Bank Marketing Analysis

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Contents

Summary

This lab report analyzes bank marketing campaigns with the goal of using machine learning to predict whether a customer will subscribe to a term deposit. The dataset, sourced from the UCI Machine Learning Repository, contains demographic and campaign-related information on customers who were contacted via phone for a Portuguese bank's direct marketing campaign (Moro and Cortez 2014). The target variable is whether or not the customer subscribed to a term deposit. This study evaluates the performance of Logistic Regression and Decision Tree models in predicting customer subscription to term deposits, using metrics such as accuracy, precision, recall, and F1 score. The Logistic Regression model achieved 88.5% accuracy with high precision (0.70) but low recall (0.20), making it suitable for minimizing false positives. Conversely, the Decision Tree model achieved 89.7% accuracy with improved recall (0.23) but lower precision (0.63), better identifying potential subscribers at the cost of higher false positives. Both models emphasize the majority class (non-subscribers) and highlight challenges in detecting true positives. Strategic recommendations include targeted marketing, personalized offers, and continuous monitoring and adjustment of the models to improve performance. By leveraging these models, banks can enhance marketing strategies, optimize resource allocation, and increase conversion rates.

Introduction

Bank marketing campaigns are a critical tool for financial institutions to promote their products and services, particularly time deposit subscriptions (Meshref 2020). However, identifying potential customers who are likely to respond positively to these campaigns can be challenging (Meshref 2020). Despite advances in targeted marketing strategies, response rates for bank marketing campaigns remain low, and ineffective campaigns can lead to wasted resources and decreased customer satisfaction (Xie et al. 2023).

One notable study in this area is "Predictive Analytics and Machine Learning in Direct Marketing for Anticipating Bank Term Deposit Subscriptions" by (Zaki et al. 2024). The authors explore how machine learning models, including the SGD Classifier, k-nearest neighbor Classifier, and Random Forest Classifier, can be used to predict bank term deposit subscriptions. The study employs various data exploration and feature engineering techniques to build and evaluate the models, ultimately identifying the Random Forest Classifier as the most effective, achieving an impressive accuracy of 87.5%. This study underscores the potential of machine learning to enhance marketing strategies in the banking sector, providing valuable insights that can help institutions refine their direct marketing approaches and improve customer acquisition.

In recent years, the use of machine learning and data mining techniques in the banking sector has gained significant traction, particularly for customer targeting and marketing optimization. A study by (Wang 2020) examines the application of machine learning algorithms, specifically the C5.0 algorithm, to classify bank customers in order to improve marketing strategies. Using the Bank Marketing dataset from the UCI Machine Learning Repository, the study demonstrates how data mining can help identify customer segments, allowing banks to tailor their marketing campaigns more effectively. The classification model results can enhance decision-making processes for banks, ultimately improving marketing efficiency and customer satisfaction. The study highlights the importance of selecting relevant features, handling outliers, and balancing the dataset to ensure more accurate predictions.

This research raises the question of whether a machine learning algorithm can predict whether a customer will subscribe to a term deposit based on customer demographics and campaign-related data. This is an important inquiry because traditional marketing methods often rely on manual segmentation or generalized strategies, which may not capture the nuances of customer behavior. Additionally, by excluding customers who are unlikely to subscribe, banks can reduce campaign costs and improve customer experience. Conversely, accurately identifying potential subscribers allows banks to concentrate efforts on the right audience, improving both efficiency and outcomes. Therefore, if a machine learning algorithm can accurately predict customer subscriptions based on the bank marketing dataset, it could enable more effective, scalable, and data-driven marketing strategies, leading to better resource allocation and enhanced campaign performance.

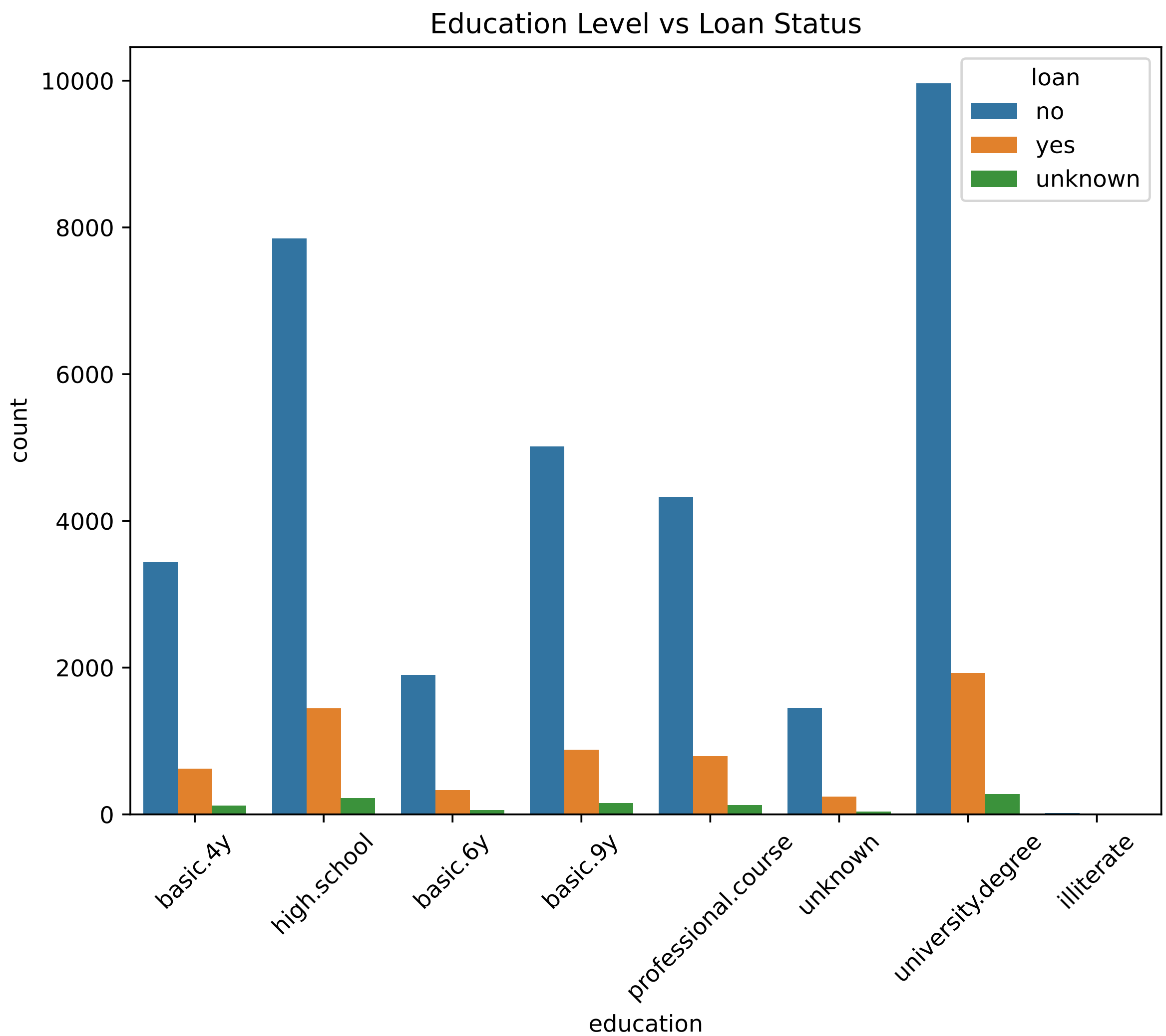
Methods

Data

The dataset used in this project is the Bank Marketing dataset, sourced from the UCI Machine Learning Repository (Moro and Cortez 2014). It contains information related to direct marketing campaigns (via phone calls) conducted by a Portuguese banking institution to predict if a client will subscribe to a term deposit. The dataset contains 45,211 rows and 17 columns and it includes features such as age, job type, marital status, education, balance, and details about previous marketing campaigns. The target variable in this study is "y," which indicates whether a customer subscribed to a term deposit (binary: "yes" or "no"). We processed and analyzed this data using Python with libraries such as pandas, scikit-learn, and matplotlib to implement data cleaning, exploratory data analysis, and machine learning models. The data has been pre-processed and contains no missing values.

```
Unknown counts in each column:
 age                0
job               330
marital            80
education        1731
default          8597
```

```
housing           990
loan              990
contact             0
month               0
day_of_week         0
duration            0
campaign            0
pdays               0
previous            0
poutcome            0
emp.var.rate        0
cons.price.idx      0
cons.conf.idx       0
euribor3m           0
nr.employed         0
y                   0
dtype: int64
```




```
Unknown counts in each column:
 age                   0
job                 330
marital              80
education          1731
default            8597
housing             990
loan                990
contact               0
month                 0
day_of_week           0
duration              0
```

```
campaign          0
pdays             0
previous          0
poutcome          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
y                 0
dtype: int64
```

