

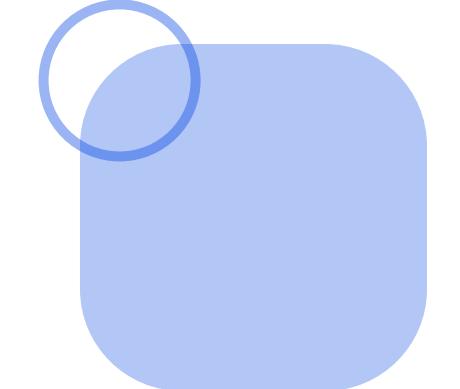
BANK MARKET ANALYSIS

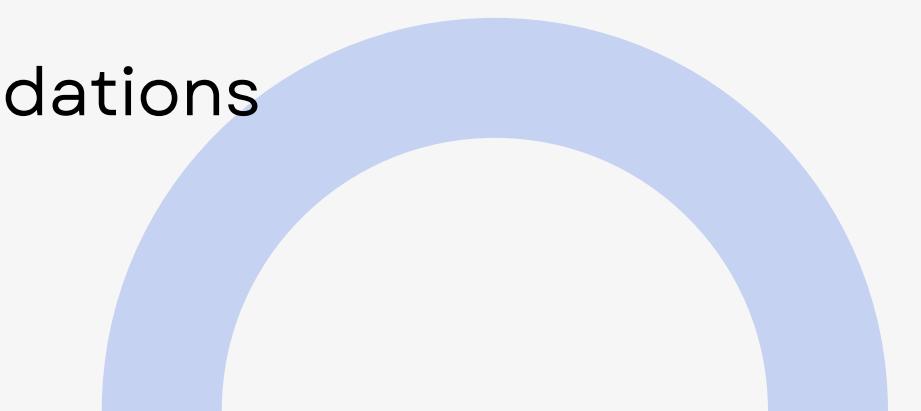
PRESENTED BY HANSEL OMONDI

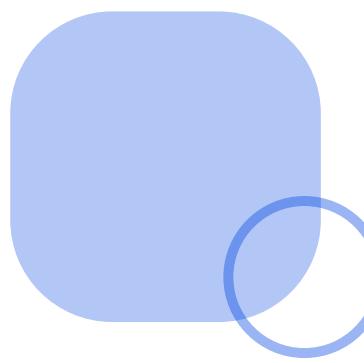
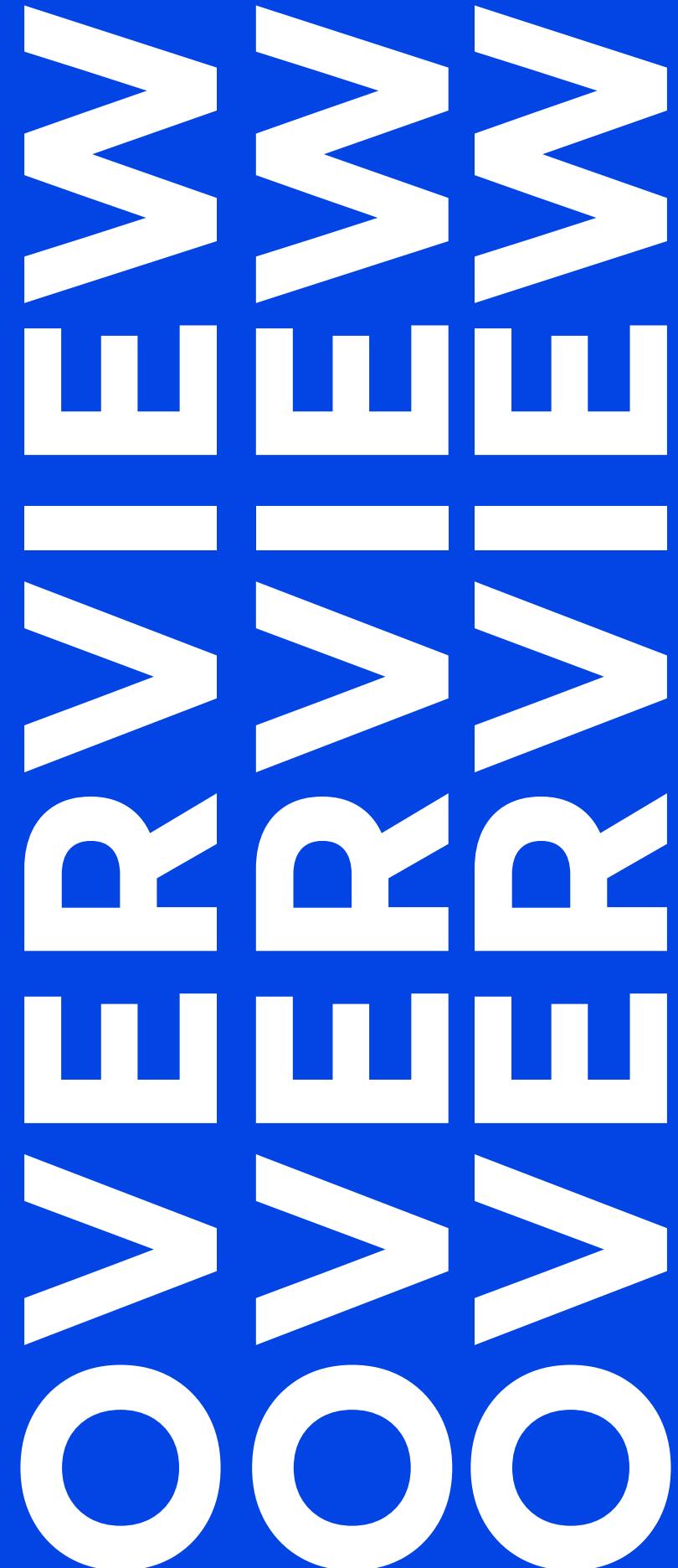




