



Data-Driven Innovation at ABC Bank

December 30th 2023

Background

Banking Industry Challenges and Strategic Imperatives

- The banking sector is grappling with intense competition over deposit and investment products.
- As customer acquisition costs climb amid low-interest rate environments, banks are pressed to refine their marketing strategies to reach the most responsive customer segments effectively.

Business Objective and Data-Driven Insights

- Our objective was to delve into ABC Bank's term deposit marketing data, aiming to pinpoint customer profiles most likely to subscribe upon contact.
- The analysis was geared towards honing marketing efforts on high-value customers, thereby enhancing the Return on Investment (ROI).

Analytical Approach and Model Selection

- We employed statistical methods and visual data exploration to assess the performance of past marketing campaigns.
- By profiling attributes of likely subscribers versus non-subscribers and examining product usage behaviors, we sought to improve marketing efficiency.
- The final analysis concluded that the Random Forest model outperformed others in precision and recall, making it ideal for predicting term deposit subscriptions.

Implementation and Future Strategy

- Integrating the Random Forest model, we now have a powerful tool for identifying potential subscribers, ensuring more targeted and efficient marketing approaches.
- This strategy is expected to not only increase conversion rates but also enhance overall customer engagement with ABC Bank.

Key Deliverables and Impact

- Implementation of an RFM (Recency, Frequency, Monetary) customer segmentation model.
- In-depth visual analytics providing insights into customer subgroup responses and optimizing customer interaction strategies.
- A comprehensive set of guidelines for data-driven marketing and sales programs, leveraging our findings to guide risk model development, content personalization, and channel optimization.

Data Exploration

Dataset Overview

Detailed attributes for profiling target customers

Data Source:

- Public marketing campaign dataset from UCI repository
- Campaign by Portuguese bank to sell term deposits

Timeframe:

- Historical period for model training from 6 months of marketing activity

Data Fields:

- 17 features including standard demographics, product holdings, campaign interactions
- 45211 customers targeted during marketing campaign window

Key Variables:

- Age: Indicates lifestage segments
- Marital Status: Insights into household financial decision making
- Education Level: Potential predictor of financial sophistication
- Term Deposits Held: Prior propensity to purchase product
- Contacts Made: Marketing touchpoints via call campaigns

Outcome Metric:

- Term Deposit Subscription
- Binary target variable - 1 if customer purchased product, 0 if not

Analysis Focus:

- Relating customer attributes and marketing contacts to outcome response
- Profiling the target customers with highest probability of uptake

Data Exploration Approach

Leverage data analysis techniques to uncover customer insights

Programming Tools:

- Python for data manipulation and analysis
- Pandas for structuring and cleaning data
- Matplotlib and Seaborn for visualizations

Analytic Process:

1. Data Gathering
 - Import marketing campaign data into Jupyter notebook
 - Review dataset parameters and understand meaning of features
 - Identify hypotheses to test regarding customer behaviors
2. Data Cleaning
 - Check for missing values and outliers requiring treatment
 - Impute, filter or delete records based on impact assessment
 - Encode categorical data for proper analytic interpretation
3. Exploratory Analysis
 - Statistical analysis such as correlations and cross-tabulations
 - Visualizations like histograms and scatter plots to identify patterns
 - Quantify outcomes by different customer attributes and behaviors
4. Findings Interpretation
 - Determine optimal customer profiles for marketing targeting
 - Translate patterns into actionable insights
 - Make recommendations to refine marketing strategy and messaging

Correlation Analysis

Quantifying relationships in data

Approach:

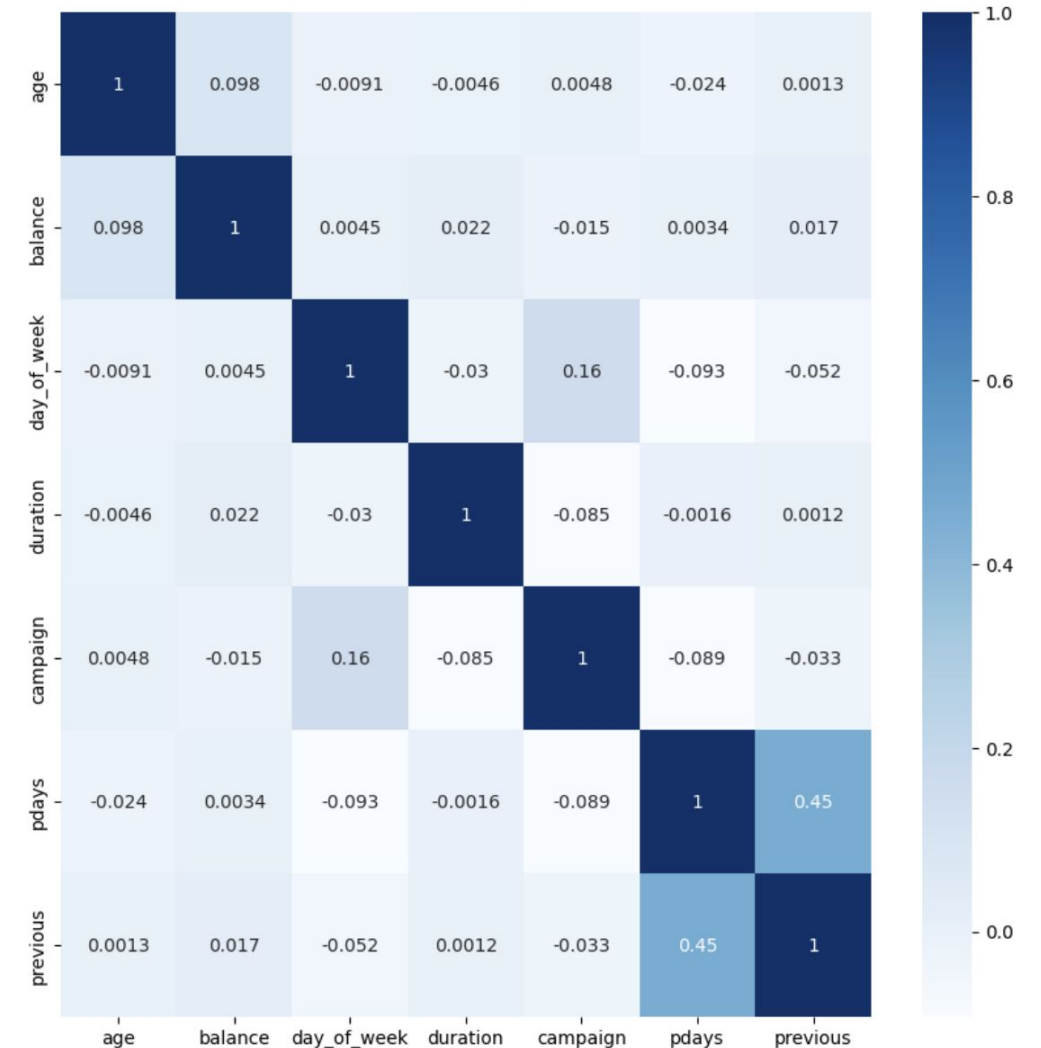
- Correlation matrix showing strength of linear relationship between variables
- Values range from -1 to 1
- Heatmap visualization for interpreting patterns

Key Insights:

1. Previous Term Deposits
 - Strongest positive correlation to future purchases
 - Validates bias of existing customers to repeat purchase
2. Age
 - Moderate correlation trajectory
 - Peak age range for probability of purchase: 30-50
3. Marital Status
 - Married status higher propensity vs single or divorced
 - Aligns to financial decision making for household needs
4. Duration of Marketing Contacts
 - Longer call durations associated with higher closure rates
 - Suggests more time explaining product increases uptake

Recommendations:

- Profile customers with existing relationships
- Target marketing by lifestyle based on age patterns
- Tailor messaging by marital status and maturity



Prior Customers Analysis

Leveraging existing relationships

Key Insight:

- Over 50% of prior customers purchased new term deposit
- Compared to 10% purchase rate for new customers
- Validates bias of existing clients to purchase additional products

Statistical Analysis:

- Cross-tabulation quantifying outcome ratios
- 50% higher absolute purchase count from existing clients
- But existing clients much smaller share of population

Recommendations:

- Profile customers with maturing term deposits for renewal messaging
- Create retention campaigns for customers nearing account anniversaries