Variable Name	Role	Type	Demographic	Description	Units	Missing Values
age	Feature	Integer	nan	Age	years	no
job	Feature	Categorical	Occupation	Type of job (categorical: 'admin.', 'blue-collar', 'entrepreneur', 'housemaid', 'management', 'retired', 'self-employed', 'services', 'student', 'technician', 'unemployed', 'unknown')	nan	no
marital	Feature	Categorical	Marital Status	Marital status (categorical: 'divorced', 'married', 'single', 'unknown'; note: 'divorced' means divorced or widowed)	nan	no
education	Feature	Categorical	Education Level	Education level (categorical: 'basic.4y', 'basic.6y', 'basic.9y', 'high.school', 'illiterate', 'professional.course', 'university.degree', 'unknown')	nan	no
default	Feature	Binary	nan	Has credit in default? (binary: 'yes', 'no')	nan	no
balance	Feature	Integer	nan	Average yearly balance (numeric)	euros	no
housing	Feature	Binary	nan	Has housing loan? (binary: 'yes', 'no')	nan	no
loan	Feature	Binary	nan	Has personal loan? (binary: 'yes', 'no')	nan	no
contact	Feature	Categorical	nan	Contact communication type (categorical: 'cellular', 'telephone')	nan	yes
day_of_week	Feature	Date	nan	Last contact day of the week (categorical: 'mon', 'tue', 'wed', 'thu', 'fri')	nan	no
month	Feature	Date	nan	Last contact month of the year (categorical: 'jan', 'feb', 'mar', …, 'nov', 'dec')	nan	no
duration	Feature	Integer	nan	Last contact duration, in seconds (numeric). Important note: this attribute highly affects the output target (e.g., if duration=0 then y='no'). It should only be included for benchmark purposes.	seconds	no

Variable Name	Role	Type	Demographic	Description	Units	Missing Values
campaign	Feature	Integer	nan	Number of contacts performed during this campaign and for this client (numeric, includes last contact)	nan	no
pdays	Feature	Integer	nan	Number of days that passed by after the client was last contacted from a previous campaign (numeric; -1 means client was not previously contacted)	days	yes
previous	Feature	Integer	nan	Number of contacts performed before this campaign and for this client	nan	no
poutcome	Feature	Categorical	nan	Outcome of the previous marketing campaign (categorical: 'failure', 'nonexistent', 'success')	nan	yes
y	Target	Binary	nan	Has the client subscribed to a term deposit? (binary: 'yes', 'no')	nan	no

Data Validation Check

```
Data validation failed with the following errors:
- Dataset contains duplicate rows.
```


```
Data validation failed with the following errors:
- Dataset contains duplicate rows.
```


```
Data passed outlier validation checks.
```


```
Data passed outlier validation checks.
```


```
Data passed category level validation checks.
```


```
Data passed category level validation checks.
```


```
Target validation passed.
```


```
Target validation passed.
```


```
Distribution of 'y':
y
no     36548
yes     4640
Name: count, dtype: int64
```

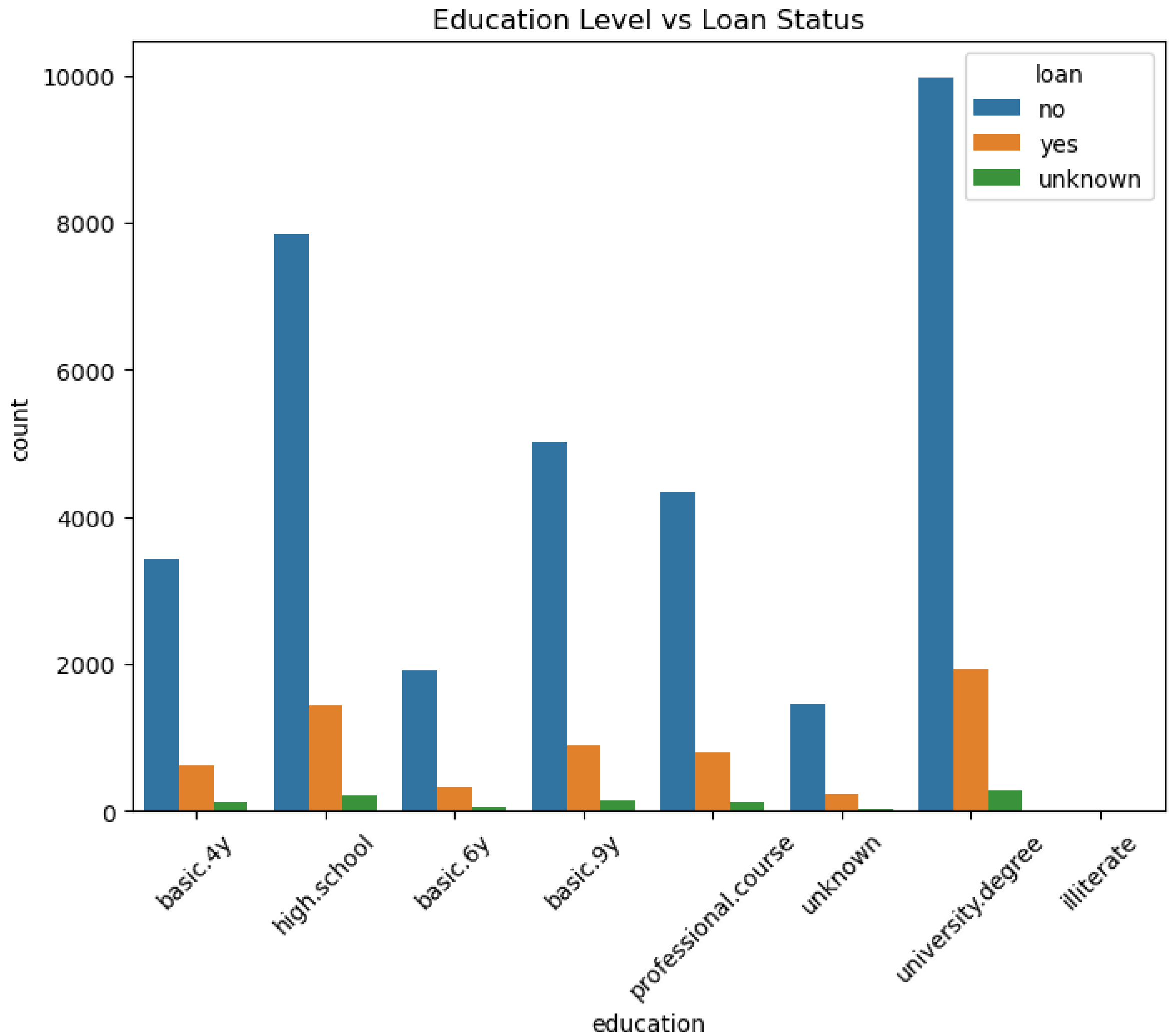
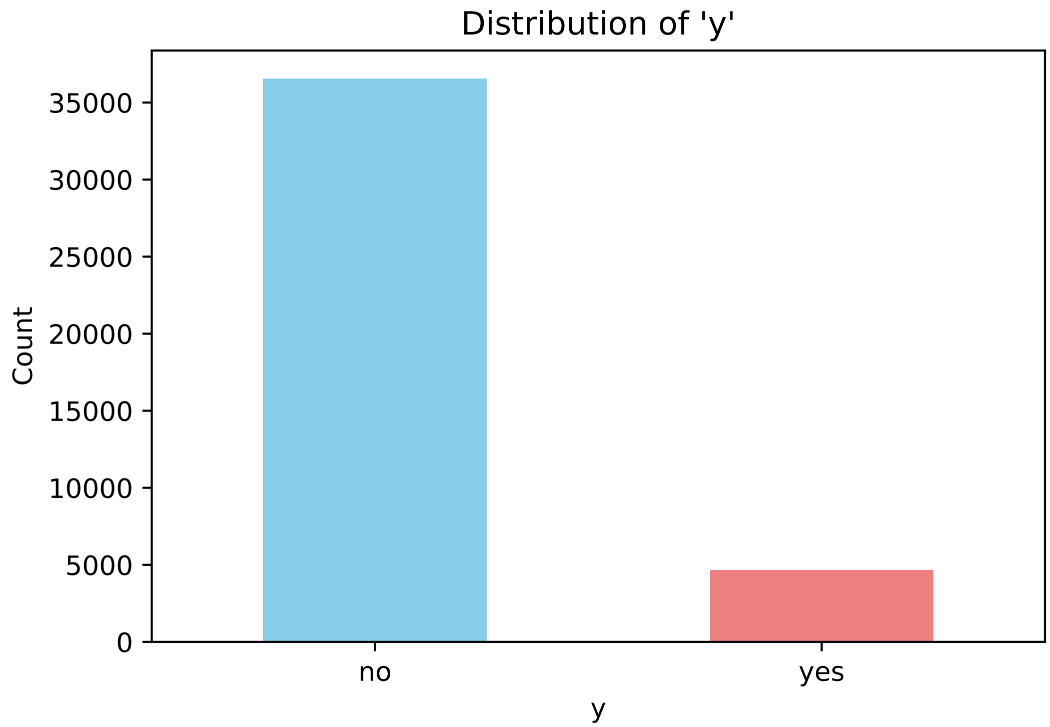


