MIS710 – Machine Learning in Business

Assessment Task – 2

Business Report (Part B)

Great Ocean Banking Group

Victoria, Australia

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Contents

Executive Summary

This report is presented to Gary Peterson, Head of Customer Experience, Great Ocean Banking Group and prepared by business analyst Sachin Bhat. It analyses bank's scenario using BACCM and machine learning models to enhance marketing campaigns' effectiveness. By deploying Post-Pruned Decision Trees for predicting sales outcomes, and k-Means clustering for customer segmentation, the bank plans to enhance campaign efficiency, sales, and customer satisfaction.

Introduction

Business Analysis Core Concept Model (BACCM):

Need: Great Ocean Bank needs to enhance its marketing campaigns' effectiveness. Current methods are inadequately targeted, leading to wasted resources and low conversion rates. Understanding the factors influencing successful sales outcomes is crucial to directing efforts towards the most promising leads and maximizing marketing ROI.

Context: This project operates within several contexts: Internally it utilises bank's existing customer data and technology. Externally it is influenced by economic conditions, market trends, regulatory requirements, and competition. Technologically it uses advanced machine learning tools like Google Colab and Python libraries ensuring scalable and robust solutions.

Stakeholder: Primary stakeholders include bank's marketing, sales, and data analytics teams, and their customers. Secondary stakeholders include senior management and IT department.

Change: This project represents a major transition from traditional marketing methods to sophisticated data-driven approaches. It involves implementing machine learning models for sales outcome prediction and customer segmentation for targeted marketing, enhancing bank's marketing efficiency and effectiveness, allowing more accurate and impactful customer interactions.

Value: This project aims to enhance campaign efficiency by concentrating on highly-probable leads, decreasing wasted costs and efforts. Customers benefit from personalised and relevant offers, leading to higher satisfaction and loyalty. Bank gains a strategic advantage through data-driven decision-

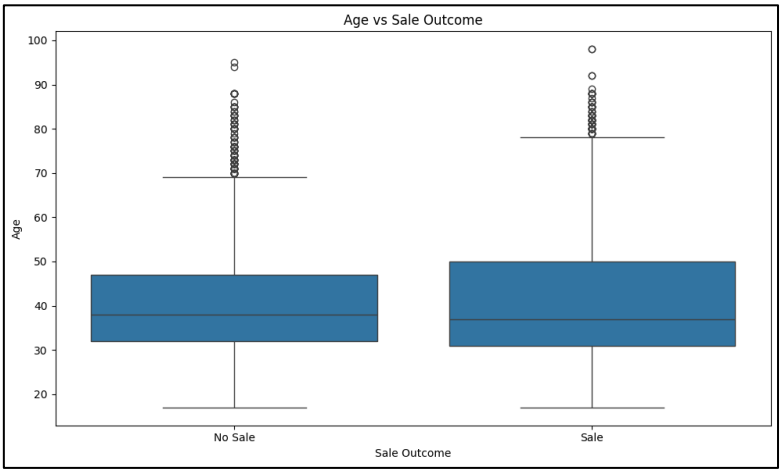
making, optimised marketing strategies, and an enhanced competitive position.

Solution: The solution involved developing and deploying two predictive models: k-Nearest Neighbours (kNN) and Post-Pruned Decision Trees for forecasting sale outcomes. Also, k-Means Clustering segments customers into distinct groups based on their attributes. This predictive and segmentation approach enables the bank to target the right customers with personalised offers, greatly enhancing marketing precision and effectiveness.

Insights from Exploratory Data Analysis (EDA)

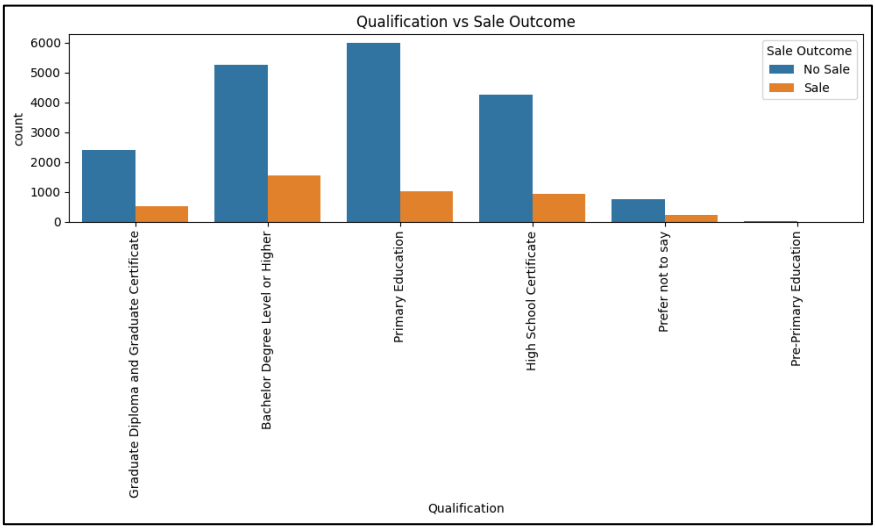
Q1.

