12% "yes" responses, slight variations exist. The region "East Midlands" shows the highest proportion of "no" responses (91.34%), while other regions like "Yorkshire and the Humber" have a slightly higher rate of positive responses (11.23%). This analysis provides insights into regional differences in customer engagement with the campaign.



6. Response Rates by Marital Status

[Appendix M] explores response rates based on marital status, revealing distinct patterns in engagement. The results show that "single" customers have the highest positive response rate (15.26%), followed by "others" at 12%, and "married" individuals with the lowest positive response rate (9.98%). The bar chart visualizes these differences, clearly illustrating how marital status correlates with customer responsiveness to the campaign, providing valuable insights for targeting specific customer segments.

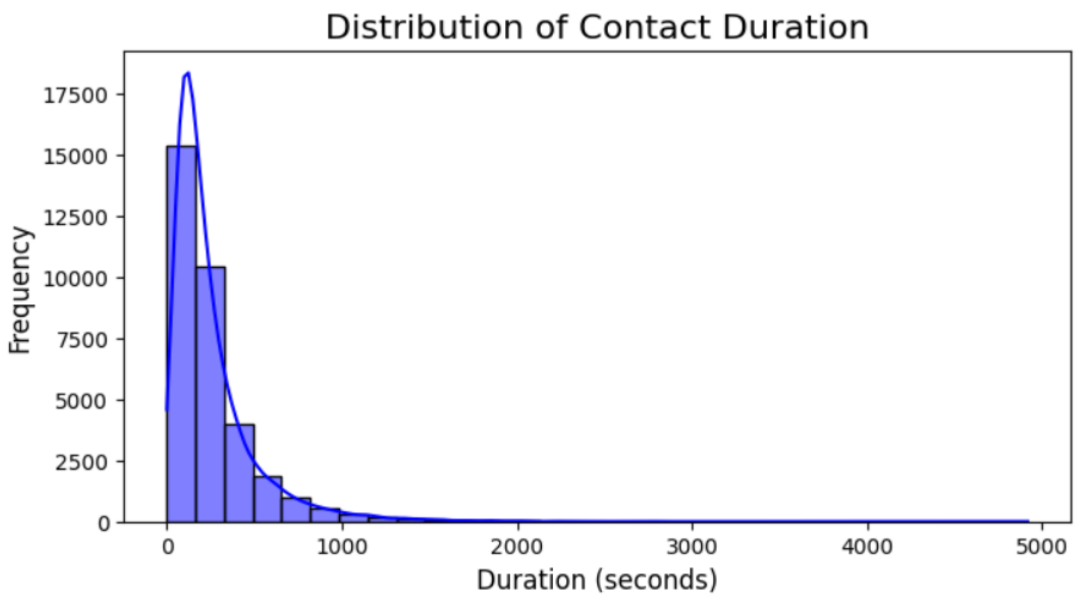


7. Contact Duration Analysis

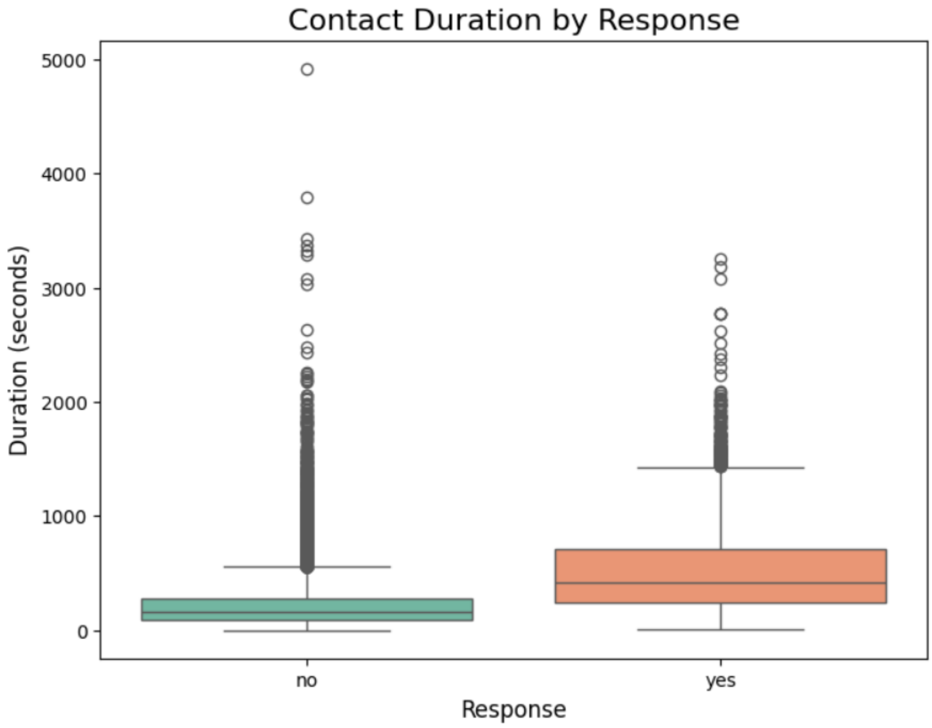
[Appendix N] analysis provides summary statistics on the contact duration, which refers to the time customers spent interacting with the campaign. The average contact duration is 257.61 seconds, with a wide range from 0 to 4918 seconds. The distribution shows that most interactions are shorter, with the 25th percentile at 103 seconds and the 75th percentile at 318 seconds. This variation suggests that some customers may have had longer interactions, possibly indicating a more engaged response or the inclusion of follow-up calls. Understanding this distribution can help assess the effectiveness of contact duration on campaign success.

```
Contact Duration Summary:

count    33909.000000
mean       257.605356
std        256.434874
min          0.000000
25%        103.000000
50%        180.000000
75%        318.000000
max       4918.000000
Name: duration, dtype: float64
```

[Appendix N] code also visualizes the distribution of contact durations using a histogram and kernel density estimate (KDE) plot. The histogram provides a clear view of how contact duration is spread across different time intervals, while the KDE adds a smoothed curve to highlight the underlying distribution. The plot reveals that most interactions are concentrated in shorter durations, with some longer outliers, indicating a mix of brief and extended customer interactions. This visualization helps in understanding the typical engagement time and can guide decisions about optimizing contact strategies for the campaign.