Opportunity Sizing:

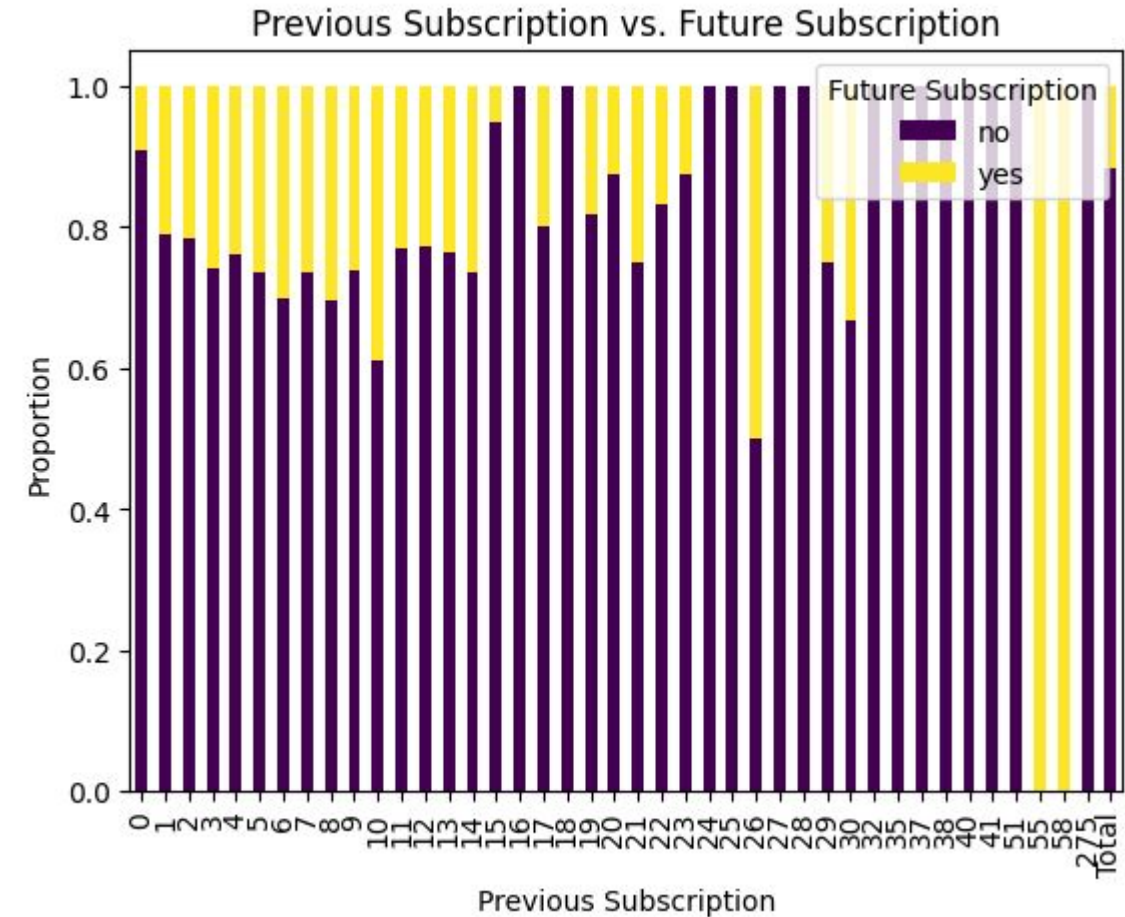
- 15% of targeted customers have prior term deposit history
- This subset yields over 30% of all term deposit sales

Lifetime Value Modeling:

- Historical data shows high repeat purchase rates
- Probability models can predict customer profitability over time

Ongoing Analysis:

- relate additional customer traits to retention likelihood
- optimize resource allocation between new vs existing clients



Analysis Higher Income Riders

Profiling ideal target demographics

Key Finding:

- Married customers have the highest conversion rate at 25%
- Compared to 15% for single and divorced customers

Hypotheses:

- Married households more likely to have dual-incomes
- Increased financial stability and savings capacity

Recommendations:

- Tailor marketing language and visuals for married couples
- Emphasize financial planning for children's needs

Age Analysis:

