Bank Marketing

Term Deposit Subscription

INFO583_FA24 DATA MINING FOR BUSSINESS

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Business Case:

The primary goal of this project is to help a Portuguese bank optimize its telemarketing campaigns for term deposits. The bank's current marketing efforts are costly and inefficient, with a low conversion rate of customers who actually subscribe to term deposits. By building predictive models, we aim to identify which customers are most likely to subscribe, allowing the bank to focus its resources on high-probability customers. This data-driven approach can improve the bank's conversion rates, reduce marketing costs, and ultimately increase profitability. Our analysis provides actionable insights to streamline these campaigns.

Goal

- **Develop predictive models** to identify customers most likely to subscribe to a term deposit.
- **Optimize marketing campaigns** by focusing on high-probability customers, reducing costs, and increasing conversions.
- Use customer demographics, financial data, and previous interactions to generate actionable insights for more effective marketing strategies.
- **Improve customer experience** by reducing irrelevant marketing contacts and increasing satisfaction and engagement.
- **Support data-driven decision making** to enhance marketing efficiency and profitability for the bank.

Data Exploration

Total Customer

45,211 rows - Represent each Customer

Subscribed

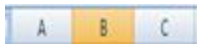
11.3%

Not Subscribed

88.7%

Target Variable

Yes = 1 = Subscribed
No = 0 = Not Subscribed



16 Columns
Represent Customer Attribute

Source

The original data source for the **Bank Marketing dataset** provided in the **UCI Machine Learning Repository** comes from a Portuguese banking institution. The data was originally used in the paper **"A Data-driven Approach to Predict the Success of Bank Telemarketing"** by **Sérgio Moro, Paulo Cortez, and Paulo Rita**, which was published in the journal **Decision Support Systems** in 2014.

- **Original source**: The research paper by Moro et al. (2014).
  Moro, S., Cortez, P., & Rita, P. (2014). A data-driven approach to predict the success of bank telemarketing. *Decision Support Systems, 62*, 22-31.
  https://www.sciencedirect.com/science/article/pii/S016792361400061X?via%3Dihub
- **Repository**: The UCI Machine Learning Repository hosts the dataset for public use.
  https://archive.ics.uci.edu/dataset/222/bank+marketing

Data Dictionary

Subscription Outcome	
Y (Binary)	Indicates if the client has subscribed to a term deposit ('1' for yes, '0' for no). **(Target Variable)**
Client Personal Information	
Age (Numeric)	Age of the client in years.
Job (Categorical)	Type of job the client holds (e.g., management, technician, entrepreneur).
Marital (Categorical)	Marital status of the client (e.g., married, single, divorced).
Education (Categorical)	Highest level of education attained by the client (e.g., tertiary, secondary, primary).
Default (Categorical)	Indicates if the client has any credit defaults (yes or no)
Contact Information	
Contact (Categorical)	Contact communication type (e.g., unknown, telephone, cellular).
Day (Numeric)	Last contact day of the month (1 to 31).
Month (Categorical)	Last contact month of the year (e.g., jan, feb, mar).
Duration (Numeric)	Duration of the last contact in seconds.
Campaign Information	
Campaign (Numeric)	Indicates if the client has subscribed to a term deposit ('1' for yes, '0' for no).
Pdays (Numeric)	Number of days since the client was last contacted from a previous campaign (-1 means client was not previously contacted).
Previous (Numeric)	Number of contacts performed before this campaign for the client.
Poutcome (Categorical)	Marital status of the client (e.g., married, single, divorced).
Financial Information	
Balance (Numeric)	Current account balance of the client in euros.
Housing (Categorical)	Indicates if the client has a housing loan ('yes' or 'no').
Loan (Categorical)	Indicates if the client has a personal loan ('yes' or 'no').