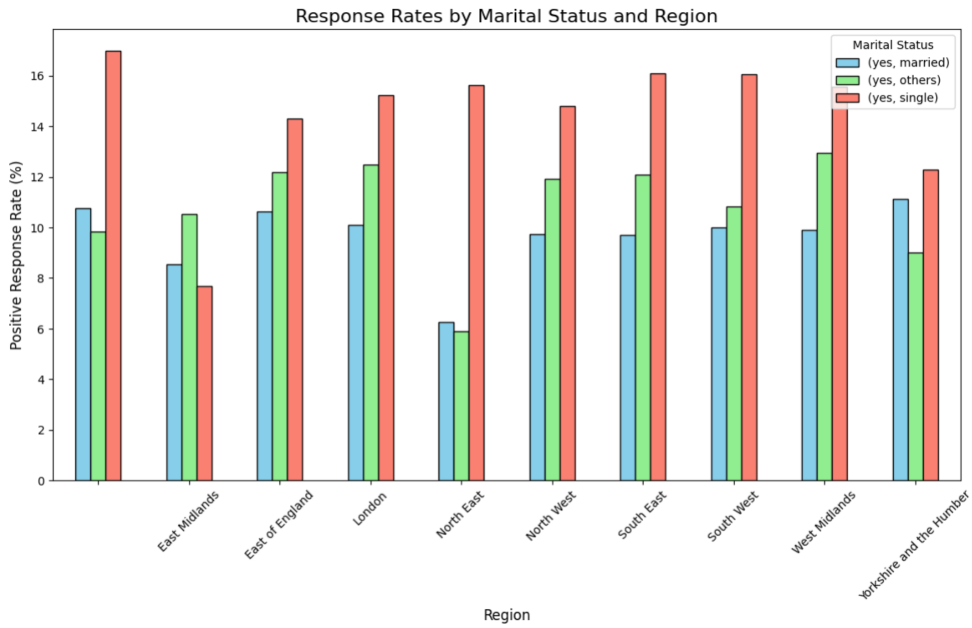
The boxplot examines the relationship between contact duration and response outcome (positive or negative). It shows that the contact duration for positive responses (marked as "yes") tends to have a wider range, with both shorter and longer durations, while negative responses ("no") are more concentrated in the lower duration range. The plot highlights that customers who engaged longer with the campaign are slightly more likely to respond positively, but the overall distribution suggests that contact duration alone may not be a strong predictor of the response. The visualization provides insight into the varying levels of engagement associated with different outcomes.



8. **Campaign Performance by Marital Status and Region**

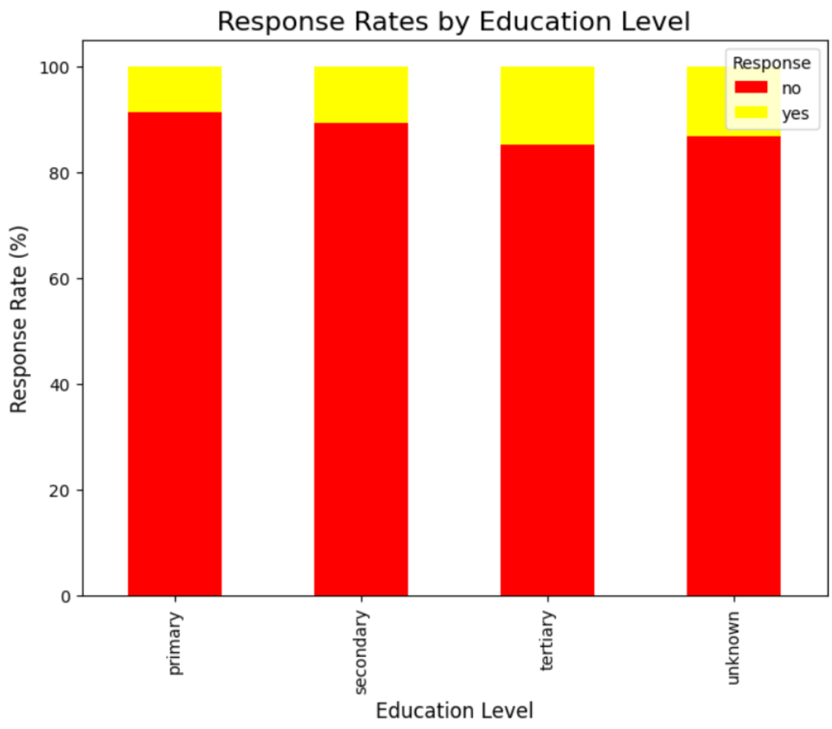
This analysis on [Appendix O]examines how response rates vary by both marital status and region, revealing interesting regional and demographic patterns. The crosstabulation output shows that "married" individuals across all regions tend to have a lower rate of positive responses compared to "single" customers, with response rates around 10-16% for "married" and 16-17% for "single". In some regions like North East, there are very low response rates for certain groups, while regions such as "East Midlands" show higher engagement for "single" customers. These insights highlight how different combinations of marital status and region influence campaign outcomes, helping tailor strategies for better engagement.

The grouped bar chart visually presents the positive response rates across different regions and marital statuses. It shows how "single" individuals tend to have a higher positive response rate than "married" or "others" in most regions. The chart clearly illustrates the regional variation, with certain regions like "North East" showing a lower positive response rate, especially for married individuals. By using distinct colors for each marital status, the chart allows for an easy comparison of how marital status interacts with regional response patterns, helping to further refine targeted marketing strategies.