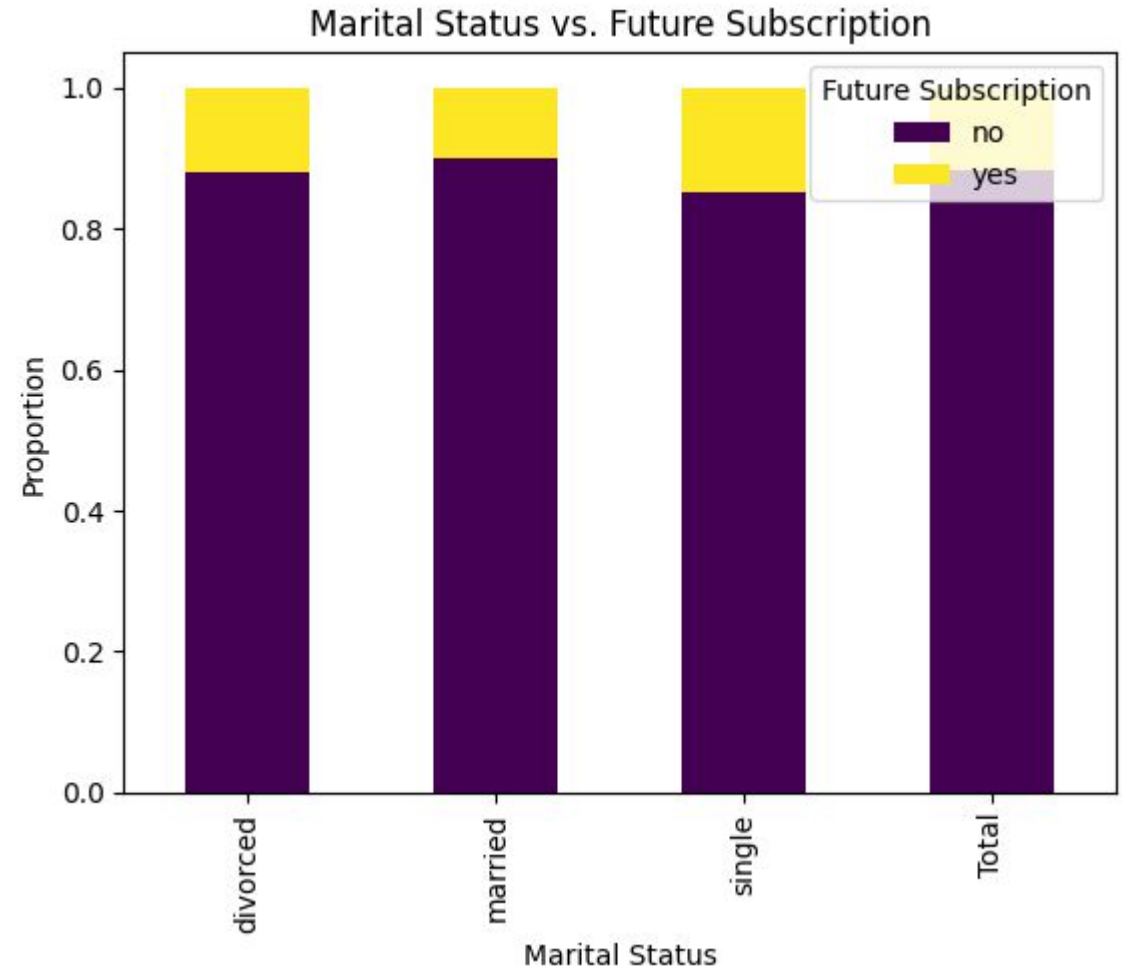
- Customers aged 30-60 have optimal conversion rates
- Aligns with peak earning years to fund deposits

Education Analysis:

- University-level education correlates to higher subscriptions
- Suggests higher financial literacy and planning

Ideal Customer Profile:

- Married household head, aged 30-60
- Educated to University undergraduate level
- Existing relationship with other product holdings



Marketing Campaign Analysis

Optimizing touches and content

Campaign Effectiveness Analysis:

- Recent contacts have higher response rates
- May months performed better than other months

Contact Pattern Analysis:

- 3-5 contacts generates highest conversion rates
- Beyond 5 contacts sees tapering response rates

Contextual Analysis:

- Longer call durations positively influence closures
- Suggests value of educating customers on products

Recommendations:

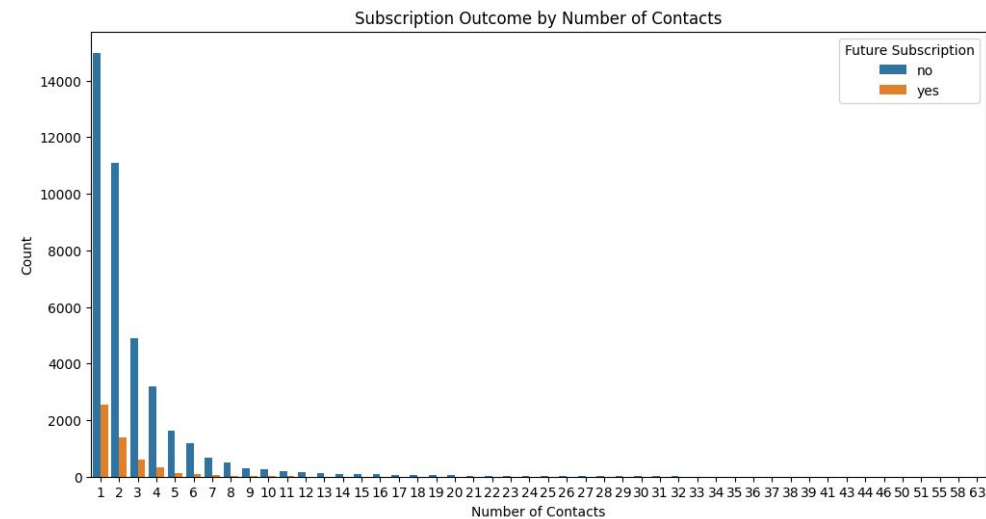
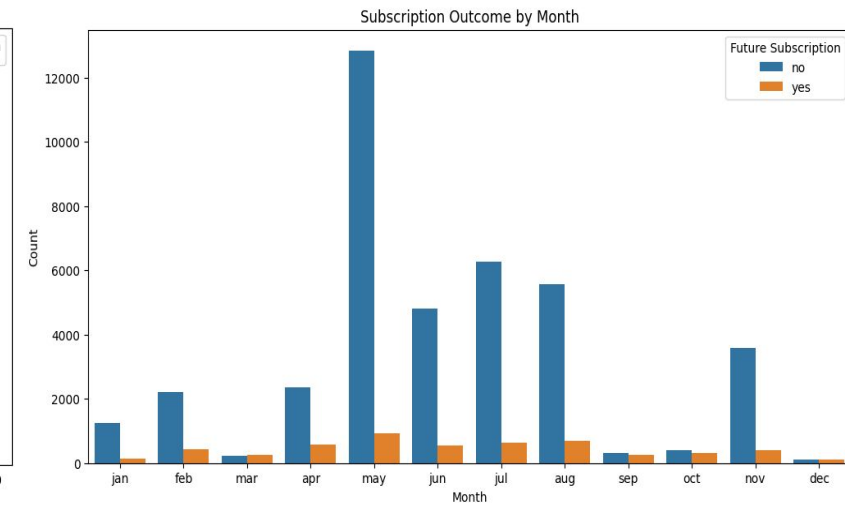
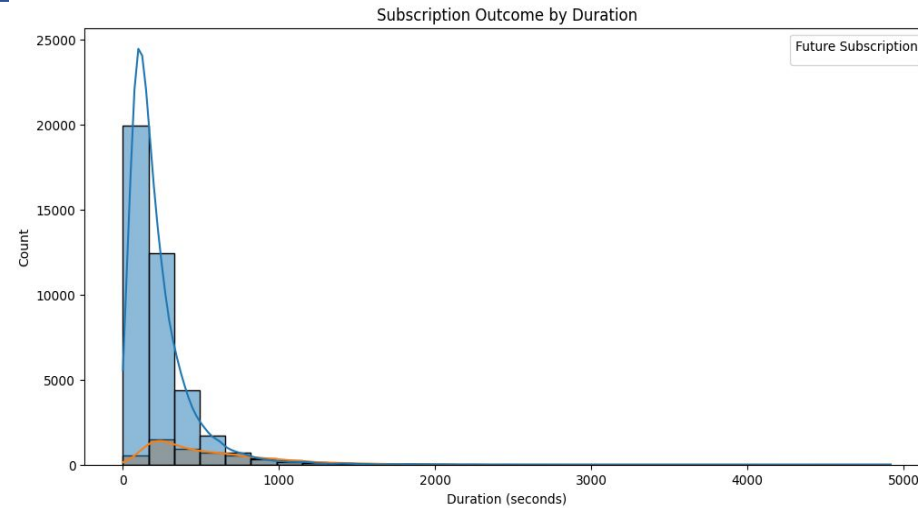
- Prioritize May-July for seasonal promotions
- Limit contacts to 3-5 touches for efficiency
- Equip agents to educate clients in call interactions