Figure 1: Loan Status distribution across education levels




```
Distribution of 'y':
y
no     36548
yes     4640
Name: count, dtype: int64


Correlations with target variable:
 age              0.030399
job              0.025122
marital          0.046203
education        0.057799
default         -0.099352
housing          0.011552
loan            -0.004909
contact         -0.144773
month           -0.006065
day_of_week      0.015967
duration         0.405274
campaign        -0.066357
```

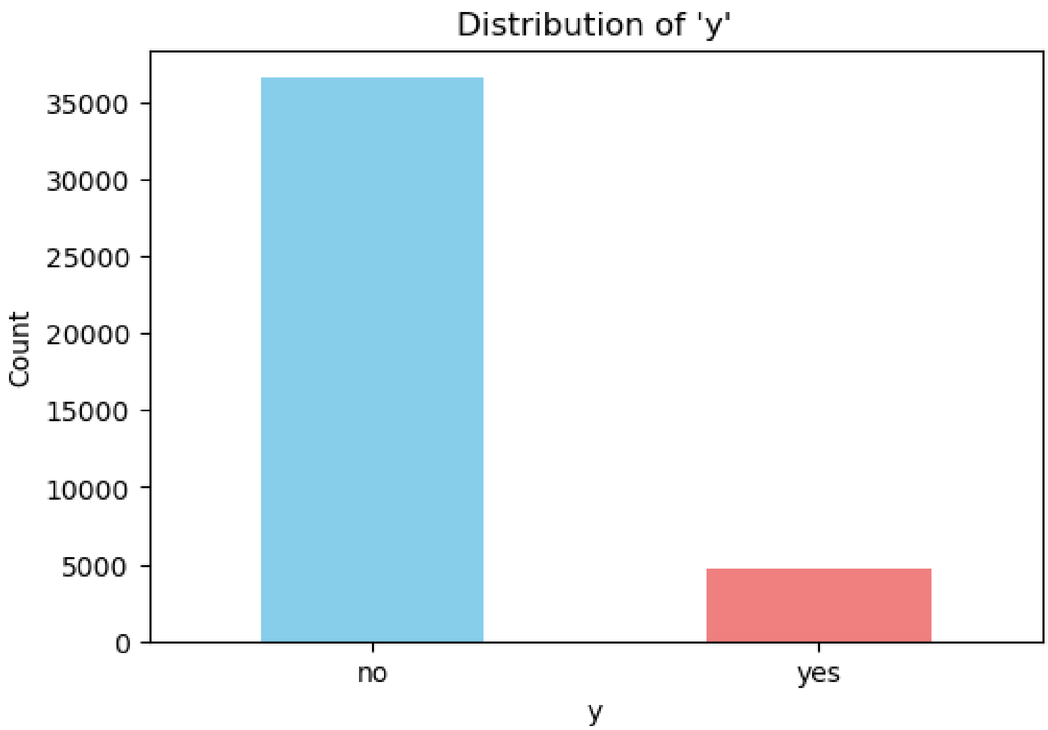


Figure 2: Distribution of Y

```
pdays            -0.324914
previous          0.230181
poutcome          0.129789
emp.var.rate     -0.298334
cons.price.idx   -0.136211
cons.conf.idx     0.054878
euribor3m        -0.307771
nr.employed      -0.354678
Name: y, dtype: float64

Correlations with target variable:
 age               0.030399
job               0.025122
marital           0.046203
education         0.057799
default          -0.099352
housing           0.011552
loan             -0.004909
contact          -0.144773
month            -0.006065
day_of_week       0.015967
duration          0.405274
campaign         -0.066357
pdays            -0.324914
previous          0.230181
poutcome          0.129789
emp.var.rate     -0.298334
cons.price.idx   -0.136211
cons.conf.idx     0.054878
euribor3m        -0.307771
nr.employed      -0.354678
Name: y, dtype: float64

Warning: Anomalous correlations between features:
                age  job  marital  education  default  housing  loan  contact  \
age             1.0  NaN      NaN        NaN      NaN      NaN   NaN      NaN
job             NaN  1.0      NaN        NaN      NaN      NaN   NaN      NaN
marital         NaN  NaN      1.0        NaN      NaN      NaN   NaN      NaN
education       NaN  NaN      NaN        1.0      NaN      NaN   NaN      NaN
default         NaN  NaN      NaN        NaN      1.0      NaN   NaN      NaN
housing         NaN  NaN      NaN        NaN      NaN      1.0   NaN      NaN
loan            NaN  NaN      NaN        NaN      NaN      NaN   1.0      NaN
```

```
contact         NaN  NaN      NaN        NaN      NaN      NaN   NaN      1.0
month           NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
day_of_week     NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
duration        NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
campaign        NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
pdays           NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
previous        NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
poutcome        NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
emp.var.rate    NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
cons.price.idx  NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
cons.conf.idx   NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
euribor3m       NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
nr.employed     NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
y               NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN

                month  day_of_week  ...  campaign  pdays  previous  poutcome  \
age               NaN          NaN  ...       NaN    NaN       NaN       NaN
job               NaN          NaN  ...       NaN    NaN       NaN       NaN
marital           NaN          NaN  ...       NaN    NaN       NaN       NaN
education         NaN          NaN  ...       NaN    NaN       NaN       NaN
default           NaN          NaN  ...       NaN    NaN       NaN       NaN
housing           NaN          NaN  ...       NaN    NaN       NaN       NaN
loan              NaN          NaN  ...       NaN    NaN       NaN       NaN
contact           NaN          NaN  ...       NaN    NaN       NaN       NaN
month             1.0          NaN  ...       NaN    NaN       NaN       NaN
day_of_week       NaN          1.0  ...       NaN    NaN       NaN       NaN
duration          NaN          NaN  ...       NaN    NaN       NaN       NaN
campaign          NaN          NaN  ...       1.0    NaN       NaN       NaN
pdays             NaN          NaN  ...       NaN    1.0       NaN       NaN
previous          NaN          NaN  ...       NaN    NaN       1.0       NaN
poutcome          NaN          NaN  ...       NaN    NaN       NaN       1.0
emp.var.rate      NaN          NaN  ...       NaN    NaN       NaN       NaN
cons.price.idx    NaN          NaN  ...       NaN    NaN       NaN       NaN
cons.conf.idx     NaN          NaN  ...       NaN    NaN       NaN       NaN
euribor3m         NaN          NaN  ...       NaN    NaN       NaN       NaN
nr.employed       NaN          NaN  ...       NaN    NaN       NaN       NaN
y                 NaN          NaN  ...       NaN    NaN       NaN       NaN

                emp.var.rate  cons.price.idx  cons.conf.idx  euribor3m  \
age                      NaN             NaN            NaN        NaN
job                      NaN             NaN            NaN        NaN
marital                  NaN             NaN            NaN        NaN
education                NaN             NaN            NaN        NaN
```

```
default               NaN           NaN         NaN        NaN
housing               NaN           NaN         NaN        NaN
loan                  NaN           NaN         NaN        NaN
contact               NaN           NaN         NaN        NaN
month                 NaN           NaN         NaN        NaN
day_of_week           NaN           NaN         NaN        NaN
duration              NaN           NaN         NaN        NaN
campaign              NaN           NaN         NaN        NaN
pdays                 NaN           NaN         NaN        NaN
previous              NaN           NaN         NaN        NaN
poutcome              NaN           NaN         NaN        NaN
emp.var.rate     1.000000           NaN         NaN   0.972245
cons.price.idx        NaN           1.0         NaN        NaN
cons.conf.idx         NaN           NaN         1.0        NaN
euribor3m        0.972245           NaN         NaN   1.000000
nr.employed      0.906970           NaN         NaN   0.945154
y                     NaN           NaN         NaN        NaN

                nr.employed    y
age                     NaN  NaN
job                     NaN  NaN
marital                 NaN  NaN
education               NaN  NaN
default                 NaN  NaN
housing                 NaN  NaN
loan                    NaN  NaN
contact                 NaN  NaN
month                   NaN  NaN
day_of_week             NaN  NaN
duration                NaN  NaN
campaign                NaN  NaN
pdays                   NaN  NaN
previous                NaN  NaN
poutcome                NaN  NaN
emp.var.rate       0.906970  NaN
cons.price.idx          NaN  NaN
cons.conf.idx           NaN  NaN
euribor3m          0.945154  NaN
nr.employed        1.000000  NaN
y                       NaN  1.0

[21 rows x 21 columns]
```

```
Feature correlation matrix:
                     age       job   marital  education   default   housing  \
age             1.000000  0.001250 -0.389753  -0.117892  0.164965 -0.001603
job             0.001250  1.000000  0.027897   0.134121 -0.028277  0.006962
marital        -0.389753  0.027897  1.000000   0.109220 -0.079450  0.010467
education      -0.117892  0.134121  0.109220   1.000000 -0.186859  0.016825
default         0.164965 -0.028277 -0.079450  -0.186859  1.000000 -0.015815
housing        -0.001603  0.006962  0.010467   0.016825 -0.015815  1.000000
loan           -0.007368 -0.010209  0.005788   0.006384 -0.003782  0.044296
contact         0.007021 -0.025132 -0.054501  -0.105726  0.135238 -0.082186
month          -0.024877 -0.033213 -0.007629  -0.082684 -0.015830 -0.018141
day_of_week    -0.017572 -0.000844  0.002202  -0.017986 -0.008701  0.003339
duration       -0.000866 -0.006490  0.010290  -0.015102 -0.011794 -0.007658
campaign        0.004594 -0.006923 -0.007240   0.000371  0.032825 -0.011010
pdays          -0.034369 -0.028468 -0.037942  -0.046626  0.080062 -0.010551
previous        0.024365  0.020965  0.038689   0.038831 -0.102416  0.021314
poutcome        0.019750  0.011504  0.001912   0.017009  0.023417 -0.011783
emp.var.rate   -0.000371 -0.008271 -0.084210  -0.043778  0.203263 -0.060196
cons.price.idx  0.000857 -0.016017 -0.057477  -0.081607  0.168073 -0.080504
cons.conf.idx   0.129372  0.052760 -0.033783   0.078799  0.026522 -0.033845
euribor3m       0.010767 -0.007880 -0.091939  -0.036380  0.195336 -0.059277
nr.employed    -0.017725 -0.019574 -0.086199  -0.041492  0.189845 -0.045862
y               0.030399  0.025122  0.046203   0.057799 -0.099352  0.011552

                    loan   contact     month  day_of_week  ...  campaign  \
age            -0.007368  0.007021 -0.024877    -0.017572  ...  0.004594
job            -0.010209 -0.025132 -0.033213    -0.000844  ... -0.006923
marital         0.005788 -0.054501 -0.007629     0.002202  ... -0.007240
education       0.006384 -0.105726 -0.082684    -0.017986  ...  0.000371
default        -0.003782  0.135238 -0.015830    -0.008701  ...  0.032825
housing         0.044296 -0.082186 -0.018141     0.003339  ... -0.011010
loan            1.000000 -0.008556 -0.005705    -0.009344  ...  0.005166
contact        -0.008556  1.000000  0.276565    -0.009575  ...  0.077368
month          -0.005705  0.276565  1.000000     0.027677  ... -0.062059
day_of_week    -0.009344 -0.009575  0.027677     1.000000  ... -0.038288
duration       -0.000916 -0.026657  0.003690     0.021950  ... -0.071699