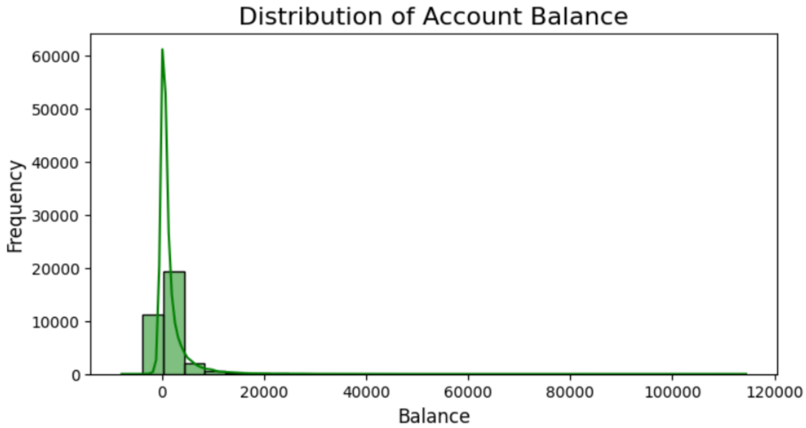
9. **Response Rates by Education Level**

[Appendix P] analysis highlights the variation in response rates based on education level, showing that individuals with tertiary education have the highest positive response rate (14.78%), followed by those with secondary education (10.71%). People with primary education have a significantly lower positive response rate (8.69%), and those with an unknown education level also show a relatively lower response (13.23%). The bar chart visually emphasizes these differences, providing a clear understanding of how education level influences engagement with the campaign. This insight could guide the bank in refining its marketing approach for different educational demographics.

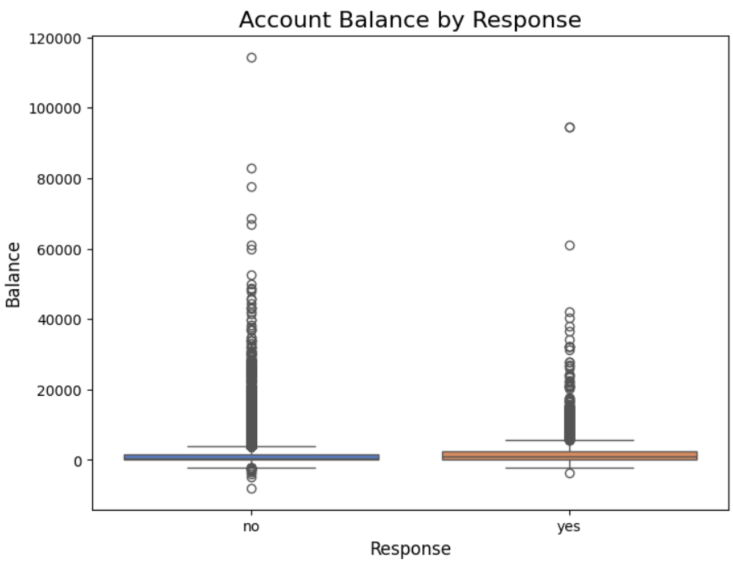


10. **Distribution of Account Balance**

The histogram with a kernel density estimate (KDE) visualizes the distribution of account balances in the dataset [Appendix Q]. It reveals that the majority of customers have a low to moderate balance, with a long tail indicating some customers with significantly higher balances. The smooth KDE curve helps in identifying the underlying trend, suggesting that most accounts are concentrated in the lower balance range, with few accounts holding high balances. This distribution is important for understanding customer financial behavior and can inform decisions on targeting specific customer segments based on their account balance.

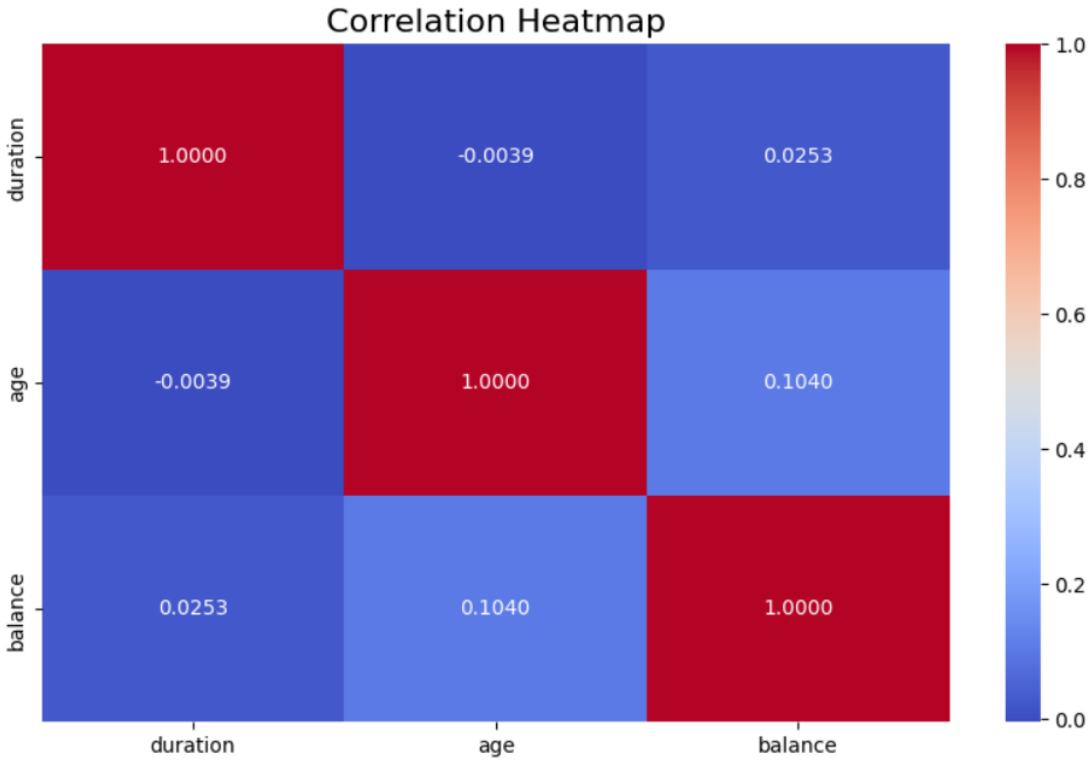


This boxplot explores the relationship between account balance and campaign response, highlighting that customers with positive responses ("yes") generally tend to have higher account balances compared to those who responded negatively ("no"). The plot also reveals that the "yes" group has a broader range of balances, with some outliers having very high values [Appendix Q]. The "no" group, on the other hand, shows a more concentrated distribution around lower balances. This suggests that individuals with more substantial financial resources may be more likely to engage positively, which can guide the bank in targeting wealthier customers for future campaigns.