Resource Optimization:

- Ideal number of contacts balances conversion growth with labor costs
- Duration analysis assists with contact center capacity planning

Ongoing Analysis:

- Relate call outcomes to agents and topics discussed
- Create feedback loops to keep improving conversion productivity



Customer Attribute Deep Dive:

Relating demographics and holdings to response

Education Level Analysis:

- Tertiary education customers have higher conversion rates
- Aligns with greater financial planning knowledge

Product Holdings Analysis:

- Customers with existing loans less likely to purchase
- Potential debt load constraining ability to add deposits

Default Analysis:

- Small subset of customers have missed payments
- Further analyze cross-sell potential after resolving issues

Recommendations:

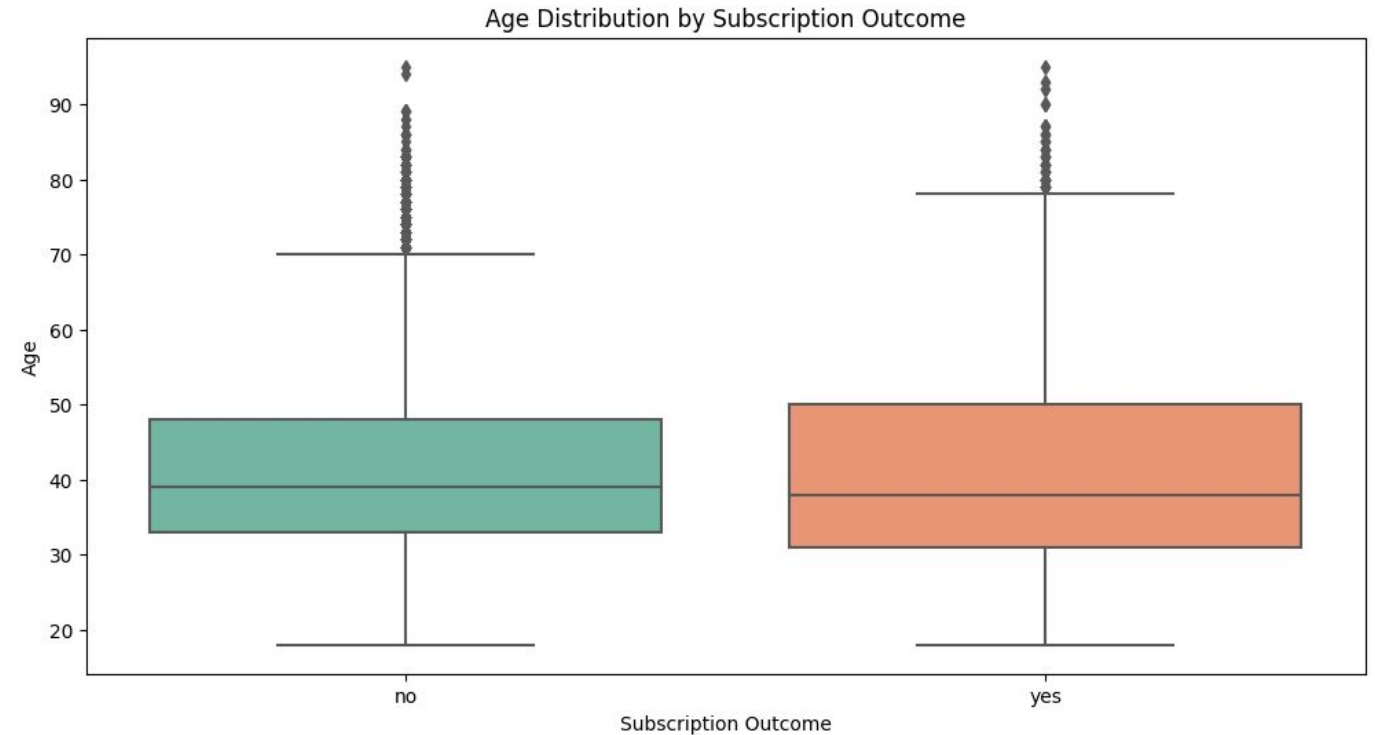
- Surface education-specific content to boost relevancy
- Customize offers based on current product holdings
- Develop remediation paths for struggling customers