Age:



Customers who made a purchase tend be on average, slightly older as compared to others who did not make a purchase. 'Sale' group suggests that successful sales span a broader age range that includes older customers.

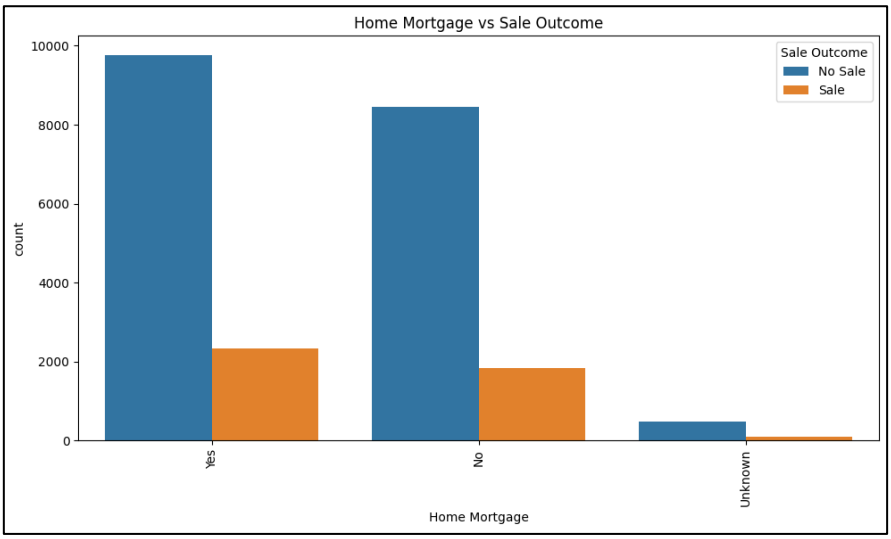
Qualification:



Higher education levels tend to correlate with higher sales outcomes suggesting that customers with higher qualifications are more likely to make purchases. Lower education levels are associated with lower sales outcomes.

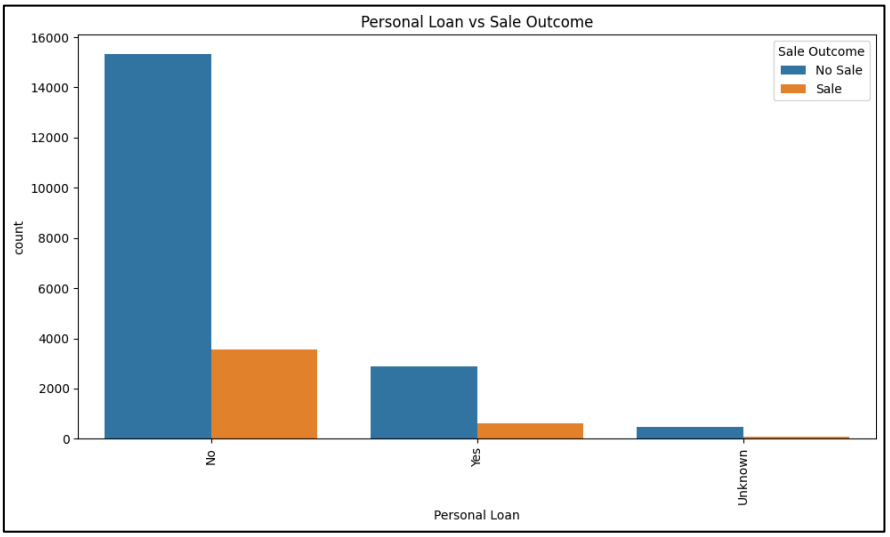
Q2.