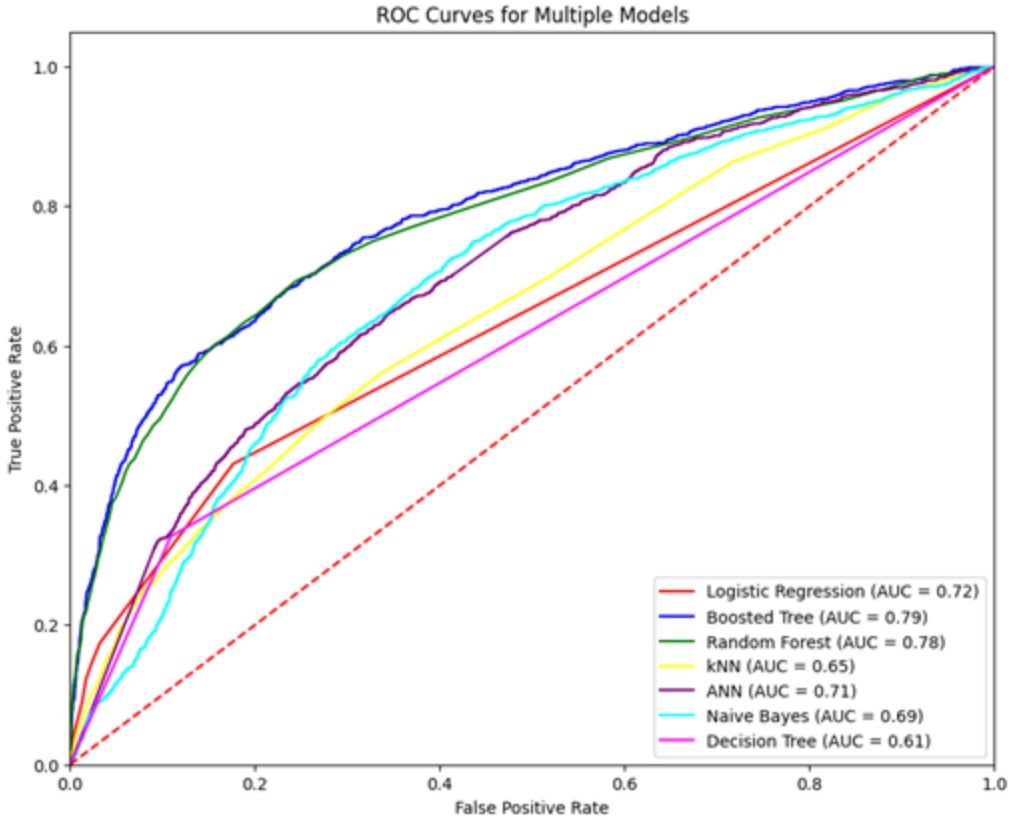
Model Approches

Model	Precision	RECALL	F1 Score	Accuracy	ROC AUC
Logistic Regression	0.55	0.01	0.02	0.88	0.72
Boosted Tree	0.66	0.17	0.27	0.89	0.79
Random Forest	0.73	0.06	0.11	0.88	0.78
kNN	0.57	0.01	0.01	0.88	0.65
ANN	0.13	0.97	0.23	0.21	0.71
Naïve Bayes	0.24	0.33	0.28	0.79	0.69
Decision Tree	0.71	0.03	0.06	0.88	0.64

