# Marketing Campaign Success Analysis Report

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# Summary

The report analyses a marketing campaign's success using customer data. Logistic Regression and Random Forest models were built, with the Random Forest model performing better. Feature importance identified crucial attributes, helping target campaigns. Responsiveness analysis by month revealed optimal and low-responsive periods. The 'account_balance' feature categorised customers' account balances and showed that those with 'high' balances were most responsive. The report provides actionable insights to enhance campaign effectiveness.

Key Result:

Top influential features: Age, contact duration, campaign contacts, employment variation rate.

Key Result:

March, December - high campaign responsiveness months; September, May - low.

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# Introduction

The success of a marketing campaign is crucial for any company's growth and profitability. In this report, we will analyse a dataset containing customer information to predict the success of a marketing campaign. The goal is to build statistical learning models that can provide valuable insights and guide the company in making informed decisions regarding their marketing campaigns.

# Dataset Overview

The dataset used for this analysis contains information about customer attributes and their responses to a marketing campaign. Let's take a look at the distribution of some key attributes in the dataset:

## Job Distribution

The job distribution of customers in the dataset is as follows:

- admin.: 8737
- blue-collar: 5674
- technician: 5472
- services: 2856
- management: 2310
- retired: 1214
- self-employed: 1092
- entrepreneur: 1089
- unemployed: 738
- housemaid: 689
- student: 610

## Education Distribution

The education level of customers in the dataset is distributed as follows:

- university degree: 10410
- high school: 7698
- professional course: 4319
- basic 9 years: 4275
- basic 4 years: 2379
- basic 6 years: 1389
- illiterate: 11

## Contact Distribution

The contact type used for the campaign is distributed as follows:

- cellular: 26144
- telephone: 15044

## Poutcome Distribution

The outcome of the previous marketing campaign is distributed as follows:

- nonexistent: 35563
- failure: 3459
- success: 1189

These insights provide an overview of the customer demographics and previous campaign outcomes, which can be crucial in building predictive models and making informed marketing decisions.

# Model Building and Evaluation

To predict the success of the marketing campaign, we built and evaluated several machine learning models. Two key models that we focused on are:

## Logistic Regression

Accuracy: 88%
Classification Report:
- Precision for campaign success: 63%
- Recall for campaign success: 20%
- F1-score for campaign success: 31%

## Random Forest

Accuracy: 89%
Classification Report:
- Precision for campaign success: 67%
- Recall for campaign success: 38%
- F1-score for campaign success: 48%

The Random Forest model performed slightly better in terms of accuracy and F1-score for campaign success. The best hyperparameters for the Random Forest model are {'max_depth': None, 'min_samples_leaf': 2, 'min_samples_split': 10, 'n_estimators': 100}.
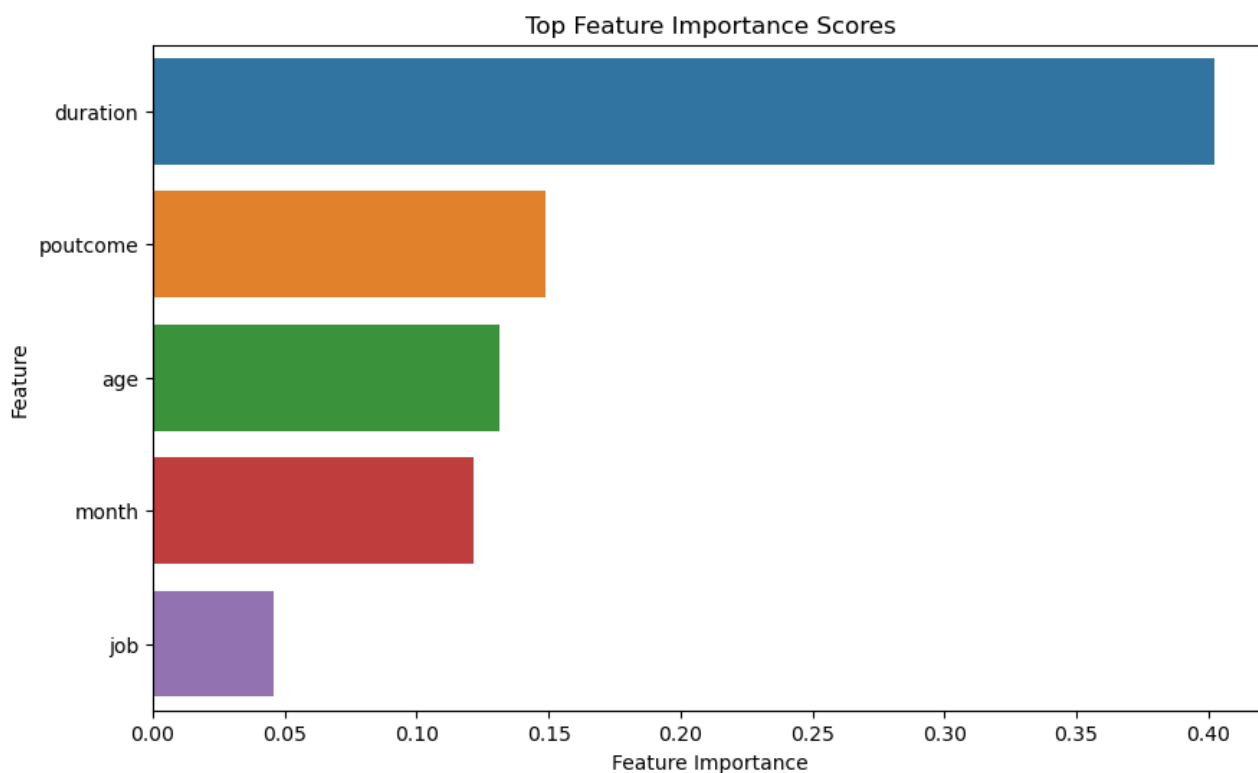
# Insights