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In an effort to **optimize marketing campaigns** for increasing term deposit subscriptions, this project utilizes data from a Portuguese bank's direct marketing efforts.

The **primary objective** is to develop predictive models that classify clients into two categories: those likely to subscribe to a term deposit and those who are not.

By focusing on attributes such as age, job type, and balance, the analysis aims to **improve the bank's marketing efficiency**, reduce unnecessary contacts, and ultimately increase the conversion rate of term deposit subscriptions.

BUSINESS UNDERSTANDING



The bank is keen on optimizing its marketing campaigns to boost the number of clients subscribing to term deposits. The challenge lies in accurately identifying which clients are most likely to subscribe, thereby enabling the bank to allocate resources more effectively and minimize operational costs. A predictive model can guide the bank in targeting high-potential leads, optimizing contact strategies, and segmenting the customer base for more focused marketing efforts. This will not only increase the conversion rate but also enhance client relationships by reducing unnecessary interactions.

DATA UNDERSTANDING

DATA ANALYSIS

About Data

The dataset used for this analysis contains information from direct marketing campaigns conducted by the bank. It includes 45,211 instances, with attributes covering demographic data (e.g., age, job type), financial details (e.g., balance), and information related to the marketing campaign (e.g., number of contacts, previous outcomes).



ANALYSIS

Exploratory Data Analysis (EDA) revealed that certain client attributes, such as age and balance, are strongly associated with the likelihood of subscribing to a term deposit.

From the Exploratory Data Analysis (EDA):

- Age: The majority of clients are between 32 and 47 years old, with an average of 40. Clients in this middle age range show a higher likelihood of subscribing.
- Duration: Longer call durations tend to result in more subscriptions, with the average call lasting around 4.3 minutes.
- Previous Contact: Clients with no or few prior contacts are more likely to subscribe than those contacted excessively in earlier campaigns.
- Economic Indicators: Low consumer confidence and variable employment rates may affect clients' willingness to commit to term deposits.

MODEL DEVELOPMENT & EVALUATION

Both models were evaluated on metrics such as accuracy, precision, recall, and the ROC-AUC score, highlighting the effectiveness of each in predicting client behavior.