Home Mortgage:



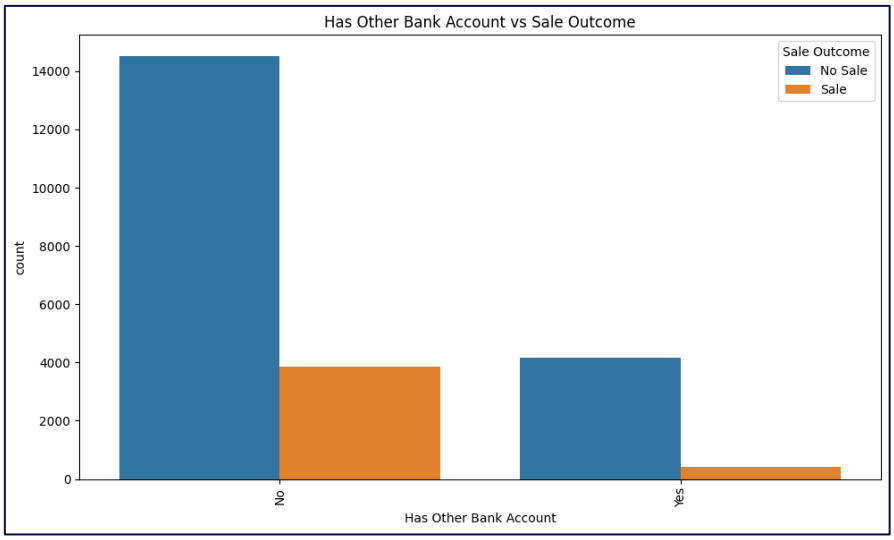
Customers with home mortgage are likely to have no sale compared to others without a mortgage. But significant numbers with a mortgage did result in a sale implying that having a mortgage does not essentially prevent additional account openings.

Personal Loan:



Customers without a personal loan are in majority for both no sales and sales. Customers with personal loan have relatively higher no sale outcome but contribute significantly to the sale outcome. Having a personal loan might correlate to no sale, there are still substantial number of customers who'd be open to additional products.

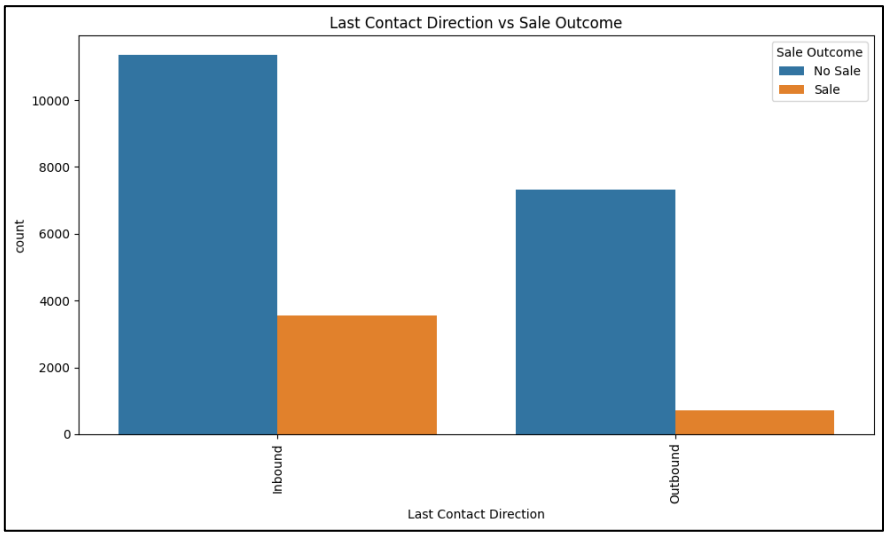
Has Other Bank Account:



Customers without other bank accounts show a higher no sale outcome as compared to those with accounts. But there is a considerable number of sales among customers with other bank accounts.

Q3.

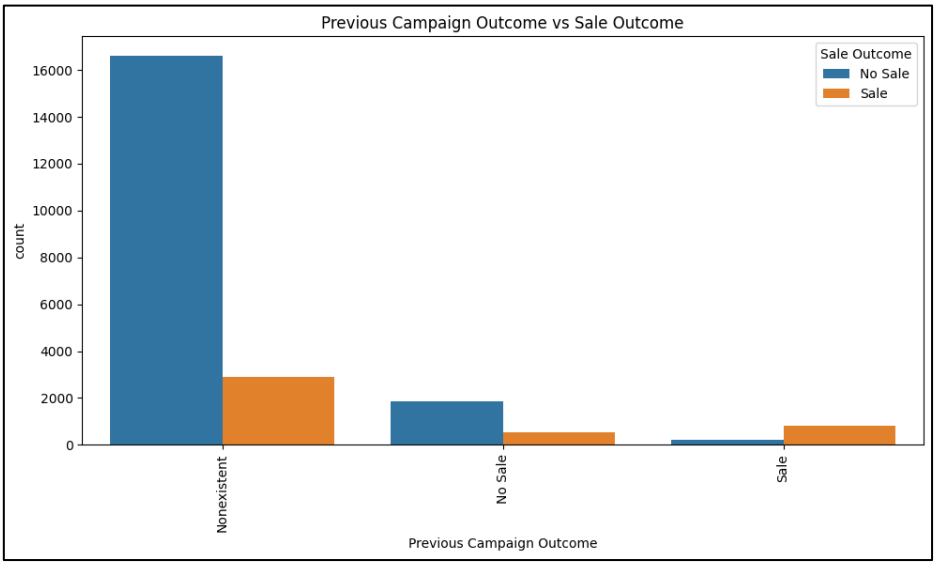
Last Contact Direction:



Inbound customers are more likely to result in a sale compared to outbound. Outbound contacts have much lower conversion rates compared to inbound.

Q4.

Previous Campaign Outcome:

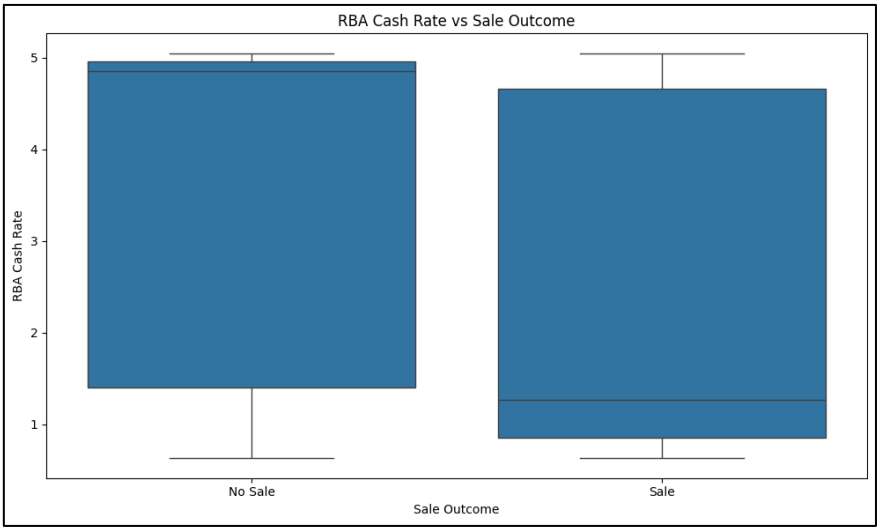


Majority of customers with no previous campaign result in no sale while significant number of sales come from this group. Unsuccessful previous campaign outcomes depict a considerable portion of sales in the current campaign. Successful previous campaign outcomes are more probable to

convert again putting a positive influence of previous successes on current sales efforts.

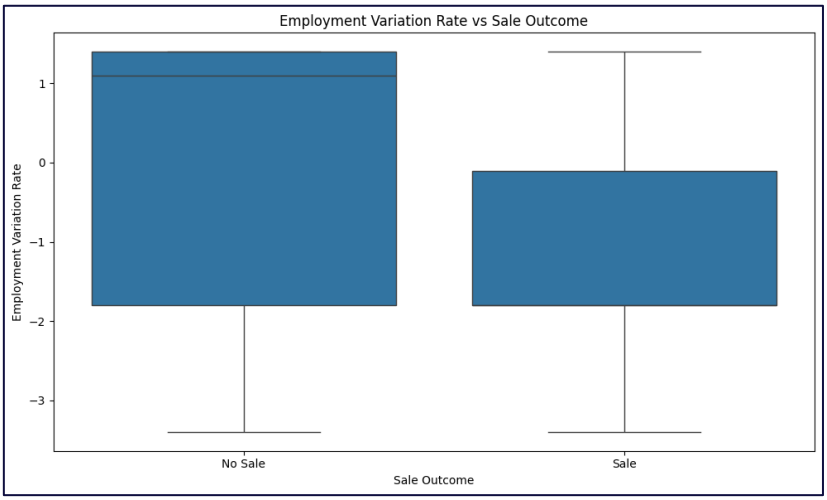
Q5.