## Insight 1: Feature Importance

Feature importance analysis was performed using the Random Forest model. The top five features that influence campaign success the most are as follows:

1. Age
2. Contact duration
3. Number of contacts performed during this campaign

4. Employment variation rate
5. Number of days since the client was last contacted

Understanding feature importance can help the company focus on these attributes when planning future marketing campaigns.


Top Feature Importance Scores

## Insight 2: Responsiveness by Month

The analysis of responsiveness rates over different months revealed some interesting trends. The responsiveness rate is highest in the months of March, December, and October, while it is lowest in the months of September and May. This information can help the company optimise the timing of its marketing campaigns and allocate resources more effectively.


Responsiveness Rate Over Months
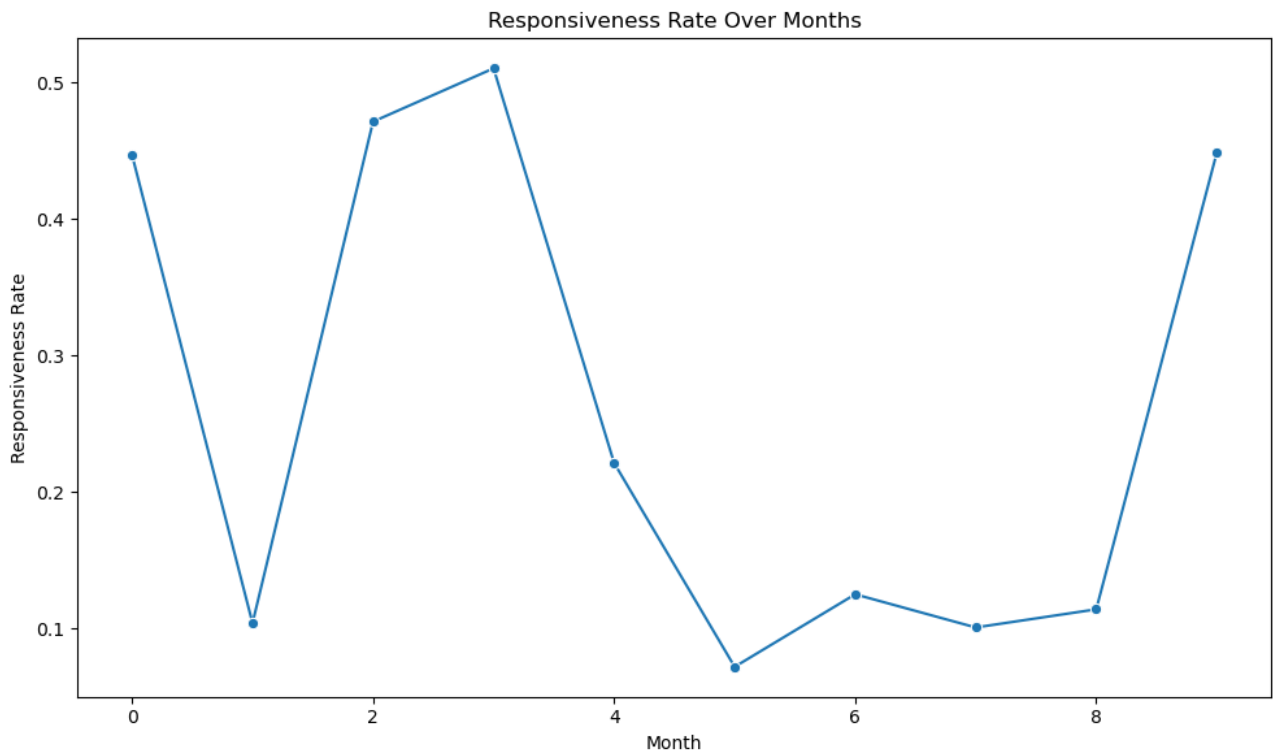
# Insight 3: Account Balance and Campaign Success