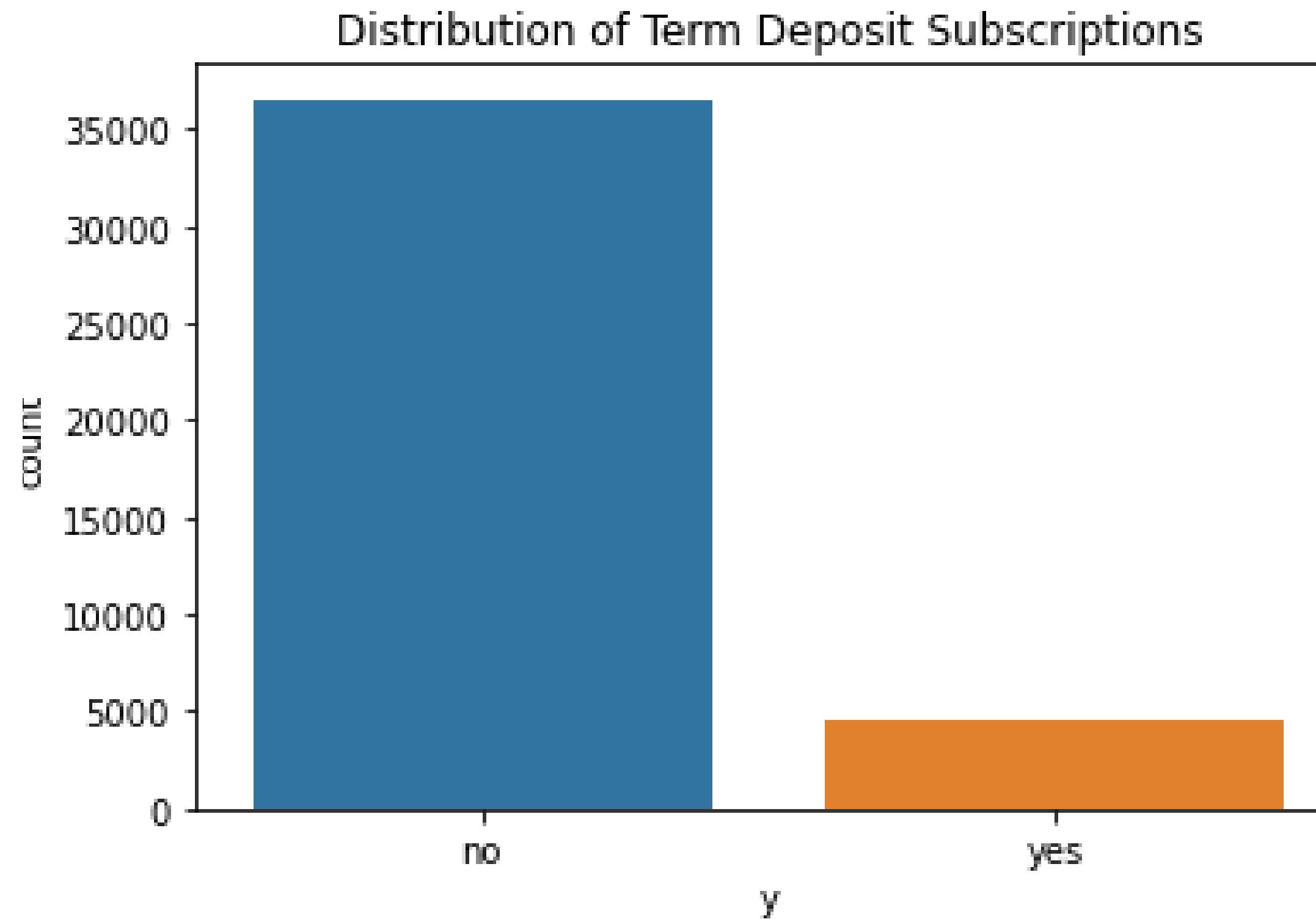
DECISION TREE

Decision Tree: This model was chosen for its interpretability. It achieved an accuracy of 88.99% with key features such as age, duration, and number of contacts influencing the outcome. The confusion matrix revealed 10,275 true negatives and 721 true positives, showing strong performance in correctly identifying both subscribers and non-subscribers.