11. Correlation Heatmap

The correlation heatmap reveals the relationships between the numerical variables in the dataset: duration, age, and balance on [Appendix R]. The correlation values show a very weak negative relationship between duration and age (-0.0039) and a weak positive correlation between balance and age (0.1040). The balance variable has a minimal positive correlation with duration (0.0253), suggesting that neither contact duration nor age significantly affects the account balance. These low correlations imply that these variables do not have strong linear relationships, indicating that other factors may be influencing the responses in the campaign



Model Building

Data Preprocessing for Model Building

[Appendix S] shows the data undergoes encoding and feature selection to prepare it for model building. The target variable, "response," is encoded as binary values (1 for 'yes' and 0 for 'no') to facilitate classification. Various categorical features, such as 'contact,' 'region,' 'job,' and others, are encoded using LabelEncoder to convert them into numerical representations suitable for machine learning models. Irrelevant or redundant features, such as 'custID,' are dropped, ensuring that only useful information remains. Finally, the dataset is split into features (X) and target (y), with a train-test split ensuring that the models are trained on 70% of the data and tested on the remaining 30%, preserving the class distribution through stratification.

1. Logistic Regression Model Evaluation

The Logistic Regression model has an accuracy of 89%, indicating that it performs reasonably well. However, when evaluating the individual classes, the model shows a precision of 0.90 for class '0' (no response) and 0.61 for class '1' (positive response). The recall for class '1' is only 0.18, suggesting that the model is not very effective in identifying positive responses (i.e., 'yes'). The F1-score of 0.28 for class '1' reflects this poor performance in capturing the minority class. This imbalance in response rates could be impacting the model's ability to predict positive responses accurately. [Appendix T].

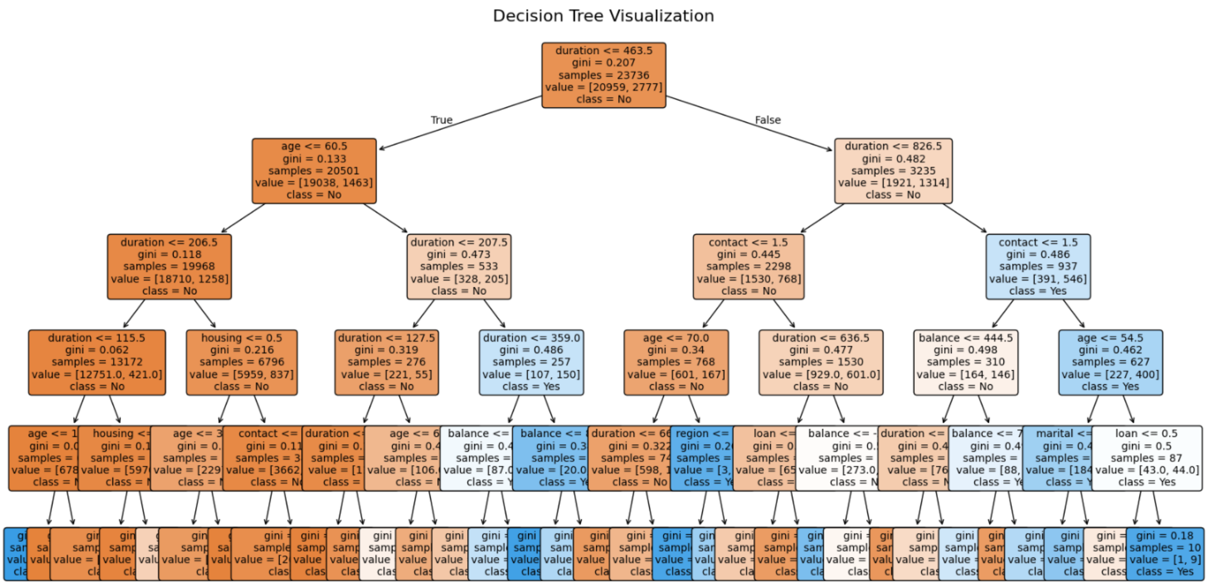
```
---- Logistic Regression ----

Classification Report (Logistic Regression):
             precision    recall  f1-score   support

           0       0.90      0.98      0.94      8983
           1       0.61      0.18      0.28      1190

    accuracy                           0.89     10173
   macro avg       0.75      0.58      0.61     10173
weighted avg       0.87      0.89      0.86     10173
```

2. Decision Tree Model Evaluation

[Appendix U] shows the code for Decision Tree model that has been fine-tuned using grid search, and the best-performing model was selected. After prediction, the model's classification report reveals that it performs better in identifying positive responses (class '1') than the Logistic Regression model. However, the recall for class '1' is still low, indicating that the model struggles with detecting all positive responses. The precision for class '1' has improved, but the recall still needs attention. The accuracy of the model might be higher than Logistic Regression due to better class discrimination, but the imbalance in the response variable still poses challenges for accurate predictions of positive responses.

```
---- Decision Tree ----

Classification Report (Decision Tree):
              precision    recall  f1-score   support

           0       0.90      0.98      0.94      8983
           1       0.62      0.20      0.30      1190

    accuracy                           0.89     10173
   macro avg       0.76      0.59      0.62     10173
weighted avg       0.87      0.89      0.87     10173
```

The Decision Tree visualization clearly outlines the conditions that drive predictions in this model. Key factors such as **duration**, **age**, and **housing** are used to classify responses. For example, a significant threshold for **duration** is **463.5 seconds**, after which the tree further splits based on **age** and **housing**. [Appendix V].