campaign        0.005166  0.077368 -0.062059    -0.038288  ...  1.000000
pdays           0.000345  0.117970 -0.047891    -0.009531  ...  0.052584
previous       -0.001327 -0.212848  0.103157    -0.004102  ... -0.079141
poutcome       -0.001511  0.118744 -0.065012     0.018732  ...  0.032586
emp.var.rate    0.001849  0.393584 -0.178782     0.033245  ...  0.150754
cons.price.idx -0.002430  0.591474 -0.004239     0.005644  ...  0.127836
cons.conf.idx  -0.012025  0.251614  0.009652     0.041465  ... -0.013733
```

```
euribor3m       0.000125  0.399773 -0.117264     0.039043  ...  0.135133
nr.employed     0.003903  0.269155 -0.221425     0.028380  ...  0.144095
y              -0.004909 -0.144773 -0.006065     0.015967  ... -0.066357

                  pdays  previous  poutcome  emp.var.rate  cons.price.idx  \
age           -0.034369  0.024365  0.019750     -0.000371        0.000857
job           -0.028468  0.020965  0.011504     -0.008271       -0.016017
marital       -0.037942  0.038689  0.001912     -0.084210       -0.057477
education     -0.046626  0.038831  0.017009     -0.043778       -0.081607
default        0.080062 -0.102416  0.023417      0.203263        0.168073
housing       -0.010551  0.021314 -0.011783     -0.060196       -0.080504
loan           0.000345 -0.001327 -0.001511      0.001849       -0.002430
contact        0.117970 -0.212848  0.118744      0.393584        0.591474
month         -0.047891  0.103157 -0.065012     -0.178782       -0.004239
day_of_week   -0.009531 -0.004102  0.018732      0.033245        0.005644
duration      -0.047577  0.020640  0.033360     -0.027968        0.005312
campaign       0.052584 -0.079141  0.032586      0.150754        0.127836
pdays          1.000000 -0.587514 -0.475619      0.271004        0.078889
previous      -0.587514  1.000000 -0.313110     -0.420489       -0.203130
poutcome      -0.475619 -0.313110  1.000000      0.192972        0.211330
emp.var.rate   0.271004 -0.420489  0.192972      1.000000        0.775334
cons.price.idx 0.078889 -0.203130  0.211330      0.775334        1.000000
cons.conf.idx -0.091342 -0.050936  0.178289      0.196041        0.058986
euribor3m      0.296899 -0.454494  0.184144      0.972245        0.688230
nr.employed    0.372605 -0.501333  0.119689      0.906970        0.522034
y             -0.324914  0.230181  0.129789     -0.298334       -0.136211

                cons.conf.idx  euribor3m  nr.employed         y
age                  0.129372   0.010767    -0.017725  0.030399
job                  0.052760  -0.007880    -0.019574  0.025122
marital             -0.033783  -0.091939    -0.086199  0.046203
education            0.078799  -0.036380    -0.041492  0.057799
default              0.026522   0.195336     0.189845 -0.099352
housing             -0.033845  -0.059277    -0.045862  0.011552
loan                -0.012025   0.000125     0.003903 -0.004909
contact              0.251614   0.399773     0.269155 -0.144773
month                0.009652  -0.117264    -0.221425 -0.006065
day_of_week          0.041465   0.039043     0.028380  0.015967
duration            -0.008173  -0.032897    -0.044703  0.405274
campaign            -0.013733   0.135133     0.144095 -0.066357
pdays               -0.091342   0.296899     0.372605 -0.324914
previous            -0.050936  -0.454494    -0.501333  0.230181
poutcome             0.178289   0.184144     0.119689  0.129789
```

```
emp.var.rate          0.196041   0.972245     0.906970 -0.298334
cons.price.idx        0.058986   0.688230     0.522034 -0.136211
cons.conf.idx         1.000000   0.277686     0.100513  0.054878
euribor3m             0.277686   1.000000     0.945154 -0.307771
nr.employed           0.100513   0.945154     1.000000 -0.354678
y                     0.054878  -0.307771    -0.354678  1.000000

[21 rows x 21 columns]
Warning: Anomalous correlations between features:
                age  job  marital  education  default  housing  loan  contact  \
age             1.0  NaN      NaN        NaN      NaN      NaN   NaN      NaN
job             NaN  1.0      NaN        NaN      NaN      NaN   NaN      NaN
marital         NaN  NaN      1.0        NaN      NaN      NaN   NaN      NaN
education       NaN  NaN      NaN        1.0      NaN      NaN   NaN      NaN
default         NaN  NaN      NaN        NaN      1.0      NaN   NaN      NaN
housing         NaN  NaN      NaN        NaN      NaN      1.0   NaN      NaN
loan            NaN  NaN      NaN        NaN      NaN      NaN   1.0      NaN
contact         NaN  NaN      NaN        NaN      NaN      NaN   NaN      1.0
month           NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
day_of_week     NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
duration        NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
campaign        NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
pdays           NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
previous        NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
poutcome        NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
emp.var.rate    NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
cons.price.idx  NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
cons.conf.idx   NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
euribor3m       NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
nr.employed     NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN
y               NaN  NaN      NaN        NaN      NaN      NaN   NaN      NaN

                month  day_of_week  ...  campaign  pdays  previous  poutcome  \
age               NaN          NaN  ...       NaN    NaN       NaN       NaN
job               NaN          NaN  ...       NaN    NaN       NaN       NaN
marital           NaN          NaN  ...       NaN    NaN       NaN       NaN
education         NaN          NaN  ...       NaN    NaN       NaN       NaN
default           NaN          NaN  ...       NaN    NaN       NaN       NaN
housing           NaN          NaN  ...       NaN    NaN       NaN       NaN
loan              NaN          NaN  ...       NaN    NaN       NaN       NaN
contact           NaN          NaN  ...       NaN    NaN       NaN       NaN
month             1.0          NaN  ...       NaN    NaN       NaN       NaN
day_of_week       NaN          1.0  ...       NaN    NaN       NaN       NaN
```

```
duration           NaN          NaN  ...       NaN   NaN       NaN       NaN
campaign           NaN          NaN  ...       1.0   NaN       NaN       NaN
pdays              NaN          NaN  ...       NaN   1.0       NaN       NaN
previous           NaN          NaN  ...       NaN   NaN       1.0       NaN
poutcome           NaN          NaN  ...       NaN   NaN       NaN       1.0
emp.var.rate       NaN          NaN  ...       NaN   NaN       NaN       NaN
cons.price.idx     NaN          NaN  ...       NaN   NaN       NaN       NaN
cons.conf.idx      NaN          NaN  ...       NaN   NaN       NaN       NaN
euribor3m          NaN          NaN  ...       NaN   NaN       NaN       NaN
nr.employed        NaN          NaN  ...       NaN   NaN       NaN       NaN
y                  NaN          NaN  ...       NaN   NaN       NaN       NaN

                emp.var.rate  cons.price.idx  cons.conf.idx  euribor3m  \
age                      NaN             NaN            NaN        NaN
job                      NaN             NaN            NaN        NaN
marital                  NaN             NaN            NaN        NaN
education                NaN             NaN            NaN        NaN
default                  NaN             NaN            NaN        NaN
housing                  NaN             NaN            NaN        NaN
loan                     NaN             NaN            NaN        NaN
contact                  NaN             NaN            NaN        NaN
month                    NaN             NaN            NaN        NaN
day_of_week              NaN             NaN            NaN        NaN
duration                 NaN             NaN            NaN        NaN
campaign                 NaN             NaN            NaN        NaN
pdays                    NaN             NaN            NaN        NaN
previous                 NaN             NaN            NaN        NaN
poutcome                 NaN             NaN            NaN        NaN
emp.var.rate        1.000000             NaN            NaN   0.972245
cons.price.idx           NaN             1.0            NaN        NaN
cons.conf.idx            NaN             NaN            1.0        NaN
euribor3m           0.972245             NaN            NaN   1.000000
nr.employed         0.906970             NaN            NaN   0.945154
y                        NaN             NaN            NaN        NaN

                nr.employed   y
age                     NaN NaN
job                     NaN NaN
marital                 NaN NaN
education               NaN NaN
default                 NaN NaN
housing                 NaN NaN
loan                    NaN NaN
```

```
contact                    NaN  NaN
month                      NaN  NaN
day_of_week                NaN  NaN
duration                   NaN  NaN
campaign                   NaN  NaN
pdays                      NaN  NaN
previous                   NaN  NaN
poutcome                   NaN  NaN
emp.var.rate          0.906970  NaN
cons.price.idx             NaN  NaN
cons.conf.idx              NaN  NaN
euribor3m             0.945154  NaN
nr.employed           1.000000  NaN
y                          NaN  1.0

[21 rows x 21 columns]
```