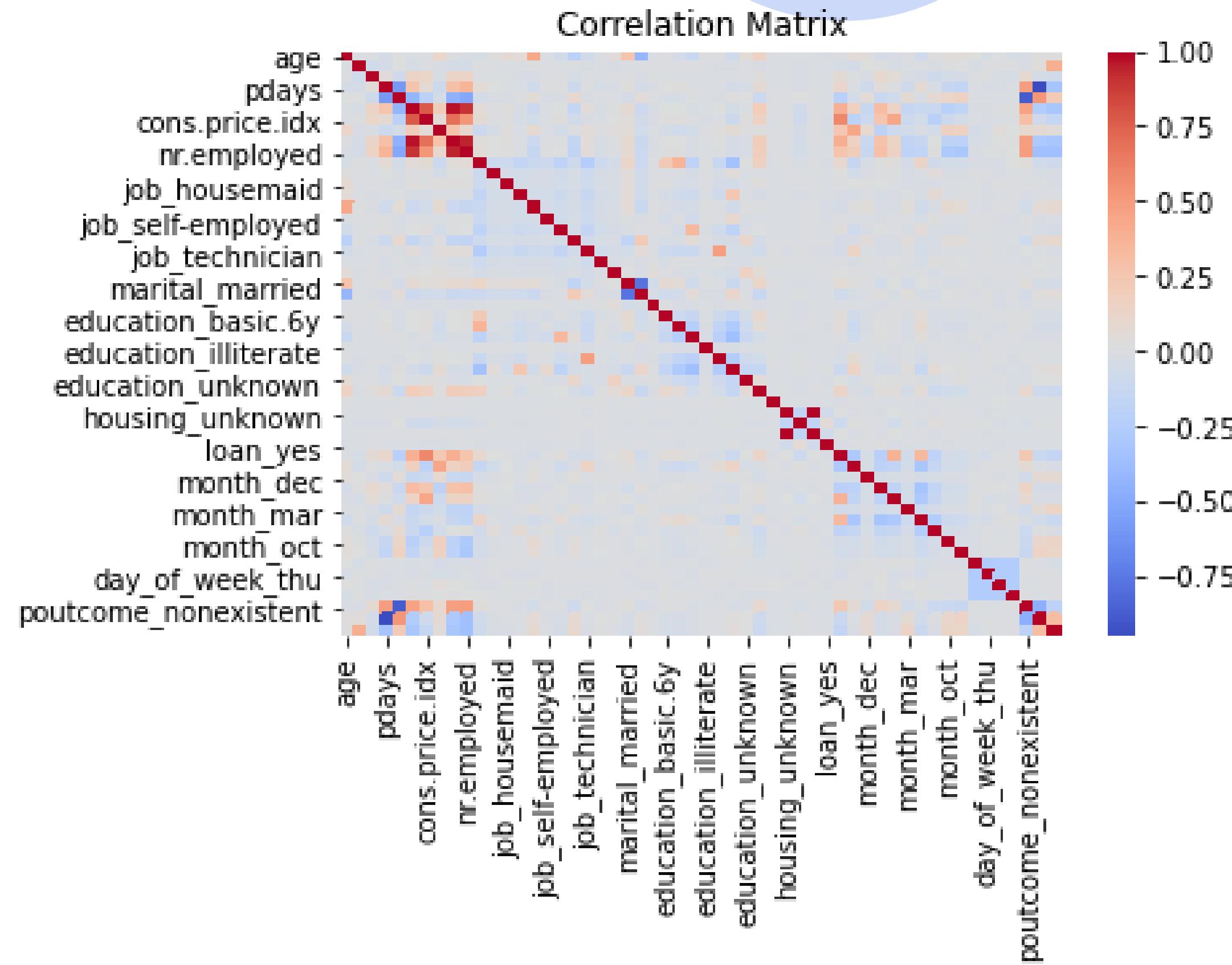
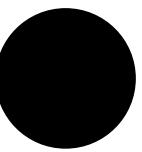
LOGISTIC REGRESSION

Logistic Regression: Used for its ability to provide probabilities, this model also achieved a high accuracy and demonstrated that client characteristics like age, job type, and economic variables were significant predictors of term deposit subscriptions.

