Banco Federal de Finanças

Marketing Campain Analysis

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I. Introduction

Purpose: This project was initiated to help Banco Federal de Finanças improve the effectiveness of its telemarketing campaigns by identifying customers most likely to subscribe to a term deposit. The bank's management was dissatisfied with the results of the previous campaign and believes machine learning can provide a more targeted approach. By leveraging predictive modeling, the goal is to refine the customer selection process, ensuring that outreach efforts are focused on those most likely to respond positively, thereby increasing overall conversion rates and efficiency.

Objective: Identify customers most likely to subscribe to a term deposit using machine learning.

II. Business Problem & Objectives

- Current Challenge: The bank's traditional marketing efforts underperformed.
- Main Goals:
  - Identify high-potential customer segments.
  - Optimize marketing strategies with Machine learning insights.
  - Ensure targeted campaigns outperform random selection.
  - Evaluate the impact of campaign frequency and economic conditions on customer response.

Data & Methodology

- Dataset:
  - The dataset includes customer demographics (age, marital status), financial details (home loan, loan status), and past marketing campaign interactions (previous contact outcome, number of contacts). It also incorporates economic & social indicators such as the employment variation rate and consumer confidence index. The target variable indicates whether a customer subscribed to a term deposit (`y` = Yes, `n` = No).
- Preprocessing:
  - Handling missing data, encoding categorical variables, and feature selection. Binning categorical features for improved prediction.
  - Dropped non-contributory variables such as 'day_of_week', 'contact', and 'job' after evaluating their impact.
- Model Selection:
  - Implemented a Decision Tree Classifier with hyperparameter tuning to optimize performance.
  - Used ensemble methods such as Random Forest and Boosting techniques to enhance prediction accuracy.
  - Applied class weighting to address imbalanced data.
  - Model training and evaluation conducted using train-test splits with a 40% test size.
- Evaluation Metrics
  - Used Accuracy, Precision, Recall, F1-score, and Confusion Matrix to assess model performance. Final best-performing model achieved an accuracy score of 90.35% and an F1-score of 0.388.
- Model Deployment:
  - Models are persisted for future use via Python's pickle module.

Suggested Visuals:

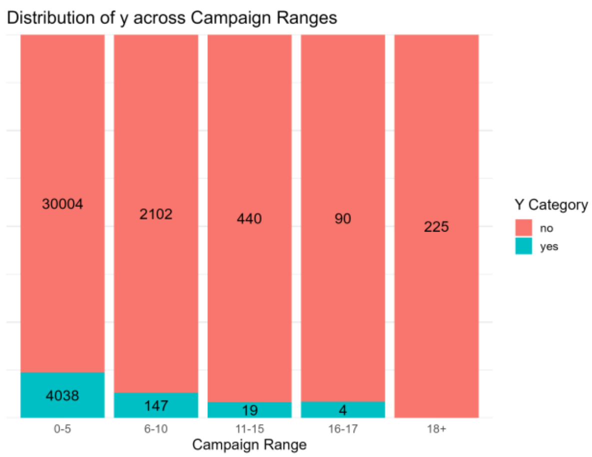
Dataset summary (e.g., table with key variables)

Flowchart of methodology (data processing → model training → evaluation)

III. Key Findings & Insights

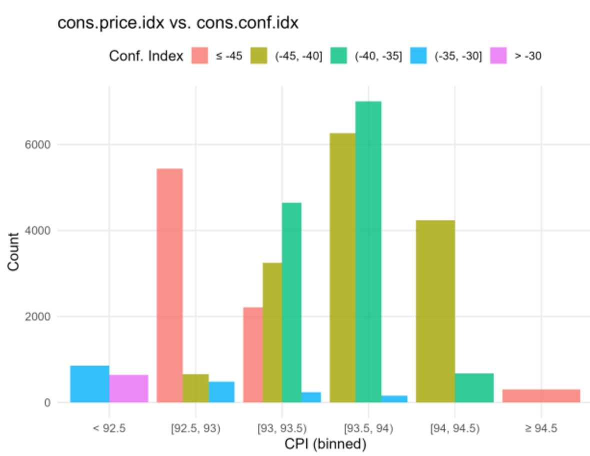
Customer Segments:

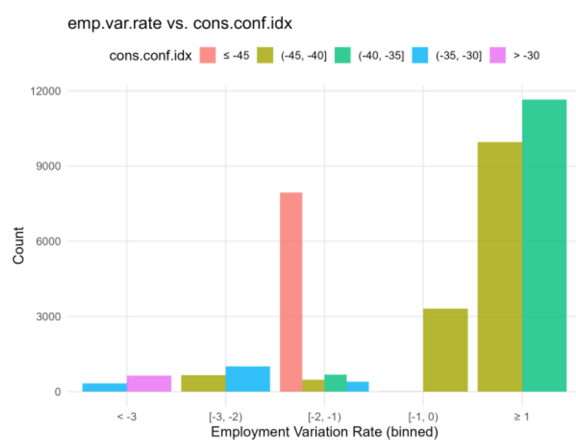
- Best response groups (e.g., working professionals, specific age groups).
- Low-performing groups (e.g., students, retirees).