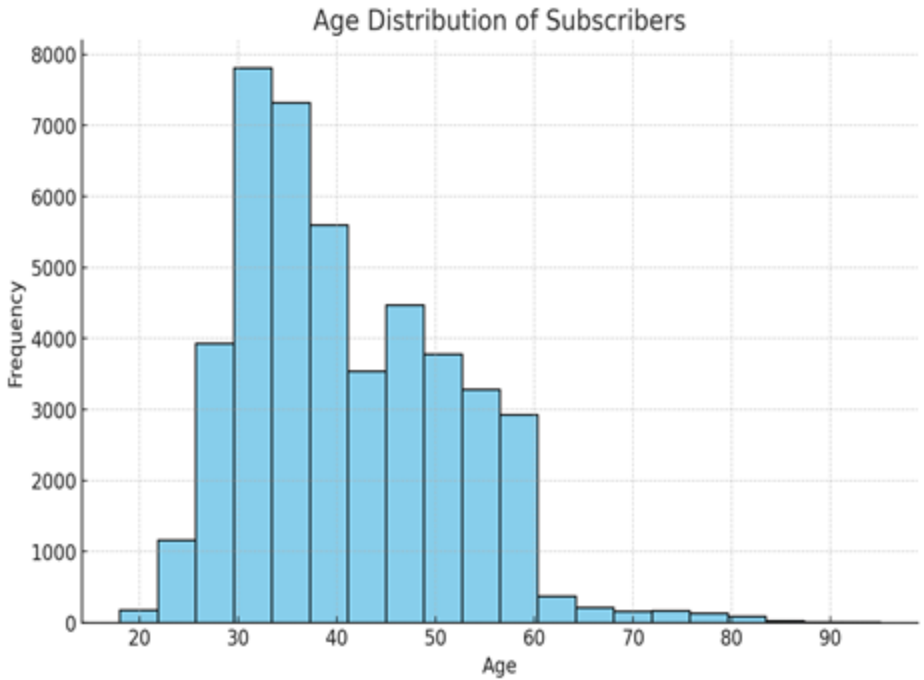
Model Selection

Highest ROC AUC =

Boosted Tree Model

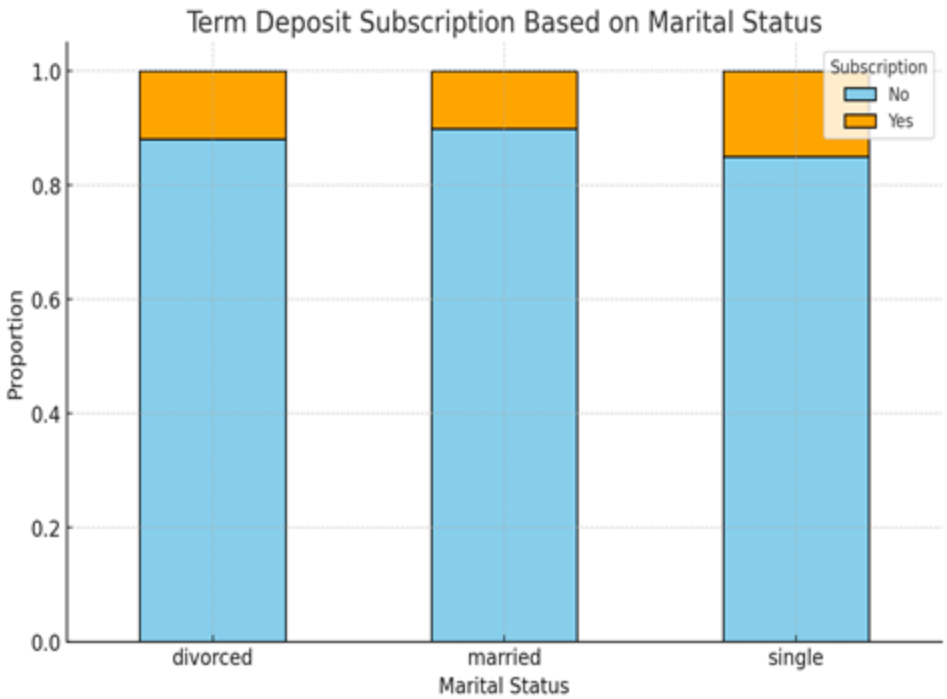


Data Visualizations & Insights



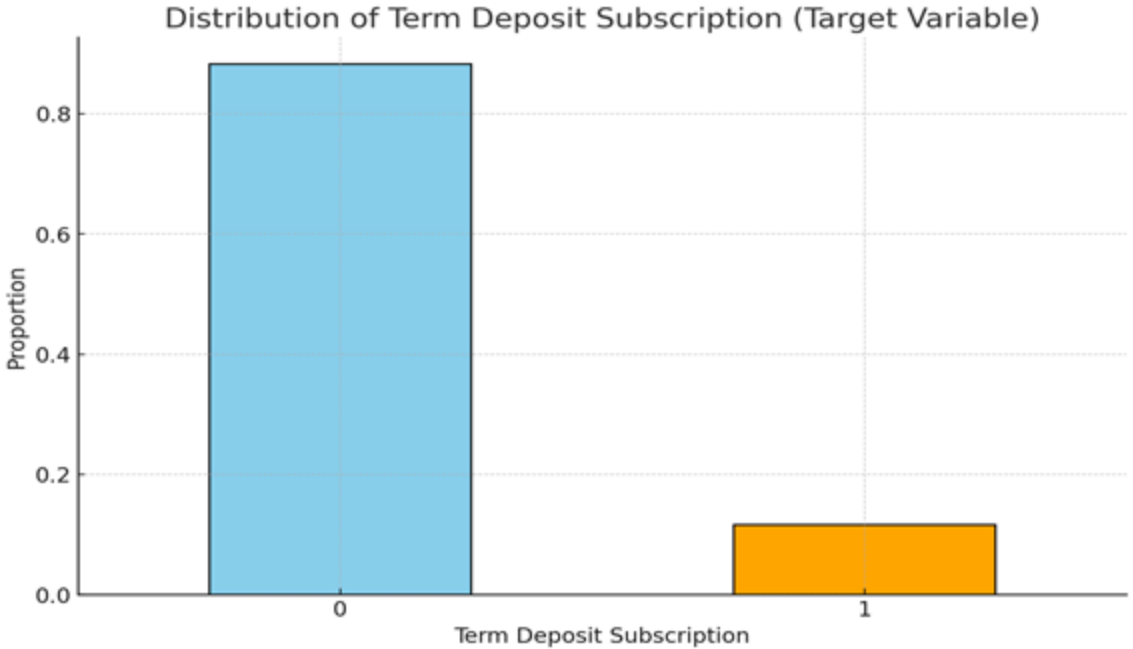
- The histogram shows the age distribution of the subscribers. The Subscribers appears to be fairly spread across different age groups, with some peaks in the middle-aged groups (30–50 years). This suggests that the middle-aged population may be more engaged in term deposits.
- Insight: Middle-aged individuals may form a significant target audience for marketing campaigns related to term deposits.