EDA GRAPHICAL RESULTS

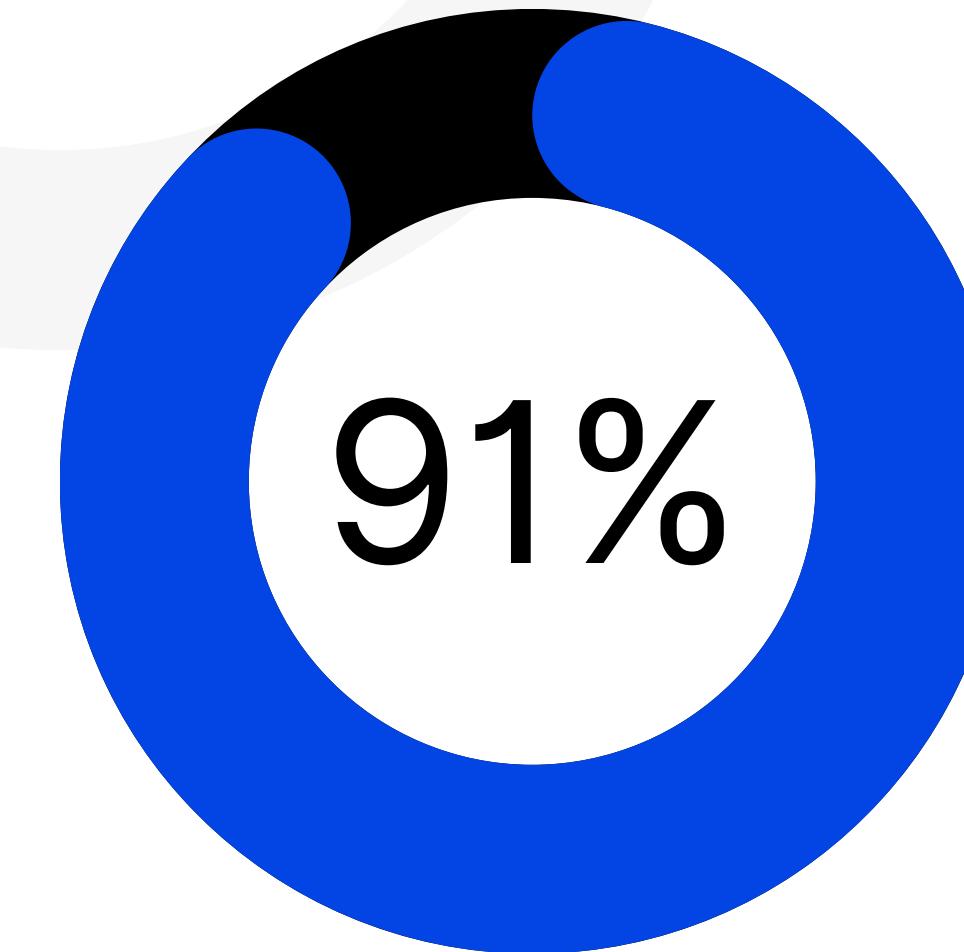


EDA GRAPHICAL RESULTS



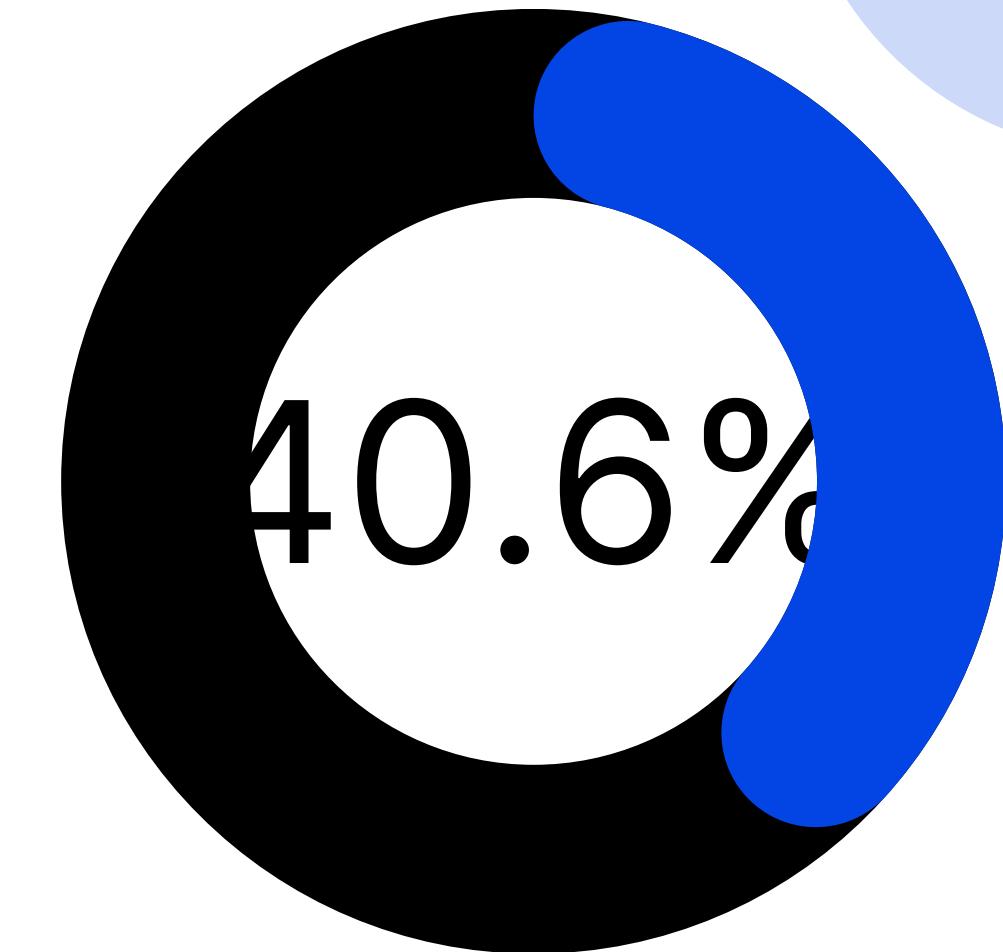
CLASSIFICATION METRICS RESULTS

ACCURACY



The model correctly predicts whether a client will subscribe or not 91% of the time.