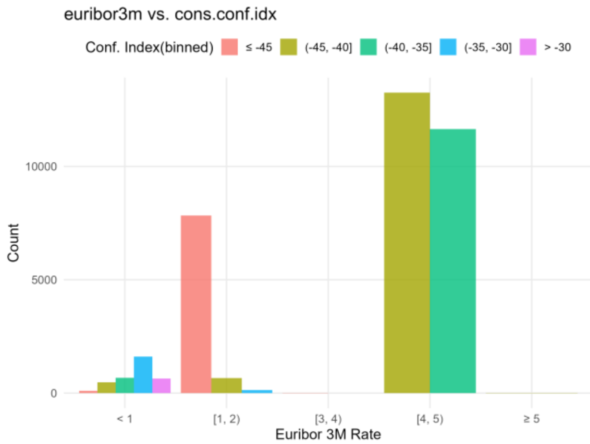


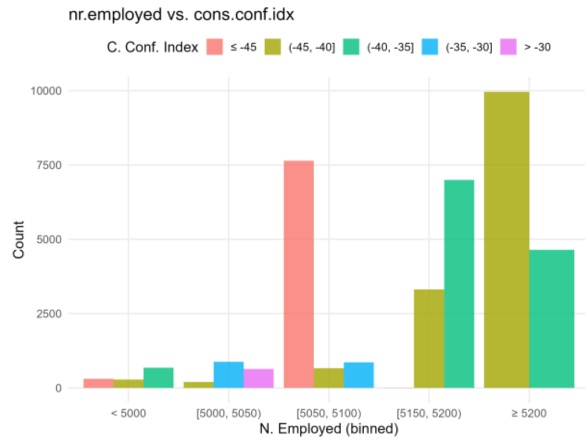
Answer to Mr Ferreira's question

Yes, as we can see the percentage of individuals who open a term deposit account went down with the number of contacts. We notibly see that anyone contacted 18 or more times did not open a term deposit account.









Responding to Beatriz concern of social and economic indicators. We can see that consumer confidence is highest when CPI is low. Consumer confidence appears to be average to high from -1 emp.var.rate and greater. Consumer confidence is average and high from a Euribor 3 month rate of 4 to 5. This can obviously point out that during certain social and economic indicators consumer confidence will be higher and lower so it makes a difference. For example, a high cpi, with employment variation from -2 to -1, euribor 3m rate from 1 to 2, and employment variation from 5050 to 5100 will show the lowest consumer confidence so avoid making campaigns during this combination of social and economic indicators.

Marketing Strategy Recommendations:

- Best Contact Days: Insights on optimal calling days/times.
- Call Frequency: Over-contacting negatively impacts responses.
- Economic Sensitivity: Different models perform better under high vs. low consumer confidence.

Predictive Model Performance:

- Accuracy and efficiency of the final model.
- Performance comparison against previous marketing strategies.

Suggested Visuals:

Performance metrics comparison (e.g., bar chart of Precision/Recall)

Segmentation heatmap or decision tree illustration

IV. Business Impact & Recommendations

Projected Improvement:

- Expected increase in campaign efficiency and conversion rates.
- Cost savings from reduced ineffective outreach.

Actionable Recommendations:

- Short-Term: Implement predictive targeting in upcoming campaigns.
- Long-Term: Integrate real-time economic data to adjust strategies dynamically.

Addressing Skepticism (for Chairman Ferreira):

- Evidence-based proof that AI outperforms traditional methods.

Suggested Visuals:

- ROI impact graph (before vs. after targeted marketing)
- Final recommendation summary (bullet points/table)

V. Conclusion

Final Summary:

- Machine learning significantly improves marketing effectiveness.
- Targeted approaches yield better engagement and reduce wasted effort.

Next Steps:

- Deploy the model into production.
- Monitor real-world impact and refine strategies.
- Continue exploring external economic factors for further improvements.

Below is a link to our Github Repository full of notebooks and quarto files we used during this case study:

Machine-Learning/bank_project at main · 1Ramirez7/Machine-Learning

Here is the file where our final algorithm was made and tested:

Machine-Learning/bank_project/david_bank.ipynb at main · 1Ramirez7/Machine-Learning