RBA Cash Rate:



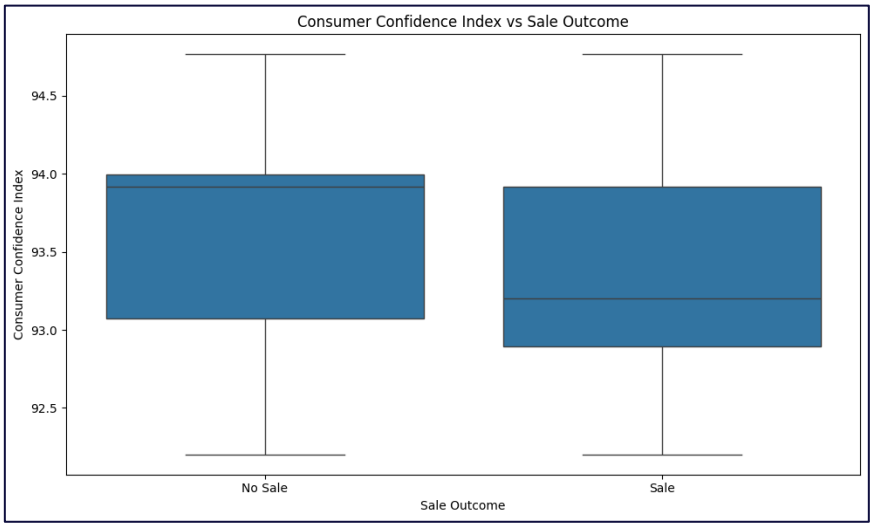
RBA Cash Rate significantly impacts customer purchasing decisions. Lower rates correlate with higher sale outcomes and higher rates with no sale outcomes.

Employment Variation Rate:



Employment Variation Rate significantly impacts customer purchasing decisions. Negative rates favouring higher sale outcomes and vice versa.

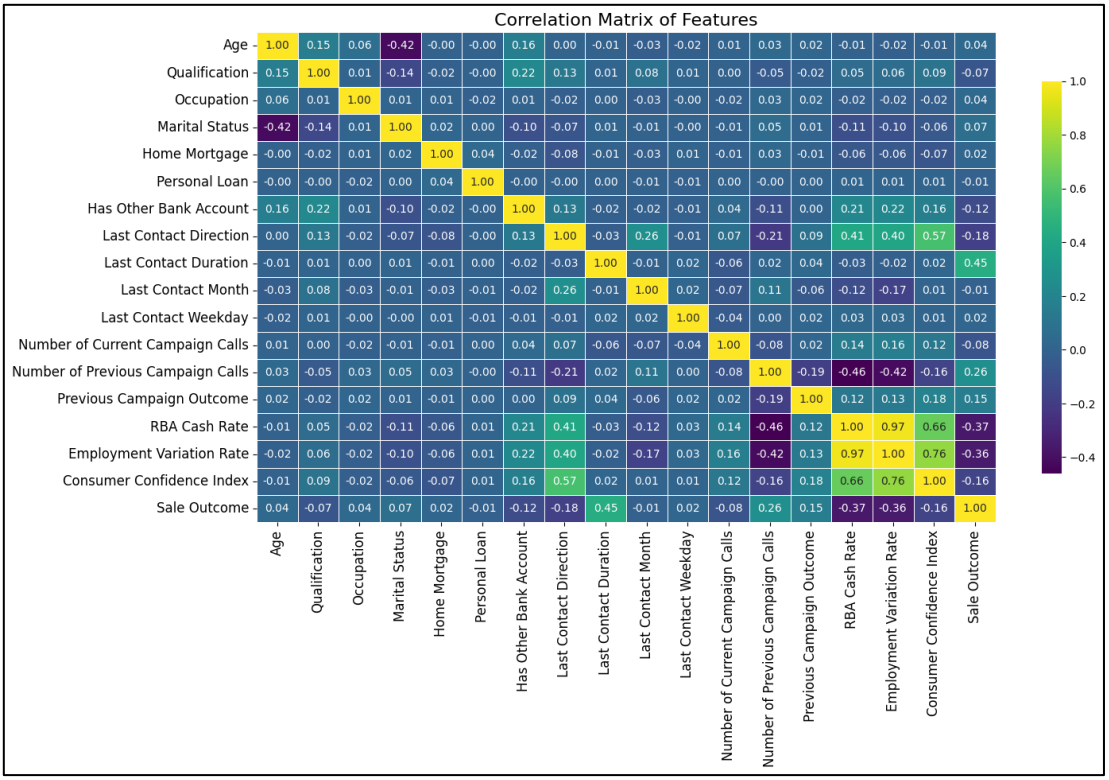
Consumer Confidence Index:



Consumer Confidence Index significantly impacts customer purchasing decisions. Lower confidence indexes correlate with higher sale outcomes and vice versa.