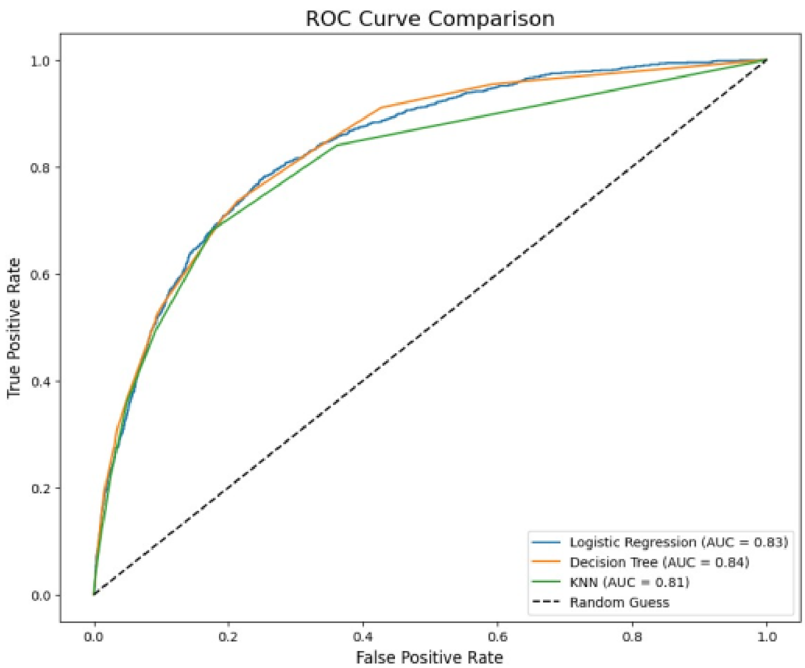
3. KNN Model Evaluation

The K-Nearest Neighbors (KNN) model achieved an overall accuracy of 89%. For the "no" response, the model showed a high **precision** of 0.90 and a **recall** of 0.97, indicating strong performance in correctly identifying the majority class. However, for the "yes" response, the **precision** dropped to 0.54, and the **recall** was just 0.22, reflecting a challenge in detecting the minority class. The **f1-score** for the "yes" class was low at 0.31, further highlighting the imbalance in class detection. While the model performs well for the majority class, it struggles with the minority class, suggesting that further adjustments like addressing the class imbalance or optimizing hyperparameters may improve its ability to predict positive responses.

```
---- KNN ----

Classification Report (KNN):
              precision    recall  f1-score   support

           0       0.90      0.97      0.94      8983
           1       0.54      0.22      0.31      1190

    accuracy                           0.89     10173
   macro avg       0.72      0.60      0.63     10173
weighted avg       0.86      0.89      0.87     10173
```

ROC Curve:

The ROC curve comparison of the three models [Appendix X]—Logistic Regression, Decision Tree, and KNN— shows varying performance in terms of Area Under the Curve (AUC). The Decision Tree model performed the best with an **AUC of 0.84**, closely followed by Logistic Regression with an **AUC of 0.83**. The KNN model showed a slightly lower performance, with an **AUC of 0.81**. All models performed better than random guessing, represented by the diagonal dashed line. These results suggest that while all models perform relatively well, the Decision Tree shows the highest ability to distinguish between the positive and negative classes, closely trailed by Logistic Regression. KNN's performance, while still decent, was slightly lower.



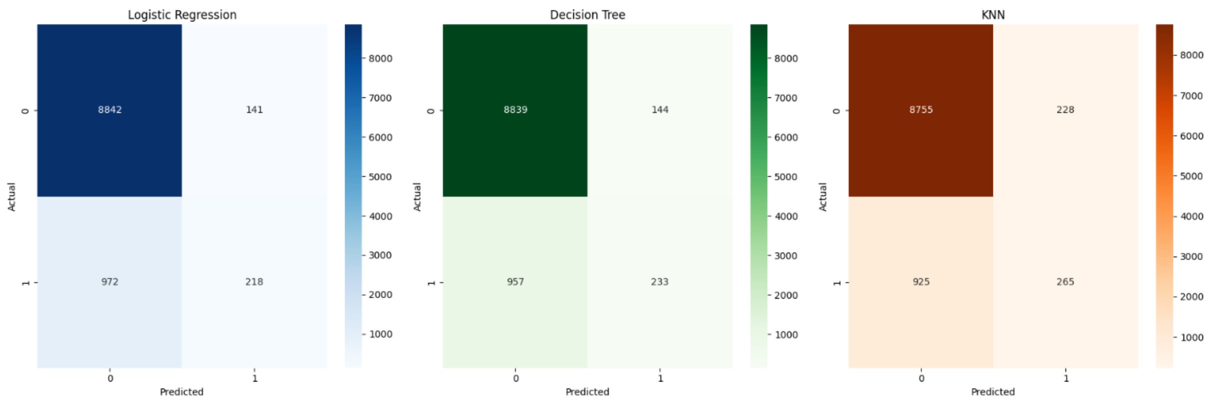
Model Performance Evaluation and Comparison

The confusion matrices for each model [Appendix Y]—Logistic Regression, Decision Tree, and KNN—provide a detailed view of the models' classification performance. All three models perform well, with the confusion matrix showing the true positive, true negative, false positive, and false negative counts.