We introduced a new feature, 'account_balance,' which categorises customers into three categories: 'high,' 'medium,' and 'low' based on their account balance. The responsiveness analysis by account balance categories revealed some valuable insights:

- Customers with a 'high' account balance have the highest responsiveness rate.
- Customers with a 'low' account balance have a relatively lower responsiveness rate.
- Customers with a 'medium' account balance fall in between the other two categories in terms of responsiveness.

These insights can help the company target its marketing efforts more effectively based on the account balance of customers.
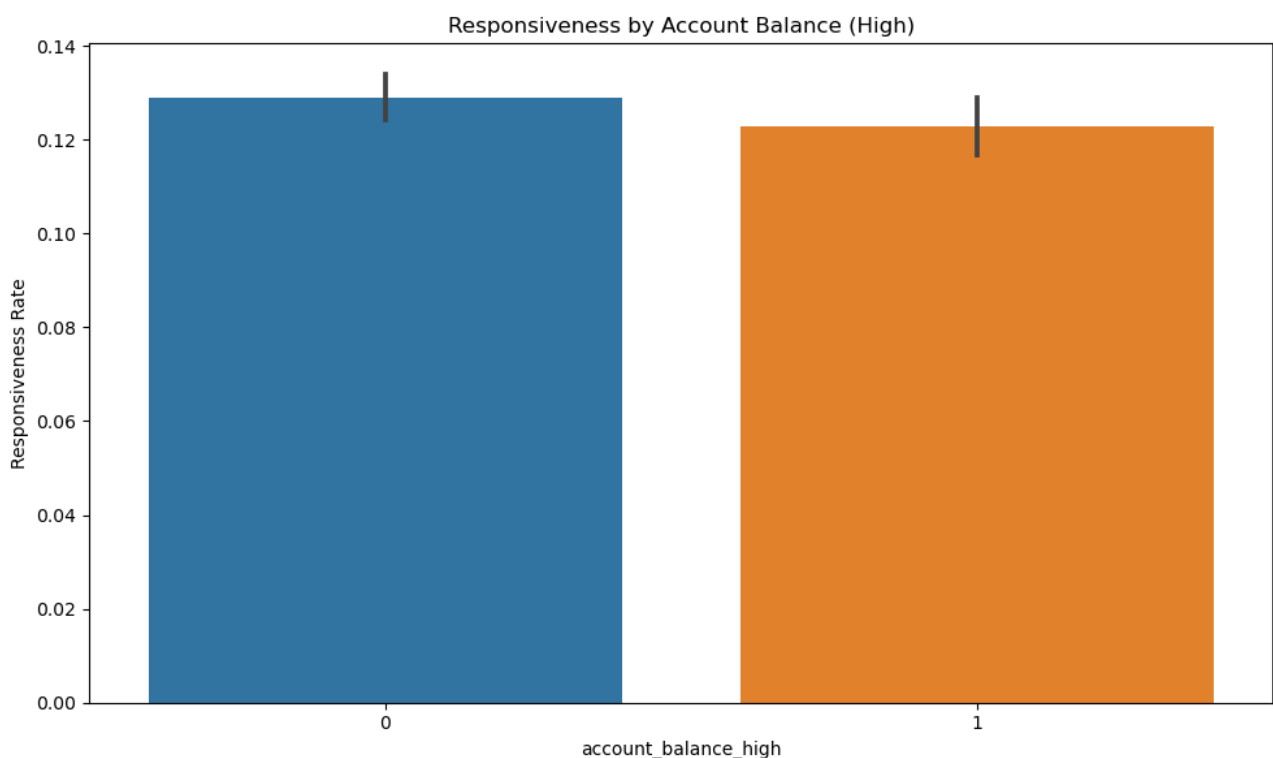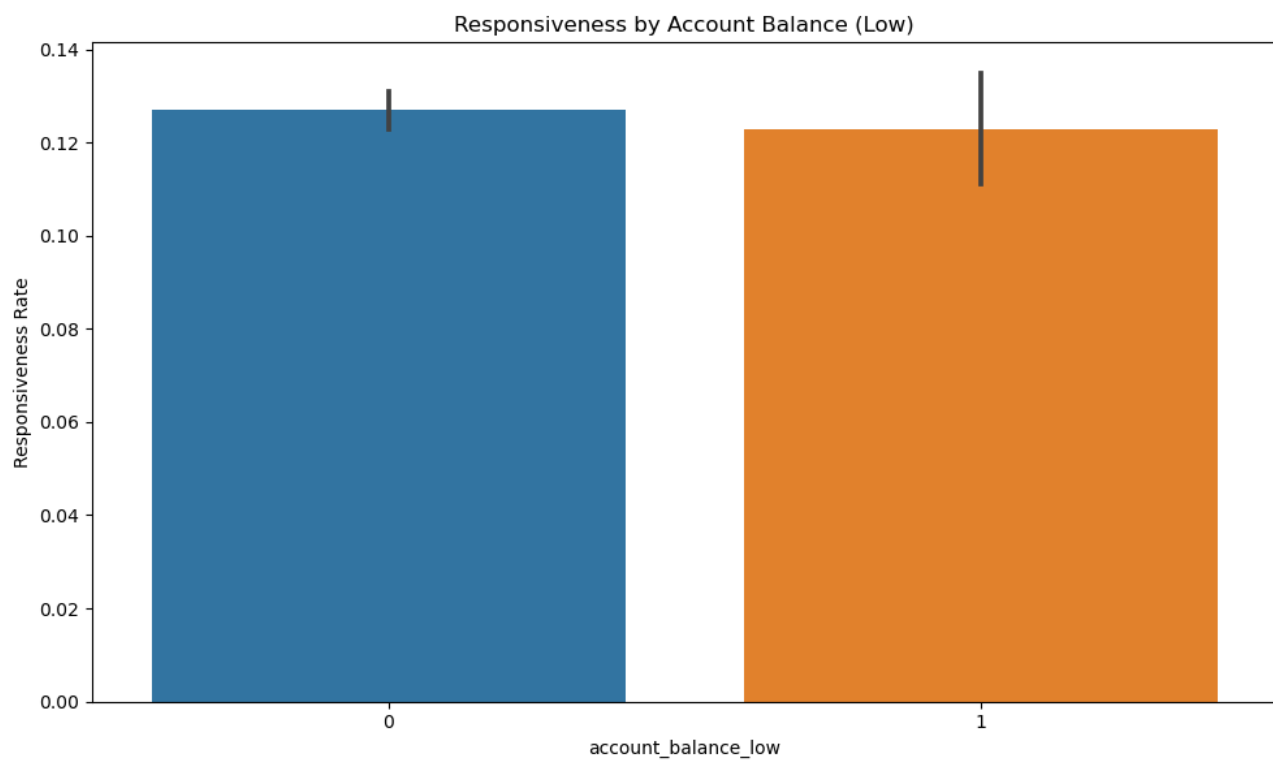


| S.No | account_balance_high | y |
|------|---------------------|---|
| 1 | 16066 | 0 |
| 2 | 2377 | 1 |