Analysis

The analysis began with loading and preprocessing the dataset, addressing missing values, encoding categorical features, and scaling numeric variables to ensure consistency across features. The dataset was then split into training and testing sets, with 20% allocated for testing to evaluate model performance. A logistic regression model was chosen for binary classification, implemented through a Pipeline to streamline preprocessing, encoding, and model fitting. To optimize model accuracy, GridSearchCV was used for hyperparameter tuning, and cross-validation was employed to assess the model's robustness. After training the model, its performance was evaluated using various metrics such as accuracy, precision, recall, and F1-score, with confusion matrices and heatmaps created using Seaborn for better visualization. These tools provided insights into the model's ability to differentiate between classes.

Results

To evaluate the utility of each predictor in predicting the response variable (y) for the bank marketing dataset, we visualized the distributions of each predictor in the training dataset, coloring them by the class (yes: orange and no: blue). These visualizations include univariate distributions, pairwise correlations, and scatterplots, as seen in the attached figures. In analyzing these plots, we observe significant differences in the distribution centers and spreads of predictors like duration and campaign between the two classes. However, some variables, such as age and balance, show overlapping distributions with less apparent class separation. Furthermore, categorical predictors, such as job and month, exhibit class imbalance but may still hold valuable predictive information. Based on these insights, predictors demonstrating clear separability and meaningful patterns are prioritized for inclusion in the predictive model, while those showing little to no differentiation may be considered for exclusion.

```
alt.ConcatChart(...)
```

```
# Look at the univariate distributions (counts) for categorical variables
# Changing 'target' to an object dtype just for the data passed to the chart
aly.dist(
    bank_data.assign(target=lambda bank_data: bank_data['y'].astype(object)),
    dtype='object',
    color='y'
)
```

```
# Visualize pairwise correlations for quantitative variables
aly.corr(bank_data)
```

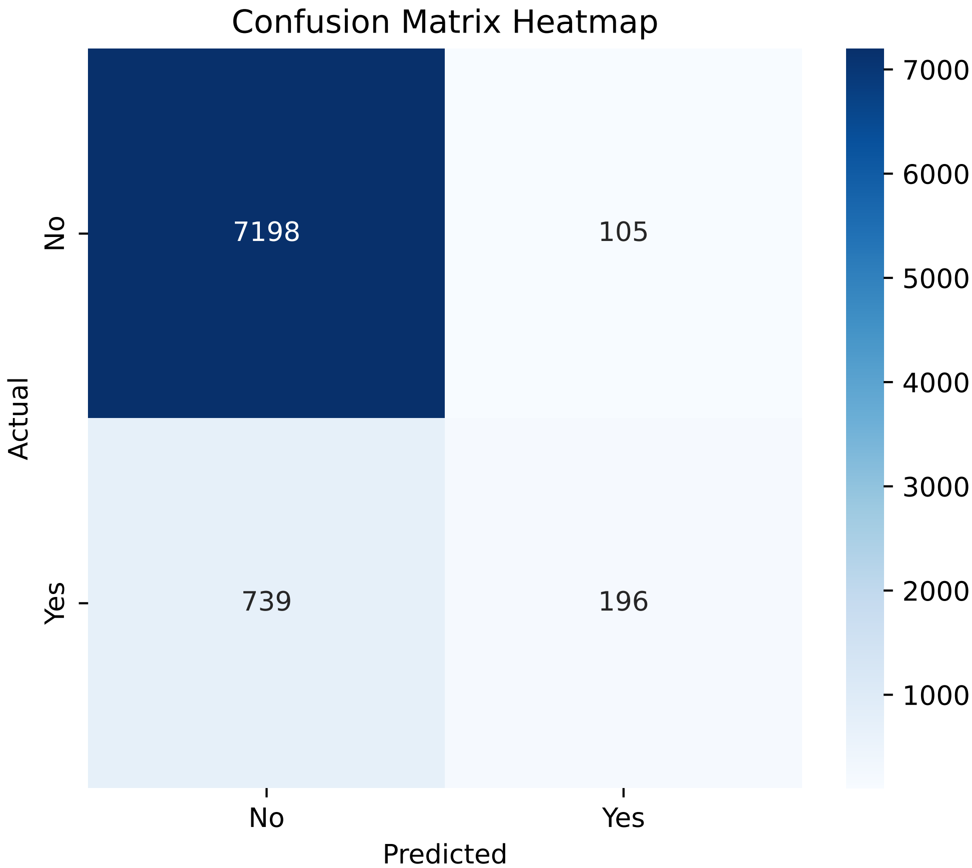
```
# Visualize pairwise scatterplots for quantitative variables with high correlations
# Identify columns with at least one high correlation
high_corr_columns = [
    "age",
    "duration",
    "campaign",
    "previous",
    "y",  # Always include the target as well
]

# Sampling the DataFrame to not saturate the charts
aly.pair(bank_data[high_corr_columns].sample(300), color='y')
```