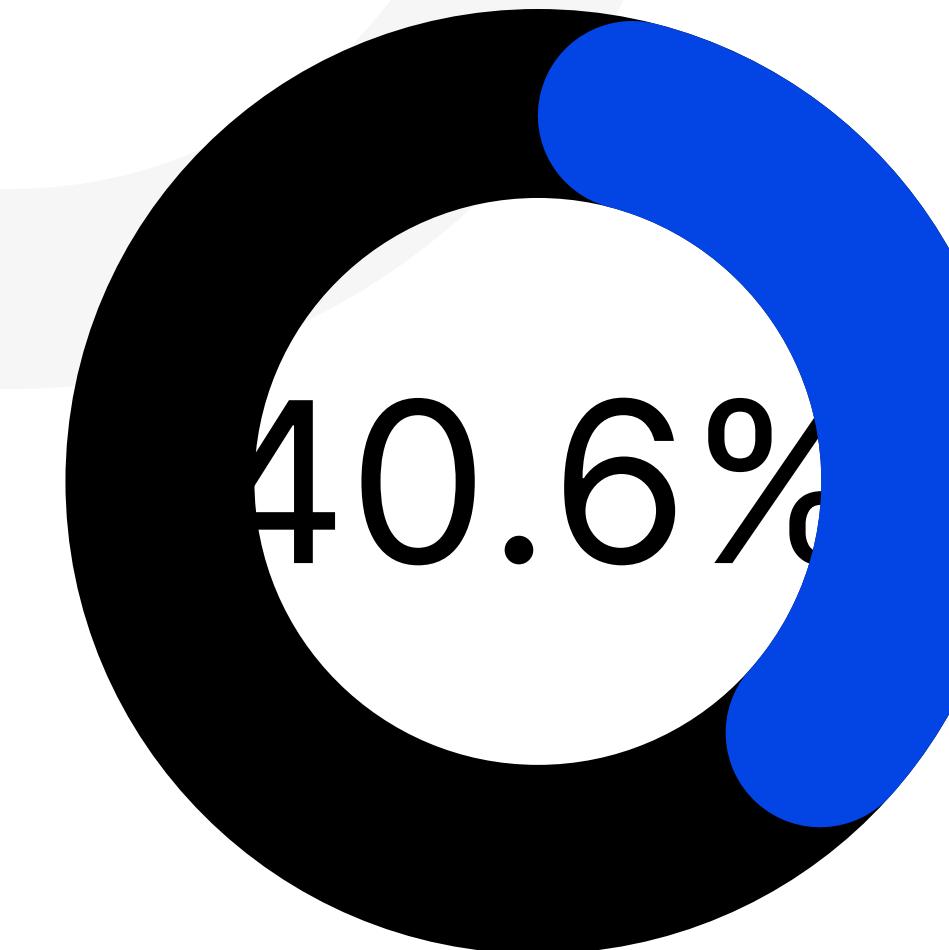
PRECISION



Out of all the clients the model predicted would subscribe, only 66.4% actually subscribed. This suggests that when the model predicts a positive outcome (subscription), it's not always reliable, with about one-third of the predicted subscribers not actually subscribing (false positives).