Data Visualizations & Insights:



- The stacked bar chart compares the proportion of term deposit subscriptions across different marital statuses (married, single, divorced). "No" indicates non-subscribers, while "Yes" indicates subscribers.
- Insight: Married individuals seem to have a slightly higher likelihood of subscribing to term deposits compared to single and divorced individuals, although non-subscription remains dominant across all groups.

Data Visualizations & Insights:



- The bar chart reveals that the majority of people did not subscribe to a term deposit (denoted by '0'). Only a smaller fraction subscribed (denoted by '1'),
- Insight: This unbalanced distribution suggests that most customers do not opt for term deposits, which can guide future targeting strategies.

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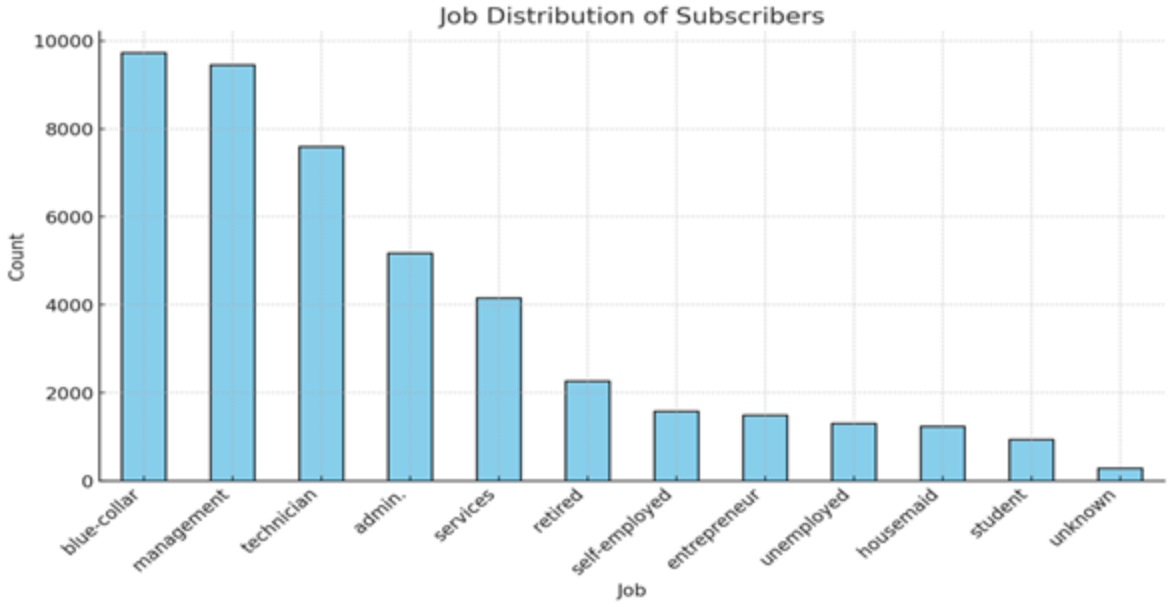

- The bar chart shows the distribution of jobs among subscribers. Jobs like "blue collar," "management," and "technician" are among the most common, while jobs such as "unknown" have fewer representations.
- Insight: Blue-collar workers form a significant portion of the subscribers, indicating a diverse range of occupations among the bank's clientele. Strategies to target specific job categories might be helpful in improving term deposit subscriptions.

Recommendations and Next Steps

Targeted Marketing: Use insights from the visualizations to concentrate marketing efforts on groups with a higher likelihood of signing up, such as divorced individuals with a high school education who have no outstanding mortgage. This focused approach can enhance conversion rates and optimize resource use.

Offer Incentives: Attract new customers by launching unique campaigns with special incentives. Consider increasing term deposit interest rates, particularly for new customers.

Streamlined Processes: Simplify the process of opening term deposit accounts by boosting efficiency. Implement digital tools to minimize paperwork and improve the ease and user-friendliness of account setup, meeting today's demand for convenience.

Recommendations and Next Steps

Customer Engagement: Maintain close contact with current clients to emphasize the benefits of term deposits. Keep them informed about interest rates, maturity dates, and other pertinent details to sustain their interest and encourage repeat subscriptions.

Clear Communication: Ensure depositors receive transparent communication, providing them with essential information to improve their deposit potential and a clear explanation of factors influencing decision-making.

Key Predictors

Top Predictors:

1. **Balance**: Higher account balances correlate with a higher chance of subscribing.
2. **Outcome**: A successful outcome from a previous marketing campaign increases the likelihood of a customer subscribing again.
3. **Previous Contacts**: More previous contacts suggest familiarity with the product, boosting subscription probability.
4. **Campaign**: The number of current campaign contacts—balanced, effective follow-ups lead to higher conversion.

Other Influential Predictors:

1. **Age**: Older customers may be more inclined to invest in term deposits.
2. **Housing Loan**: Customers without housing loans might have more disposable income to invest.

Thank You

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