Model Creation

Initially without Hyperparameter optimization using grid search

```
Accuracy: 0.8975479485311969
Confusion Matrix:
 [[7198  105]
 [ 739  196]]
Logistic Regression Evaluation:
Accuracy: 0.90
Precision: 0.65
```

```
Recall: 0.21
F1 Score: 0.32
```




```
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 [[7198  105]
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Accuracy: 0.90
Precision: 0.65
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```

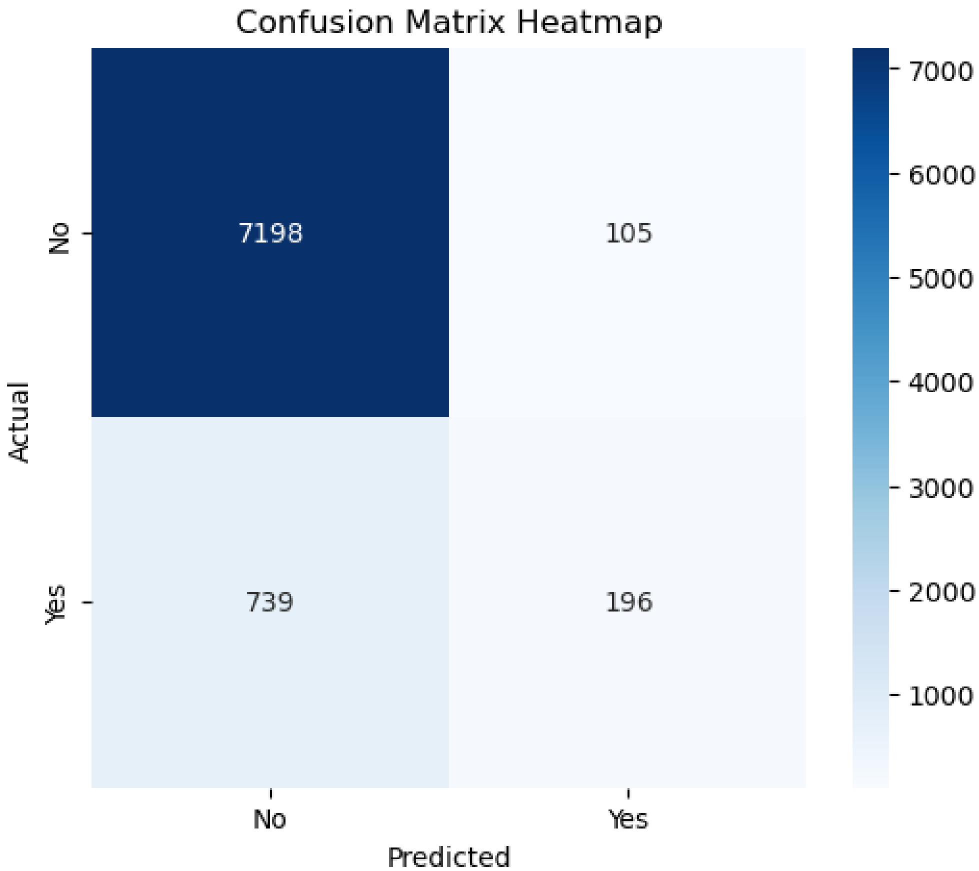
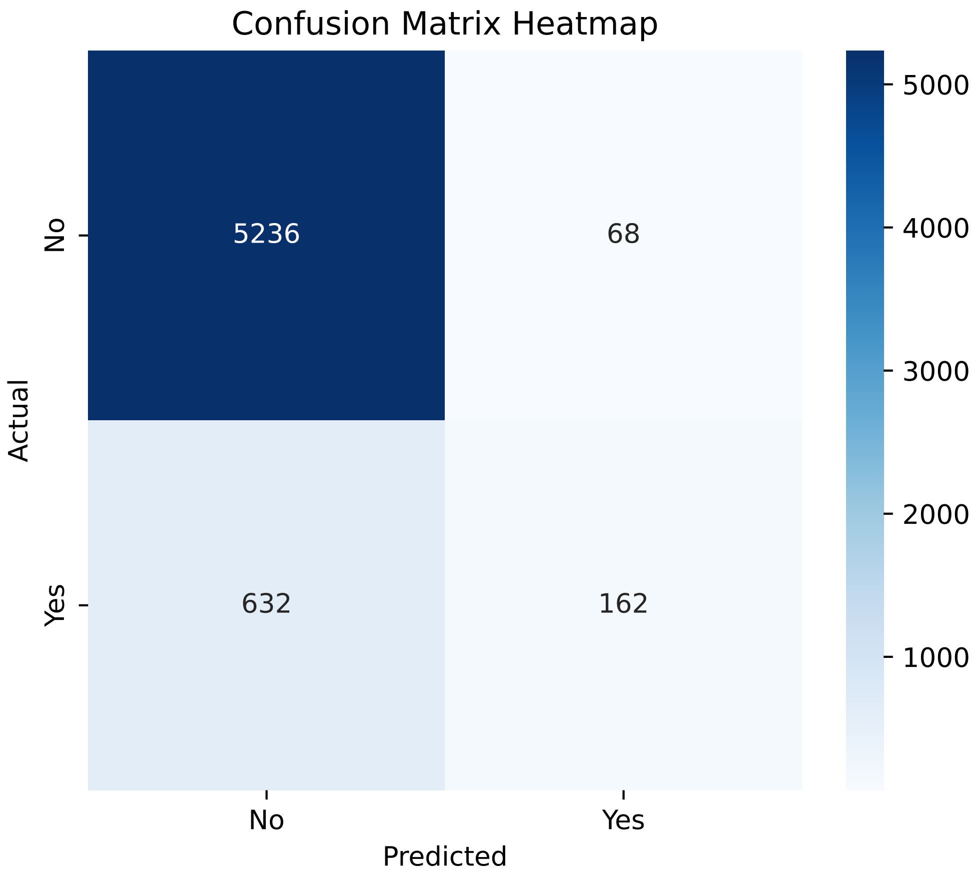


Figure 3: png

```
Best hyperparameters found:  {'classifier__C': 0.1, 'classifier__max_iter': 300, 'classifier_
Accuracy: 0.8852082650049197
Confusion Matrix:
 [[5236   68]
 [ 632  162]]
Logistic Regression Evaluation:
Accuracy: 0.89
Precision: 0.70
Recall: 0.20
F1 Score: 0.32
```




```
Best hyperparameters found:  {'classifier__C': 0.1, 'classifier__max_iter': 300, 'classifier_
Accuracy: 0.8852082650049197
Confusion Matrix:
 [[5236   68]
 [ 632  162]]
Logistic Regression Evaluation:
Accuracy: 0.89
Precision: 0.70
Recall: 0.20
F1 Score: 0.32
```

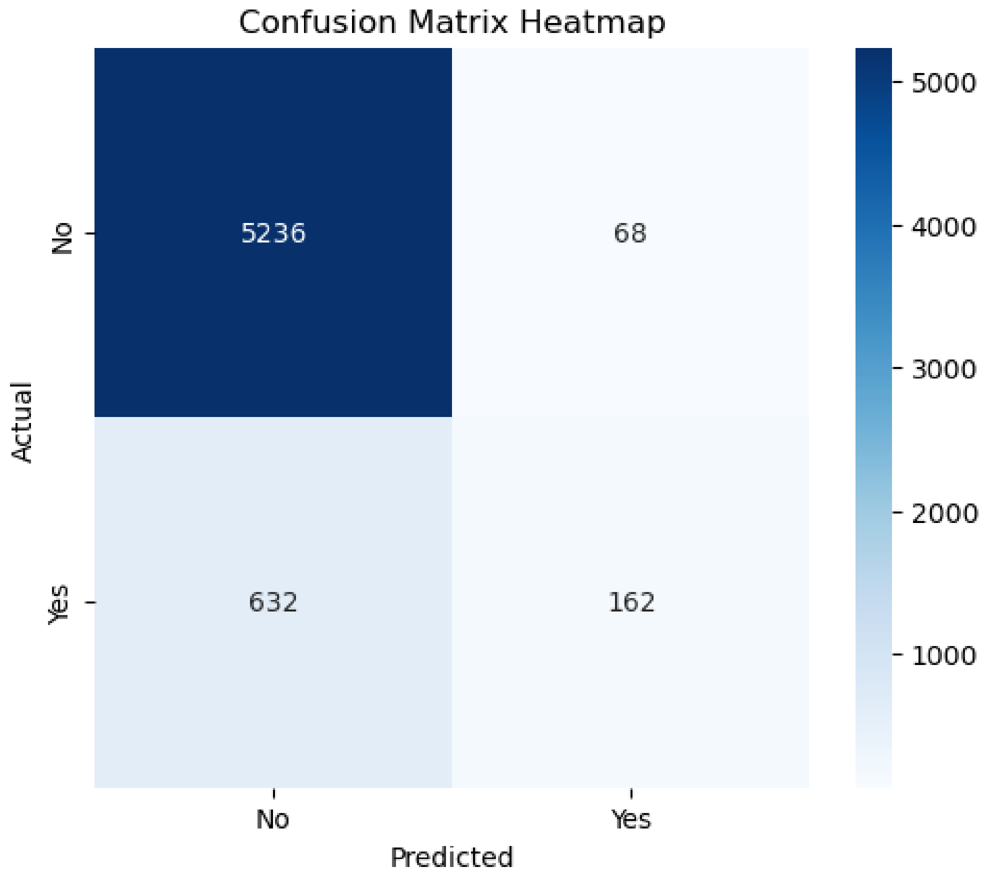
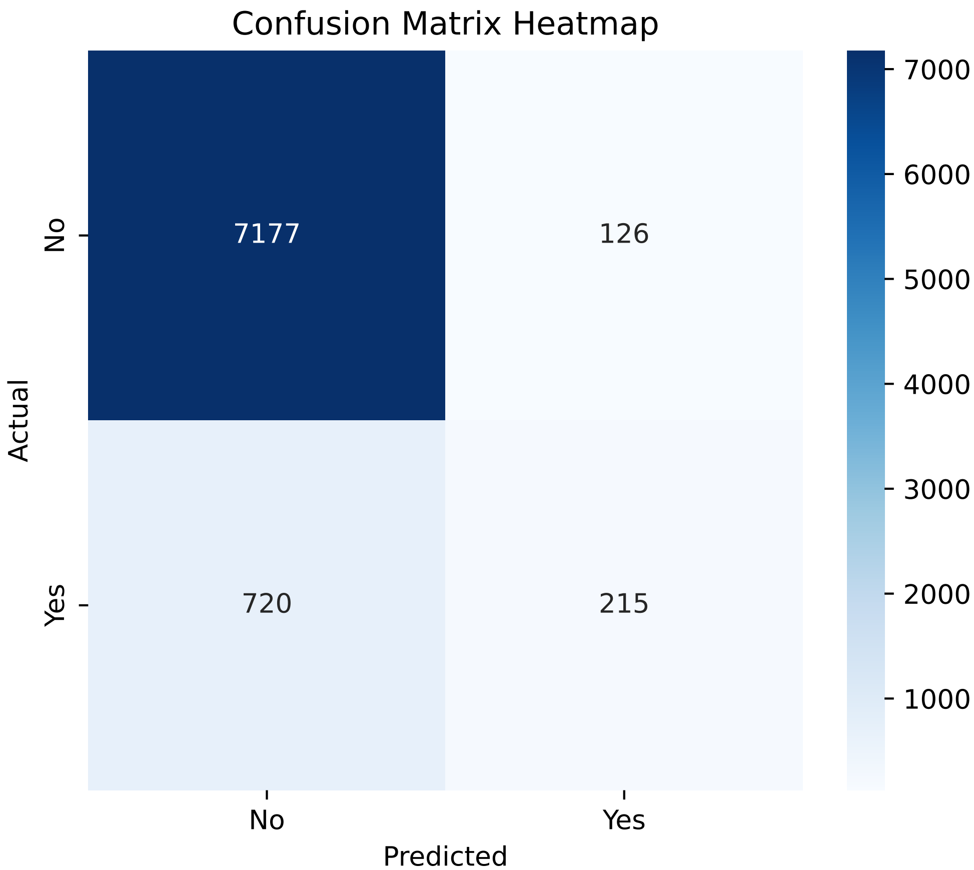


Figure 4: png