1. **Logistic Regression (Left Panel)**
    - **Strengths**: The majority class (0) is predicted very accurately, with 8,842 correct predictions.
    - **Weaknesses**: The minority class (1) is harder for the model to predict. It correctly identifies only 218 instances of 1, while it misclassifies 972 instances of 1 as 0.

2. **Decision Tree (Middle Panel)**
    - **Strengths**: Slightly better than Logistic Regression at identifying the minority class (1), with 233 correct predictions and 957 misclassified.
    - **Weaknesses**: Similar performance for the majority class (0), with 8,839 correct predictions.

3. **KNN (Right Panel)**
    - **Strengths**: Performs the best among the three at identifying the minority class (1), with 265 correct predictions (fewer false negatives).
    - **Weaknesses**: Slightly worse at predicting the majority class (0), with 8,755 correct predictions and 228 misclassified.



Recommendation: Adopt Decision Tree Model

Based on the model evaluation, the **Decision Tree** is the most suitable choice for the bank. It achieves the highest AUC score (**0.84**), indicating the best ability to discriminate between the two classes (positive and negative responses). The Decision Tree also strikes a balance between precision and recall, providing an effective model for predicting responses with fewer false positives and negatives.

The **Logistic Regression** model also performs well with an AUC of **0.83**, but its performance slightly lags behind the Decision Tree in terms of handling both classes effectively. The **KNN** model, while still viable, is less efficient with the lowest AUC of **0.81**, suggesting that it may not offer as reliable predictions as the other models.

Justification:

- The Decision Tree's interpretability is another advantage, as the model is easy to understand and can be explained in clear rules, making it valuable for decision-making in a business context.
- It handles both categorical and numerical data well and does not require intensive feature scaling, making it a more robust choice for real-world applications. Thus, the bank should adopt the **Decision Tree** model for its superior performance, interpretability, and flexibility in handling different types of data.

Recommendations for Using the Response Model:

1. Targeted Marketing Campaigns:

The bank can use the response model to identify those customers who are more likely to respond positively to marketing campaigns, i.e., a "yes" response. This enables **targeted outreach**, such as personalized emails or offers tailored to specific customer segments based on their predicted response likelihood. For example, customers with certain features (e.g., age, contact duration, education level) who have a higher probability of responding can be prioritized for high-value campaigns.

2. Resource Allocation:

The model can help the bank optimize its resources. By predicting which customers are less likely to respond, the bank can allocate fewer resources (e.g., time, marketing budget) toward those individuals, reducing unnecessary costs. This also helps improve overall campaign efficiency and ROI (return on investment).

3. Customer Retention Efforts:

It helps identify customers likely to disengage or show disinterest in future offers. The bank can proactively target these customers with retention strategies, such as tailored incentives or personalized services, to reduce churn and improve long-term customer relationships.

4. Real-Time Decision Making:

The model can be integrated into the bank's customer relationship management (CRM) system, enabling real-time prediction of customer responses as they interact with various marketing channels (e.g., websites, mobile apps). This could allow the bank to adjust offers or interactions dynamically based on predicted likelihood of response.

Additional Data for Enhancing Model Performance:

1. Transaction Data:

Including **transaction history** (e.g., frequency, amount, types of transactions) could enhance the model by providing deeper insights into customer behavior. Customers who frequently make transactions or show consistent patterns might have different response tendencies than those with irregular transaction activity.

2. Customer Lifetime Value (CLV) or Financial Products Usage:

Integrating features related to a customer's **lifetime value** or the number of financial products they hold (e.g., loans, credit cards, insurance) could improve the

model's ability to predict responses from high-value customers or those more engaged with the bank's services.

3. Time-of-Day and Seasonal Effects:

Data on **time of day** and **seasonality** (e.g., campaign effectiveness based on time of year, holidays, or customer's typical activity patterns) could help adjust the model to predict responses more effectively during peak times or special promotions.

Appendix

Appendix A:

```
# Importing necessary libraries
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score,
roc_auc_score, roc_curve, precision_recall_curve
from sklearn.tree import export_text, plot_tree
```

Appendix B:

```
# Load the datasets
campaign_data = pd.read_csv("all_campaign.csv")
personal_data = pd.read_csv("all_personal.csv")

# Display the first few rows of each dataset
print("\nFirst 5 rows of Campaign Data:")
campaign_data.head()

print("\nFirst 5 rows of Personal Data:")
personal_data.head()
```

Appendix C:

```
# Inspect the datasets
print("Campaign Data:")
campaign_data.info()


print("\nPersonal Data:")
personal_data.info()
```

Appendix D:

```
# Check for missing values in each dataset
print("\nMissing values in Campaign Data:")
print(campaign_data.isnull().sum())

print("\nMissing values in Personal Data:")
print(personal_data.isnull().sum())
```

Appendix E:

```
# Handle missing values
# For the 'education' column in personal_data, fill missing values with 'unknown'
personal_data['education'] = personal_data['education'].fillna('unknown')
```

Appendix F:

```
# Check for duplicates in each dataset
print("\nDuplicate rows in Campaign Data:", campaign_data.duplicated().sum())
print("Duplicate rows in Personal Data:", personal_data.duplicated().sum())
```

Appendix G:

```
# Merge the datasets on the 'custID' column
merged_data = pd.merge(campaign_data, personal_data, on='custID', how='inner')

print("\nFirst 5 rows of Merged Data:")
merged_data.head()
```

Appendix H:

```
print("\nSummary Statistics:")
merged_data.describe(include='all')
```

Appendix I:

```
# Analyze campaign performance (response rates)
response_counts = merged_data['response'].value_counts()
response_rates = merged_data['response'].value_counts(normalize=True) * 100
```

```
print("\nResponse Counts:")
print(response_counts)
print("\nResponse Rates (%):")
response_rates

# Visualize the response rates
plt.figure(figsize=(6, 4))
sns.barplot(x=response_counts.index, y=response_counts.values, hue=response_counts.index, dodge=False, palette='viridis', legend=False)
plt.title("Response Counts", fontsize=16)
plt.xlabel("Response", fontsize=12)
plt.ylabel("Count", fontsize=12)
plt.show()
```