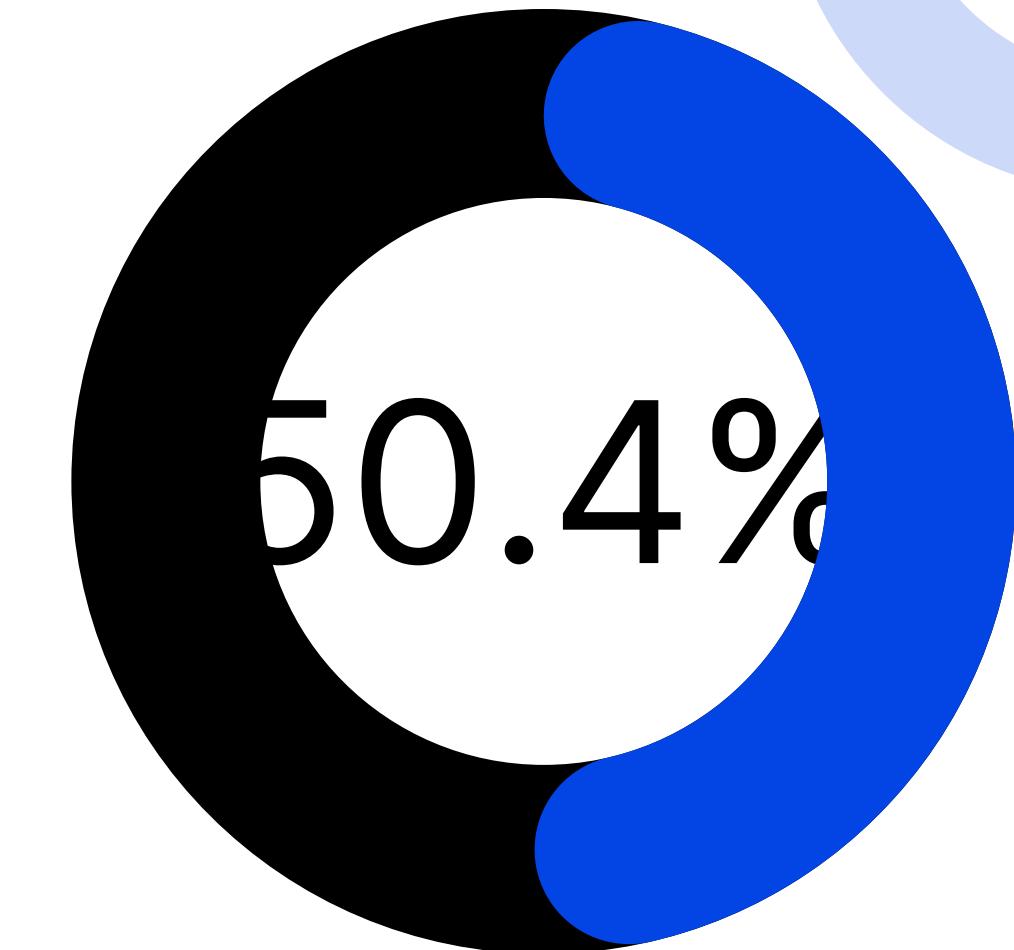
CLASSIFICATION METRICS RESULTS

RECALL



The model correctly identifies 40.6% of the actual subscribers. In other words, it misses about 59.4% of the clients who would have subscribed (false negatives).

F1 SCORE



The F1 score is the harmonic mean of precision and recall. At 50.4%, the F1 score suggests a balanced performance but with room for improvement. A low F1 score is usually due to a trade-off between precision and recall, as seen in this case.

CLASSIFICATION METRICS RESULTS

ROC AUC

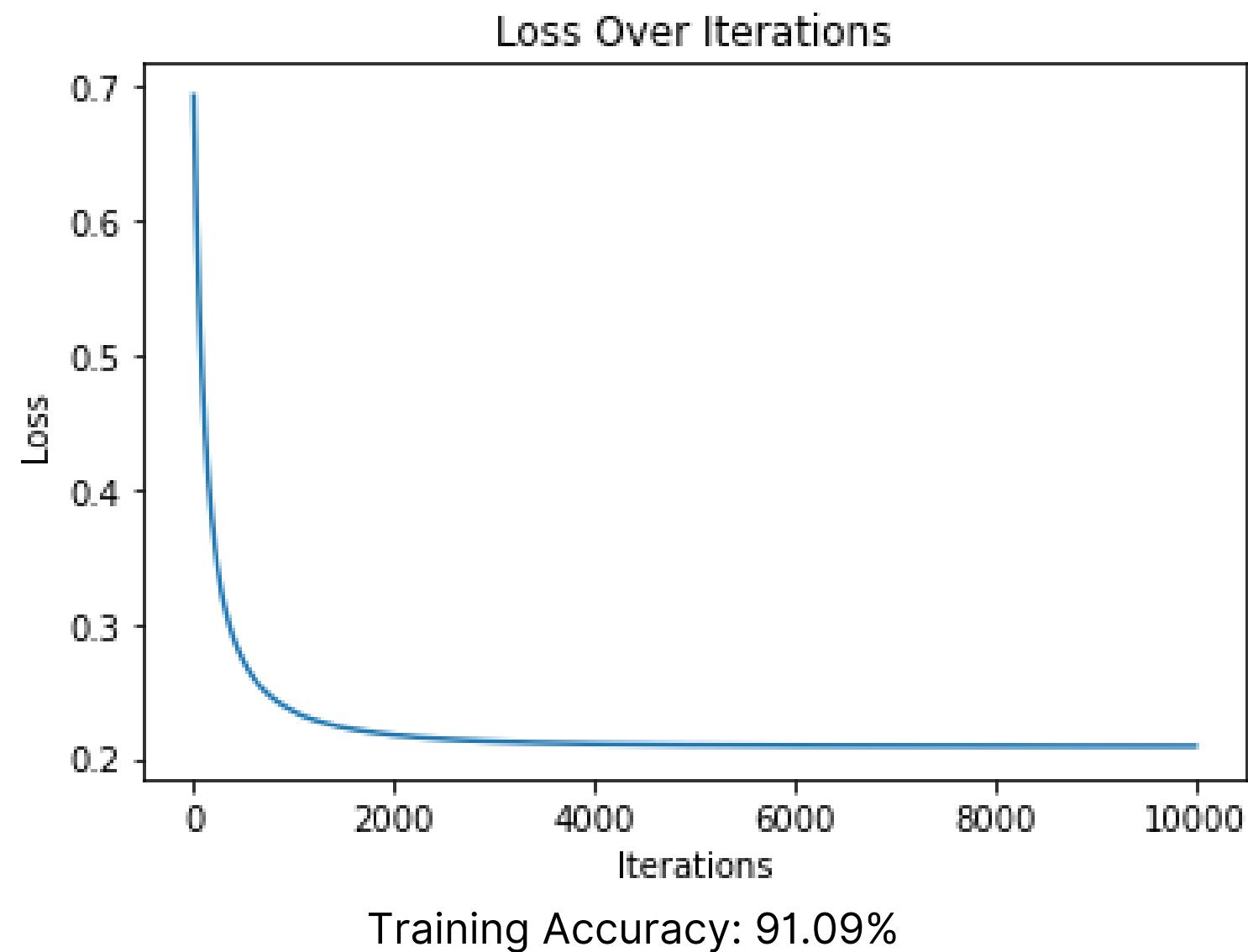
The ROC AUC score of 0.934 is very high, indicating that the model has excellent discriminatory power. This means the model is effective at distinguishing between clients who will subscribe and those who won't, even though precision and recall are not perfect.