```
Fitting 5 folds for each of 90 candidates, totalling 450 fits
Best Parameters from Grid Search: {'classifier__criterion': 'entropy', 'classifier__max_deptl
Accuracy: 0.8973051711580481
Confusion Matrix:
 [[7177  126]
 [ 720  215]]
Decision Tree Evaluation with Optimized Hyperparameters:
Accuracy: 0.90
Precision: 0.63
Recall: 0.23
F1 Score: 0.34
```




```
Fitting 5 folds for each of 90 candidates, totalling 450 fits
Best Parameters from Grid Search: {'classifier__criterion': 'entropy', 'classifier__max_depth
Accuracy: 0.8973051711580481
Confusion Matrix:
 [[7177  126]
 [ 720  215]]
Decision Tree Evaluation with Optimized Hyperparameters:
Accuracy: 0.90
Precision: 0.63
Recall: 0.23
F1 Score: 0.34
```

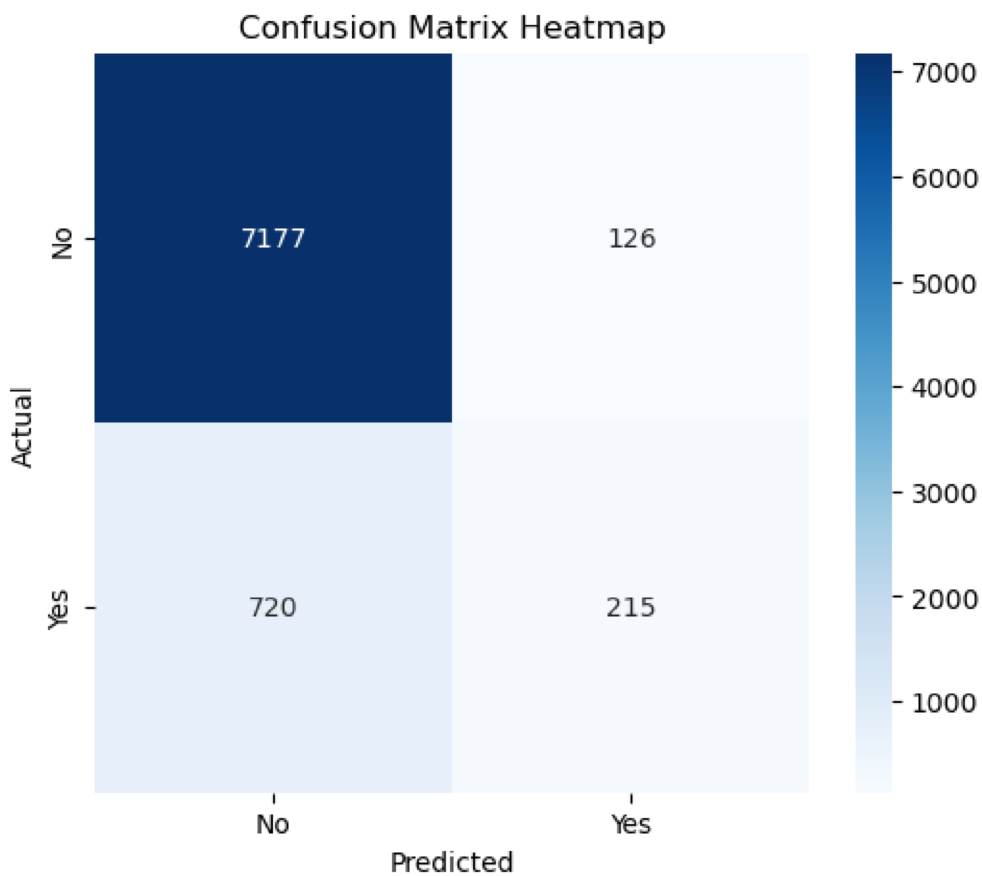
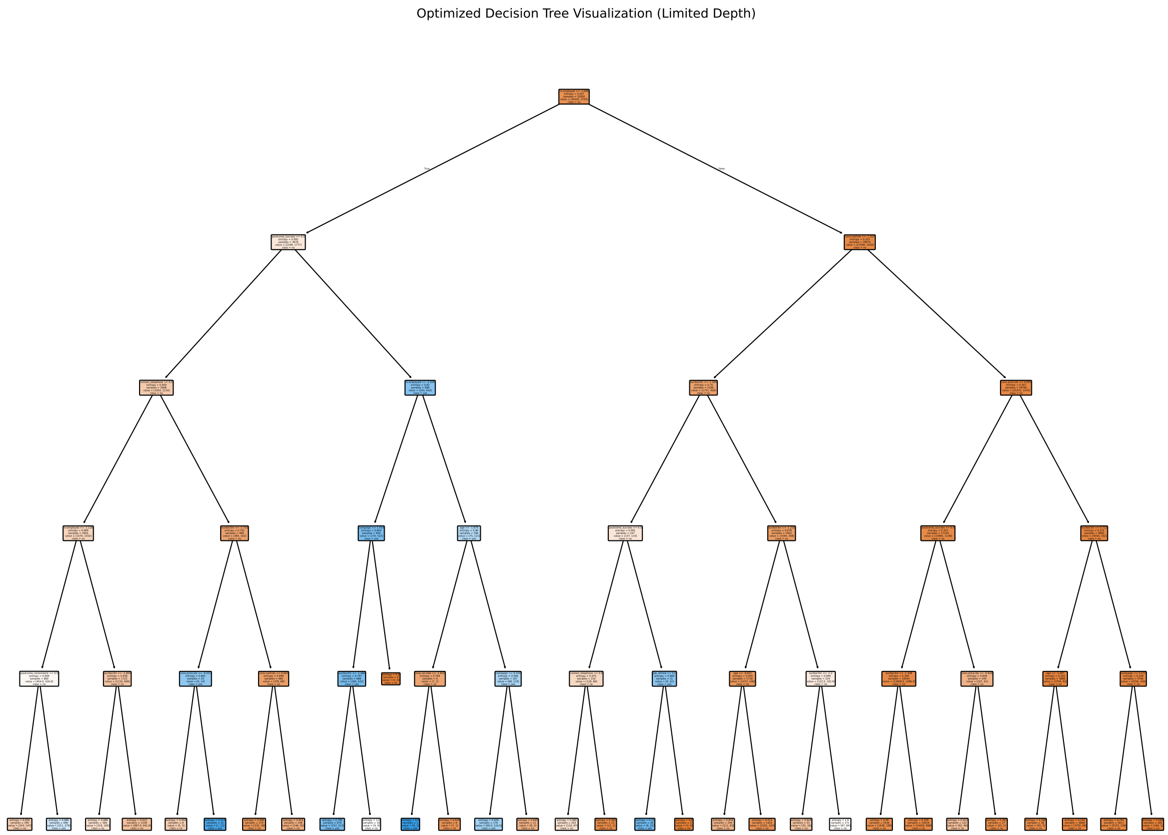


Figure 5: Confusion Matrix Heat Map



Discussion

Logistic Regression Model:

The Logistic Regression model has achieved an accuracy of approximately 88.5%, with the best hyperparameters found as: `{'classifier__C': 0.1, 'classifier__max_iter': 100, 'classifier__penalty': 'l1', 'classifier__solver': 'liblinear'}`. The confusion matrix for this model is as follows:

- **True Negatives (5236)**: The model correctly identified 5236 non-subscribers, which indicates its strong performance in predicting the majority class (non-subscribers).
- **False Positives (68)**: There are 68 instances where the model incorrectly predicted that non-subscribers would subscribe. This is a relatively low number, indicating that the model is relatively efficient at avoiding unnecessary targeting.

Optimized Decision Tree Visualization (Limited Depth)

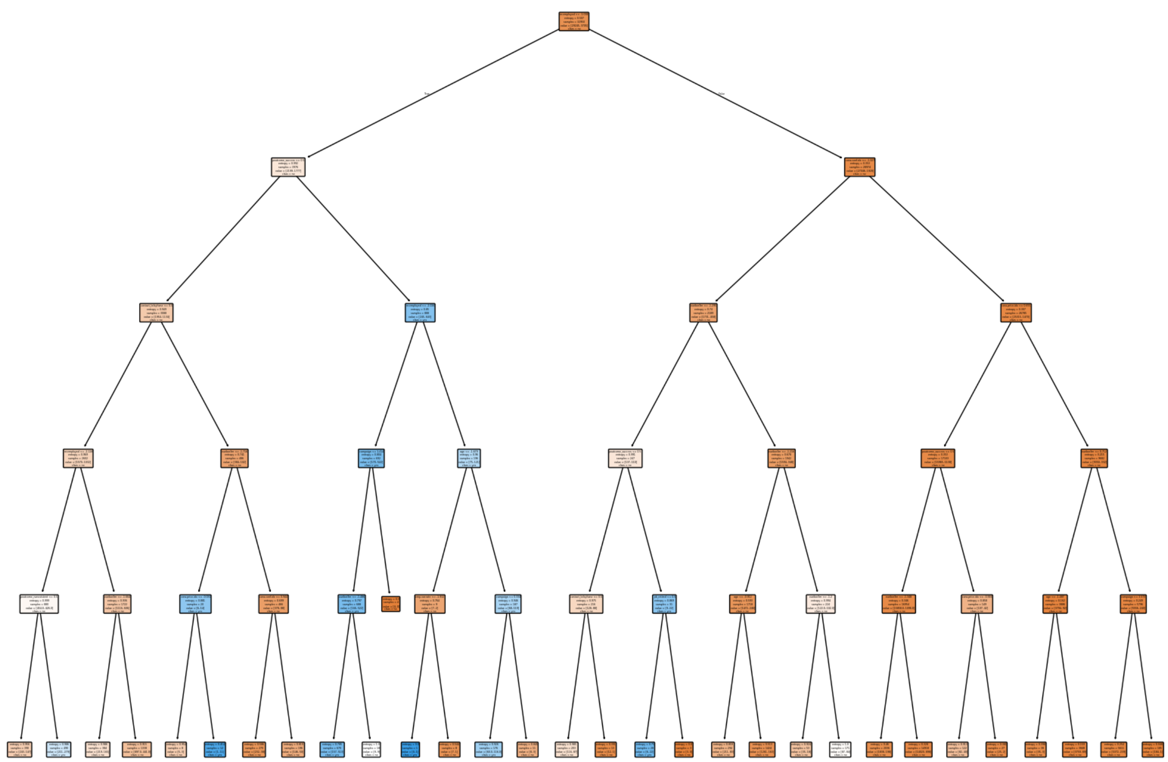


Figure 6: Optimized Decision Tree Visualization

- **False Negatives (632)**: The model missed 632 actual subscribers, which is a significant number and highlights the low recall.
- **True Positives (162)**: The model correctly predicted 162 subscribers, but this number is still quite low, reflecting the model's struggle to identify potential subscribers.

The **Precision** is 0.70, meaning that 70% of the customers predicted as subscribers are actually subscribers. However, the **Recall** is only 0.20, meaning the model captures just 20% of the actual subscribers, which is quite low. This results in an **F1 Score** of 0.32, reflecting a poor balance between precision and recall. Despite the good precision, the low recall suggests that the model is not effectively identifying many actual subscribers, pointing to a significant trade-off between false positives and false negatives. This version of Logistic Regression is more suited to scenarios where **precision** (minimizing false positives) is prioritized over **recall** (capturing all potential subscribers).

Decision Tree Model:

After performing a grid search for hyperparameter optimization, the best hyperparameters found are: `{'classifier__criterion': 'entropy', 'classifier__max_depth': 5, 'classifier__min_samples_leaf': 1, 'classifier__min_samples_split': 2}`. The model achieved an accuracy of approximately 89.7%, with the confusion matrix as follows:

- **True Negatives (7177)**: The Decision Tree correctly predicted 7177 non-subscribers, showing solid performance in predicting the majority class (non-subscribers).
- **False Positives (126)**: There are 126 instances where the model incorrectly predicted non-subscribers as subscribers, which is a moderate number compared to the Logistic Regression model, indicating a higher sensitivity to identifying potential subscribers.
- **False Negatives (720)**: The model failed to predict 720 actual subscribers, a somewhat higher number, reflecting a lower recall than might be ideal.
- **True Positives (215)**: The Decision Tree correctly predicted 215 subscribers, which is an improvement over the Logistic Regression model, suggesting it is better at identifying potential subscribers.

The **Precision** is 0.63, meaning 63% of the customers predicted as subscribers are indeed subscribers. The **Recall** is 0.23, meaning the model captures only 23% of actual subscribers, indicating it still misses a significant portion. This results in an **F1 Score** of 0.34, which is slightly higher than the Logistic Regression model but still reflects an imbalance between precision and recall. The Decision Tree model performs better than Logistic Regression in terms of recall but still struggles to capture a large proportion of the potential subscribers. It might benefit from further adjustments, such as pruning, to reduce the number of false positives and improve its recall.