Appendix J:

```
merged_data['age_group'] = pd.cut(merged_data['age'], bins=[18, 30, 45, 60, 80],
                    labels=['18-30', '31-45', '46-60', '61-80'])

age_response = merged_data.groupby('age_group', observed=False)['response'].value_counts(normalize=True).unstack() * 100

print("\nResponse Rates by Age Group (%):")
age_response

# Visualize response rates by age group
age_response.plot(kind='bar', stacked=True, figsize=(8, 6), colormap='viridis')
plt.title("Response Rates by Age Group", fontsize=16)
plt.xlabel("Age Group", fontsize=12)
plt.ylabel("Response Rate (%)", fontsize=12)
plt.legend(title="Response", loc='upper right')
plt.show()
```

Appendix K:

```
# Calculate response rate by age group
age_response_rate = merged_data.groupby('age_group', observed=False)['response'].value_counts(normalize=True).unstack() * 100
print("\nResponse Rates by Age Group (%):")
print(age_response_rate)

# Use a horizontal bar chart for better readability
age_response_rate['yes'].plot(kind='barh', figsize=(10, 6), color='lightblue', edgecolor='black')
plt.title("Positive Response Rates by Age Group", fontsize=16)
plt.xlabel("Response Rate (%)", fontsize=12)
```

```
plt.ylabel("Age Group", fontsize=12)
plt.show()

# Drop the temporary 'age_group' column
merged_data = merged_data.drop(columns='age_group', axis=1)
```

Appendix L:

```
# Response by Region
region_response =
merged_data.groupby('region')['response'].value_counts(normalize=True).unstack() * 100
print("\nResponse Rates by Region (%):")
region_response

# Visualize response rates by region
region_response.plot(kind='bar', stacked=True, figsize=(10, 6), colormap='plasma')
plt.title("Response Rates by Region", fontsize=16)
plt.xlabel("Region", fontsize=12)
plt.ylabel("Response Rate (%)", fontsize=12)
plt.legend(title="Response", loc='upper right')
plt.show()
```

Appendix M:

```
# Response by Marital Status and Education
marital_response =
merged_data.groupby('marital')['response'].value_counts(normalize=True).unstack() * 100
print("\nResponse Rates by Marital Status (%):")
marital_response

# Visualize response by marital status
marital_response.plot(kind='bar', stacked=True, figsize=(8, 6), colormap='coolwarm')
plt.title("Response Rates by Marital Status", fontsize=16)
plt.xlabel("Marital Status", fontsize=12)
plt.ylabel("Response Rate (%)", fontsize=12)
plt.legend(title="Response", loc='upper right')
plt.show()
```

Appendix N:

```
# Contact Duration Analysis
# Analyze the distribution of contact durations
print("\nContact Duration Summary:")
```

```
merged_data['duration'].describe()

# Visualize contact duration
plt.figure(figsize=(8, 4))
sns.histplot(merged_data['duration'], bins=30, kde=True, color='blue')
plt.title("Distribution of Contact Duration", fontsize=16)
plt.xlabel("Duration (seconds)", fontsize=12)
plt.ylabel("Frequency", fontsize=12)
plt.show()

# Relationship between contact duration and response
plt.figure(figsize=(8, 6))
sns.boxplot(x='response', y='duration', data=merged_data, palette='Set2', hue='response',
dodge=False)
plt.title("Contact Duration by Response", fontsize=16)
plt.xlabel("Response", fontsize=12)
plt.ylabel("Duration (seconds)", fontsize=12)
plt.legend([], [], frameon=False)
plt.show()
```

Appendix O:

```
# Campaign performance by marital status and region
# Use a grouped bar chart to visualize this relationship
marital_region_response = pd.crosstab(
    [merged_data['marital'], merged_data['region']],
    merged_data['response'],
    normalize='index'
) * 100

print("\nResponse Rates by Marital Status and Region:")
marital_region_response

# Plot grouped bar chart
marital_region_response[['yes']].unstack(level=0).plot(
    kind='bar', figsize=(14, 7), color=['skyblue', 'lightgreen', 'salmon'], edgecolor='black'
)
plt.title("Response Rates by Marital Status and Region", fontsize=16)
plt.xlabel("Region", fontsize=12)
plt.ylabel("Positive Response Rate (%)", fontsize=12)
plt.legend(title="Marital Status", loc='upper right')
plt.xticks(rotation=45)
plt.show()
```

Appendix P:

```
education_response =
merged_data.groupby('education')['response'].value_counts(normalize=True).unstack() * 100
print("\nResponse Rates by Education (%):")
education_response

# Visualize response by education level
education_response.plot(kind='bar', stacked=True, figsize=(8, 6), colormap='autumn')
plt.title("Response Rates by Education Level", fontsize=16)
plt.xlabel("Education Level", fontsize=12)
plt.ylabel("Response Rate (%)", fontsize=12)
plt.legend(title="Response", loc='upper right')
plt.show()
```

Appendix Q:

```
# Analyze financial indicators (balance, housing, loan)
# Distribution of account balance
plt.figure(figsize=(8, 4))
sns.histplot(merged_data['balance'], bins=30, kde=True, color='green')
plt.title("Distribution of Account Balance", fontsize=16)
plt.xlabel("Balance", fontsize=12)
plt.ylabel("Frequency", fontsize=12)
plt.show()

# Relationship between balance and response
plt.figure(figsize=(8, 6))
sns.boxplot(x='response', y='balance', data=merged_data, palette='muted', hue='response',
dodge=False)
plt.title("Account Balance by Response", fontsize=16)
plt.xlabel("Response", fontsize=12)
plt.ylabel("Balance", fontsize=12)
plt.show()
```