Q6.

Inter-Feature Influence:

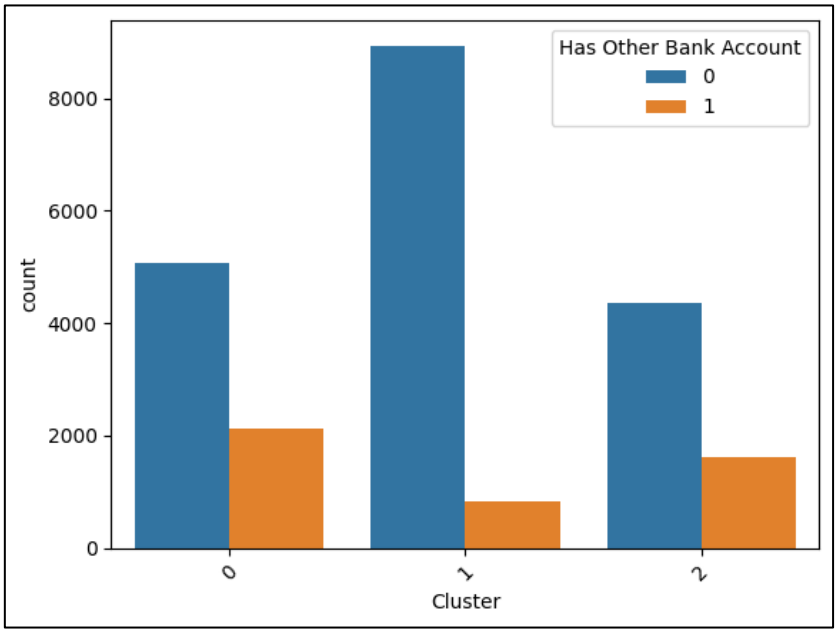


Strong Positive Correlations: Last Contact Duration and RBA Cash Rate. Employment Variation Rate and RBA Cash Rate. Consumer Confidence Index and Employment Variation Rate.

Additional Insights:

1. Customer loyalty: Existence of repeat sales from previous campaign outcomes implies the value of customer retention strategies and loyalty programs.

2. Cluster 0: 5076 customers (without other bank accounts), 2134 (with). Cluster 1: 8941 customers (without), 825 (with). Cluster 2: 4361 customers (without), 1603 (with).



Proposed Machine Learning Solution

To enhance bank's marketing campaign efficiency, we are recommending Post-Pruned Decision Tree model for forecasting sale outcomes because of its higher accuracy (88%), precision (66%), recall (76%), F1-score (70%), and AUC (93%).

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[[5092  509]
 [ 312  969]]
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TN: 5092, FP: 509, FN: 312, TP: 969.

	Precision	Recall	f1-score
Class 0:	0.94	0.91	0.93
Class 1:	0.66	0.76	0.70

Pros: Easy to understand and interpret, has good visual representation, is non-parametric, needs less effort for data preparation (no normalisation), can work for both numerical and categorical targets, and can handle non-linear relationships.

Cons: Depending on its implementation, data preparation is needed (numerical or categorical), has high probability of overfitting, is sensitive to training datasets and small variations leading to overfitting and instability respectively, has loss of information when predicting continuous targets because of the discretisation of continuous variables, and becomes complex when having multi-class targets.

Recommendations and Conclusions

For business applications:

1. Enhanced targeted marketing using predictive models for identifying high-potential leads.

2. Tailored marketing strategies based on distinct customer segments using clustering model.

3. Leveraging predictive and clustering model insights for creating personalised offers for customers.

Benefits to stakeholders:

1. **Marketing team** will have enhanced campaign efficiency and effectiveness through targeted marketing, thereby increasing conversion rates.

2. Enhanced lead quality for the **sales team** through increased opportunities, ensuring better sales performance and higher revenue.

3. More relevant and personalised offers for the **customers**, enhancing customer satisfaction and loyalty.

4. Better data-driven decision making for **senior management**, ensuring optimised marketing strategies and improved overall business performance.

Implications:

Changes in business processes will include transitioning to data-driven marketing approach utilising predictive and clustering models. Decision making through machine learning adoption will shift towards a more data-driven approach, supporting accurate and relevant marketing decisions. Impacts of these changes are expected to yield better marketing efficiency, higher conversion rates, and enhanced customer satisfaction.

Further improvement:

Can be achieved through data quality enhancement, model refinement, customer feedback integration, technological upgrades, and cross-functional team collaborations.

References

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