CONFUSION MATRIX

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[[10683 285]
 [ 825   564]]
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The majority of non-subscribers are correctly identified (10,683 true negatives). However, there's a significant number of false negatives (825), meaning the model misses many clients who actually subscribed

GRADIENT DESCENT RESULTS



The results on the side show that the loss is decreasing over iterations.

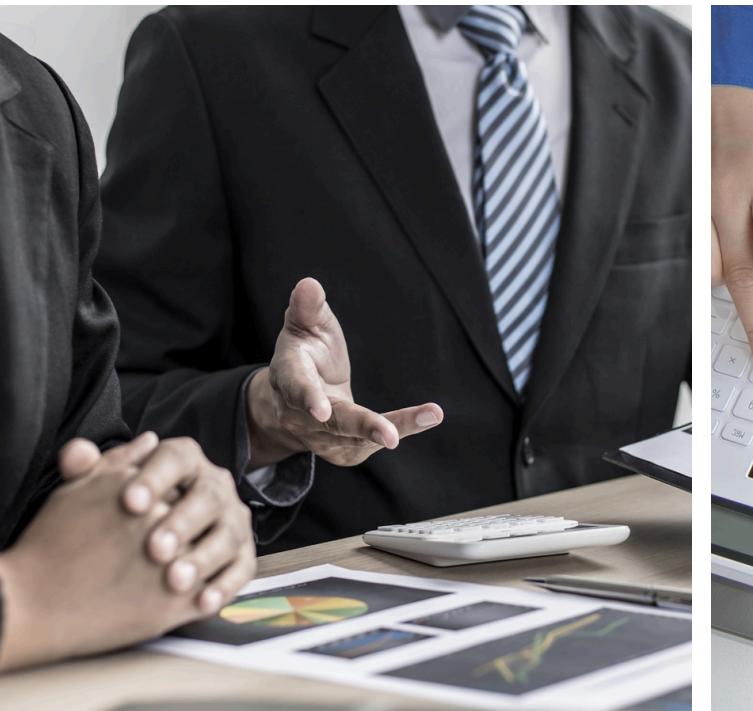
As iterations proceed from Iteration 0 the loss decreases significantly at this early stage indicating that the model is converging and learning to minimize the error between its predictions and the actual outcomes.

The plateau on the graph indicates that the model has nearly converged and is making only small adjustments in its learning process.

The model is reaching its optimal state, and further iterations are leading to diminishing returns in loss reduction.

OPTIMIZATION STRATEGY

- Model Optimization: Techniques like hyperparameter tuning were applied to the Decision Tree model to improve its performance. Logistic Regression was optimized using Gradient Descent, adjusting learning rates and iterations to minimize the loss function.
- Contact Strategy: Analysis revealed that contacting clients excessively reduced conversion rates. The bank should optimize its contact strategy by limiting the number of follow-ups and focusing on those who have shown higher responsiveness or positive outcomes in previous contacts.



INSIGHTS AND RECOMMENDATION

Key Predictive Attributes: Age, campaign duration, and economic conditions such as employment variation rates are strong indicators of term deposit subscriptions. The bank should focus its efforts on clients within the 32-47 age group who engage in longer phone calls.

Customer Segmentation: By clustering clients based on age, financial activity, and engagement, the bank can better allocate marketing resources to high-potential leads.

Resource Allocation: By targeting clients with higher subscription probabilities, the bank can reduce costs associated with marketing campaigns while achieving higher success rates. Resources can be directed toward high-value prospects, improving both efficiency and client satisfaction.

Optimized Contact Strategy: Limiting the number of contacts to an optimal level—around 1-3 contacts per campaign—can improve conversion rates while preventing customer fatigue.

THANK YOU

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