Appendix R:

```
# Correlation heatmap
plt.figure(figsize=(10, 6))
correlation = merged_data.select_dtypes(include=['int64', 'float64']).corr()
sns.heatmap(correlation, annot=True, cmap='coolwarm', fmt=".4f")
plt.title("Correlation Heatmap", fontsize=16)
plt.show()
```

Appendix S:

```
data = merged_data.copy()

# Encoding categorical variables
# Encode target variable
data['response'] = data['response'].apply(lambda x: 1 if x == 'yes' else 0)

# Encode categorical variables
categorical_features = ['contact', 'region', 'job', 'marital', 'education',
            'housing', 'loan', 'default']
encoder = LabelEncoder()
for feature in categorical_features:
  data[feature] = encoder.fit_transform(data[feature])

# Feature selection
# Drop irrelevant or highly correlated features
features_to_drop = ['custID']  # Drop features added during EDA
data = data.drop(columns=features_to_drop, axis=1)

# Define features (X) and target (y)
X = data.drop(columns=['response'])
y = data['response']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42,
stratify=y)
```

Appendix T:

```
# Logistic Regression Model
print("---- Logistic Regression ----")
logreg = LogisticRegression(random_state=42, solver='liblinear')
logreg.fit(X_train, y_train)

# Predict and evaluate Logistic Regression
y_pred_logreg = logreg.predict(X_test)
y_pred_proba_logreg = logreg.predict_proba(X_test)[:, 1]

print("\nClassification Report (Logistic Regression):")
print(classification_report(y_test, y_pred_logreg))
```

Appendix U:

```
# Decision Tree Model
print("---- Decision Tree ----")
# Perform grid search for hyperparameter tuning
dt_params = {'max_depth': [3, 5, 10], 'min_samples_split': [2, 5, 10]}
```

```
dt_grid = GridSearchCV(DecisionTreeClassifier(random_state=42), dt_params, cv=5, scoring='accuracy')
dt_grid.fit(X_train, y_train)

# Best Decision Tree Model
dt_model = dt_grid.best_estimator_
y_pred_dt = dt_model.predict(X_test)
y_pred_proba_dt = dt_model.predict_proba(X_test)[:, 1]

print("\nClassification Report (Decision Tree):")
print(classification_report(y_test, y_pred_dt))
```

Appendix V:

```
#Visualize the Decision Tree
plt.figure(figsize=(20, 10))
plot_tree(
    dt_model,
    feature_names=X.columns,
    class_names=["No", "Yes"],
    filled=True,
    rounded=True,
    fontsize=10
)
plt.title("Decision Tree Visualization", fontsize=16)
plt.show()

# Text-based Decision Tree Rules
tree_rules = export_text(dt_model, feature_names=list(X.columns))
print("Decision Tree Rules:\n")
print(tree_rules)
```

Appendix W:

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# KNN Classifier
print("---- KNN ----")
# Perform grid search for hyperparameter tuning
knn_params = {'n_neighbors': [3, 5, 7, 9], 'weights': ['uniform', 'distance']}
knn_grid = GridSearchCV(KNeighborsClassifier(), knn_params, cv=5, scoring='accuracy')
knn_grid.fit(X_train_scaled, y_train)
```

```
# Best KNN Model
knn_model = knn_grid.best_estimator_
y_pred_knn = knn_model.predict(X_test_scaled)
y_pred_proba_knn = knn_model.predict_proba(X_test_scaled)[:, 1]

print("\nClassification Report (KNN):")
print(classification_report(y_test, y_pred_knn))
```

Appendix X:

```
# Compare Model Performances with ROC Curve
plt.figure(figsize=(10, 8))
fpr_logreg, tpr_logreg, _ = roc_curve(y_test, y_pred_proba_logreg)
fpr_dt, tpr_dt, _ = roc_curve(y_test, y_pred_proba_dt)
fpr_knn, tpr_knn, _ = roc_curve(y_test, y_pred_proba_knn)

plt.plot(fpr_logreg, tpr_logreg, label='Logistic Regression (AUC = {:.2f})'.format(roc_auc_score(y_test, y_pred_proba_logreg)))
plt.plot(fpr_dt, tpr_dt, label='Decision Tree (AUC = {:.2f})'.format(roc_auc_score(y_test, y_pred_proba_dt)))
plt.plot(fpr_knn, tpr_knn, label='KNN (AUC = {:.2f})'.format(roc_auc_score(y_test, y_pred_proba_knn)))

plt.plot([0, 1], [0, 1], 'k--', label='Random Guess')
plt.title("ROC Curve Comparison", fontsize=16)
plt.xlabel("False Positive Rate", fontsize=12)
plt.ylabel("True Positive Rate", fontsize=12)
plt.legend(loc='lower right')
plt.show()
```

Appendix Y:

```
# Confusion Matrices for Models
fig, axes = plt.subplots(1, 3, figsize=(18, 6))

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

# Decision Tree Confusion Matrix
sns.heatmap(confusion_matrix(y_test, y_pred_dt), annot=True, fmt='d', cmap='Greens', ax=axes[1])
axes[1].set_title("Decision Tree")
```

```
axes[1].set_xlabel("Predicted")
axes[1].set_ylabel("Actual")

# KNN Confusion Matrix
sns.heatmap(confusion_matrix(y_test, y_pred_knn), annot=True, fmt='d', cmap='Oranges',
ax=axes[2])
axes[2].set_title("KNN")
axes[2].set_xlabel("Predicted")
axes[2].set_ylabel("Actual")

plt.tight_layout()
plt.show()

# Summary and Recommendation
print("\nModel Performance Summary:")
print(f"Logistic Regression AUC: {roc_auc_score(y_test, y_pred_proba_logreg):.2f}")
print(f"Decision Tree AUC: {roc_auc_score(y_test, y_pred_proba_dt):.2f}")
print(f"KNN AUC: {roc_auc_score(y_test, y_pred_proba_knn):.2f}")
```