Although the Decision Tree has a slightly lower accuracy, its **higher recall** (more true positives) suggests it is better at identifying potential subscribers. However, its higher **false**

positives indicate that the model might be overfitting, capturing noise in the data. This suggests that the Decision Tree is more sensitive to patterns in the data but might benefit from **regularization** or **pruning** to reduce overfitting.

Comparison and Implications:

Both models indicate that the most common outcome in the dataset is non-subscription, as reflected in the confusion matrices, where the number of true negatives vastly outweighs the number of true positives. This confirms that "no" is the statistically likely outcome for customer subscription.

- **Logistic Regression Model**: The Logistic Regression model is better suited for situations where minimizing false positives is critical, as its **precision** (0.70) is higher than that of the Decision Tree model. However, its **recall** (0.20) is lower, meaning it misses a significant portion of actual subscribers. This makes the Logistic Regression model more effective in contexts where avoiding unnecessary targeting of non-subscribers is more important than capturing every potential subscriber.
- **Decision Tree Model**: The Decision Tree model, while slightly less accurate overall (**accuracy = 89.7%**), has a better **recall** (0.23), meaning it identifies more true positives compared to Logistic Regression. However, this comes at the cost of an increased number of **false positives** (126). As such, the Decision Tree is better at capturing potential subscribers but may lead to more resources being spent on non-converting customers.

Implications:

Both models show reasonable accuracy and can be useful for the business's marketing initiatives to increase term deposits (subscriptions). The Logistic Regression model would be advantageous in scenarios where reducing false positives and minimizing resource expenditure is a priority, while the Decision Tree model could be valuable in situations where capturing more potential subscribers (even at the cost of more false positives).

Future iterations of these models should focus on improving both **precision** and **recall**, possibly through regularization, pruning, or incorporating more diverse data to better identify customers likely to subscribe. By fine-tuning the models, the business can maximize the effectiveness of its marketing campaigns and increase its return on investment.

Strategic Recommendations:

Given the insights from the evaluation of both models, here are some actionable strategies to enhance the bank's marketing efforts and improve conversion rates:

Targeted Marketing:

- Use these models to segment customers into two groups: those with a high likelihood of subscribing (identified by the model as potential positives) and those with a low likelihood (predicted as negatives). Focus marketing efforts on the high-probability segment to optimize resource allocation.

Campaign Timing:

- Refine marketing strategies by focusing efforts on customers during certain times when they are more likely to respond. The model can be expanded to include temporal features (e.g., day of the week or month) to optimize campaign timing.

Personalized Offers:

- Tailor offers to individual customers based on characteristics like age, occupation, or previous interactions with the bank (e.g., loan status). The models' predictions can guide personalized messaging, increasing engagement with customers and improving the chances of subscription.

Improve Conversion Rates:

- Implement **follow-up campaigns** targeting customers predicted as high-likelihood subscribers but who still did not convert. For those predicted as low-likelihood, consider creating new or improved offers to address specific concerns or barriers to subscription.

Monitor and Adjust:

- Continuously track the performance of both models over time, paying close attention to precision and recall. As more data becomes available, adjust the models and marketing strategies to ensure increasing accuracy and the development of more effective campaigns.

By applying these insights and strategies, the bank can improve its targeting for **long-term deposit** products, increasing conversion rates while making sure the marketing efforts are cost-effective and personalized.

–For the markdown rendering Chat-gpt was used to correct code

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