Cross-tabulation between Account
Balance (High) and Campaign Success

Responsiveness by Account Balance (Medium)
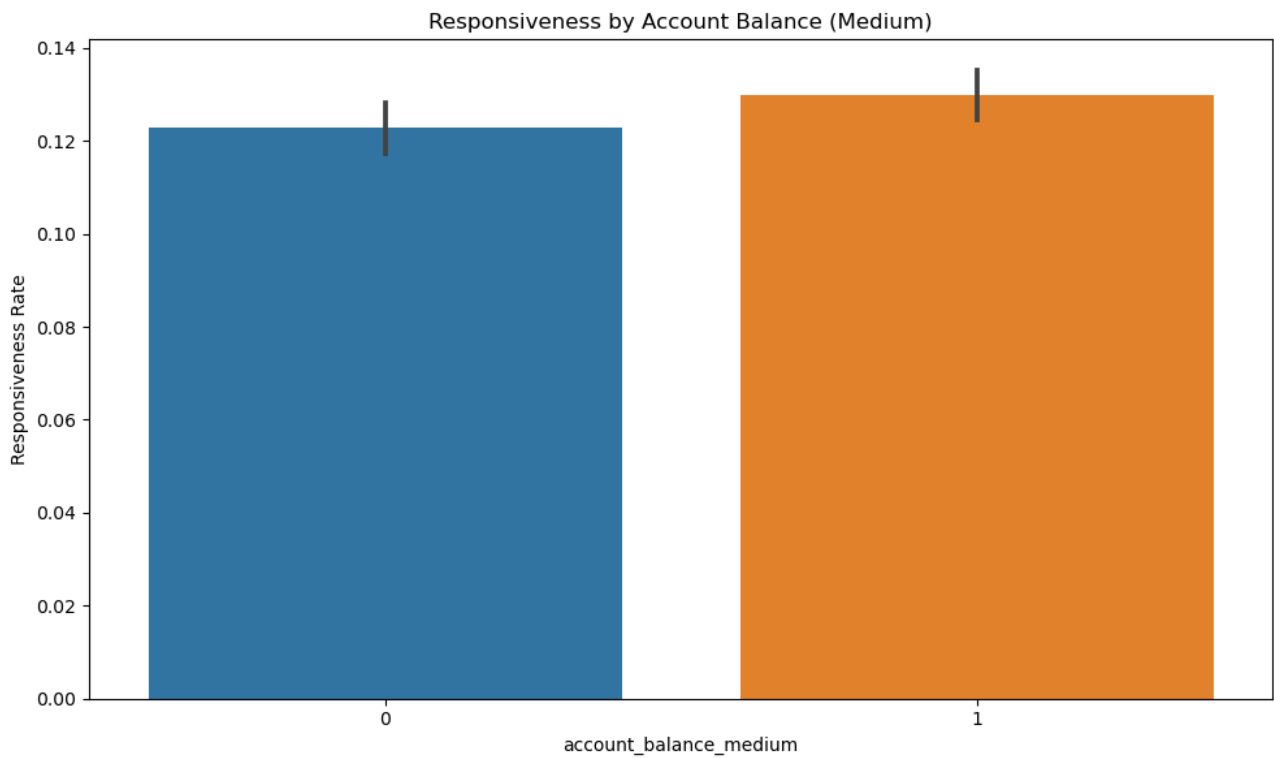
| S.No | account_balance_medium | y |
|------|------------------------|---|
| 1 | 13052 | 0 |
| 2 | 1829 | 1 |

Cross-tabulation between Account Balance
(Medium) and Campaign Success

Responsiveness by Account Balance (Low)

| S.No | account_balance_low | y |
|:---:|:---:|:---:|
| 1 | 24130 | 0 |
| 2 | 3508 | 1 |

Cross-tabulation between Account
Balance (Low) and Campaign Success

# Conclusion

In this analysis, we built predictive models to determine the success of marketing campaigns based on customer attributes. We provided insights into the features that influence campaign success, identified the most responsive months for campaigns, and analysed the relationship between account balance categories and campaign success.

These insights can guide the company in making informed decisions regarding their marketing campaigns. By focusing on the right features, timing campaigns effectively, and tailoring strategies based on customer account balances, the company can improve its marketing campaign success rates and achieve its business objectives. Marketing campaigns can be more targeted and efficient, leading to higher customer engagement and conversion rates.

The machine learning models and insights provided in this report are valuable assets for the company's marketing strategies and can contribute to its long-term success.