Ongoing Analysis:

- Overlay behavioral data to identify emerging needs
- Integrate with campaign metrics to optimize targeting
- Test content personalization through A/B testing

Key Insights:

- Mix household attributes and behaviors to uncover relationships
- Identify leading indicators of financial needs
- Proactively engage customers with relevant offers



Product Holdings & Credit Profile Analysis

Key Insights:

- Customers with existing loans less likely to purchase deposits
- Potential debt load constraints ability to add investments
- Small subset of customers have missed payments

Analysis Approach:

- Aggregated purchase counts by product holdings
- Overlaid credit default status as secondary dimension

Key Finding:

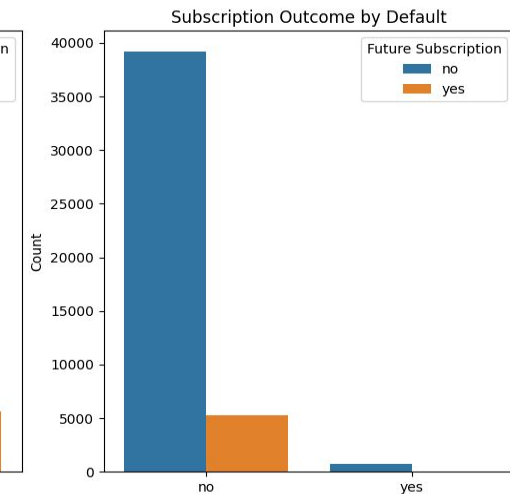
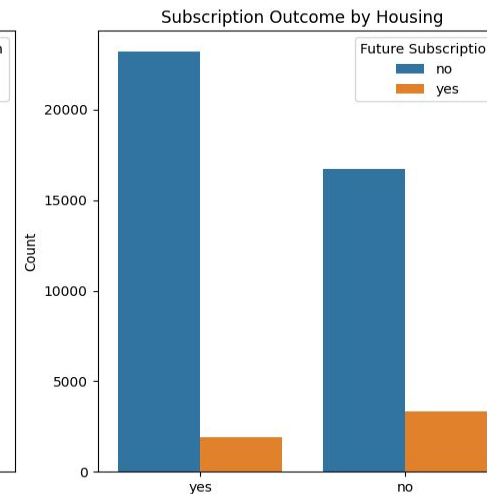
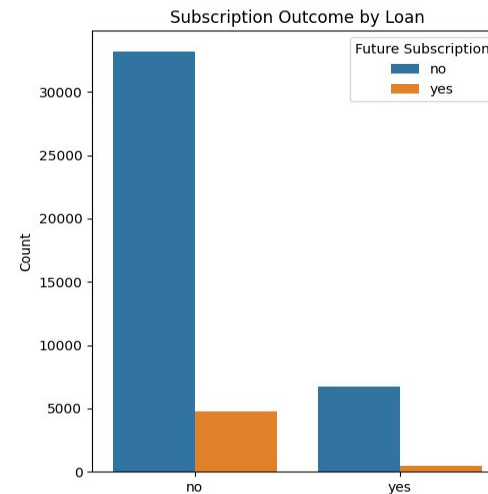
- Loan holders converted at lower rates despite marketing contacts
- Suggests debt obligations limit capacity for new deposits

Future Analysis:

- Build remediation paths for struggling customers
- Analyze purchase behaviors once defaults resolved
- Identify leading indicators of financial needs

Recommendations:

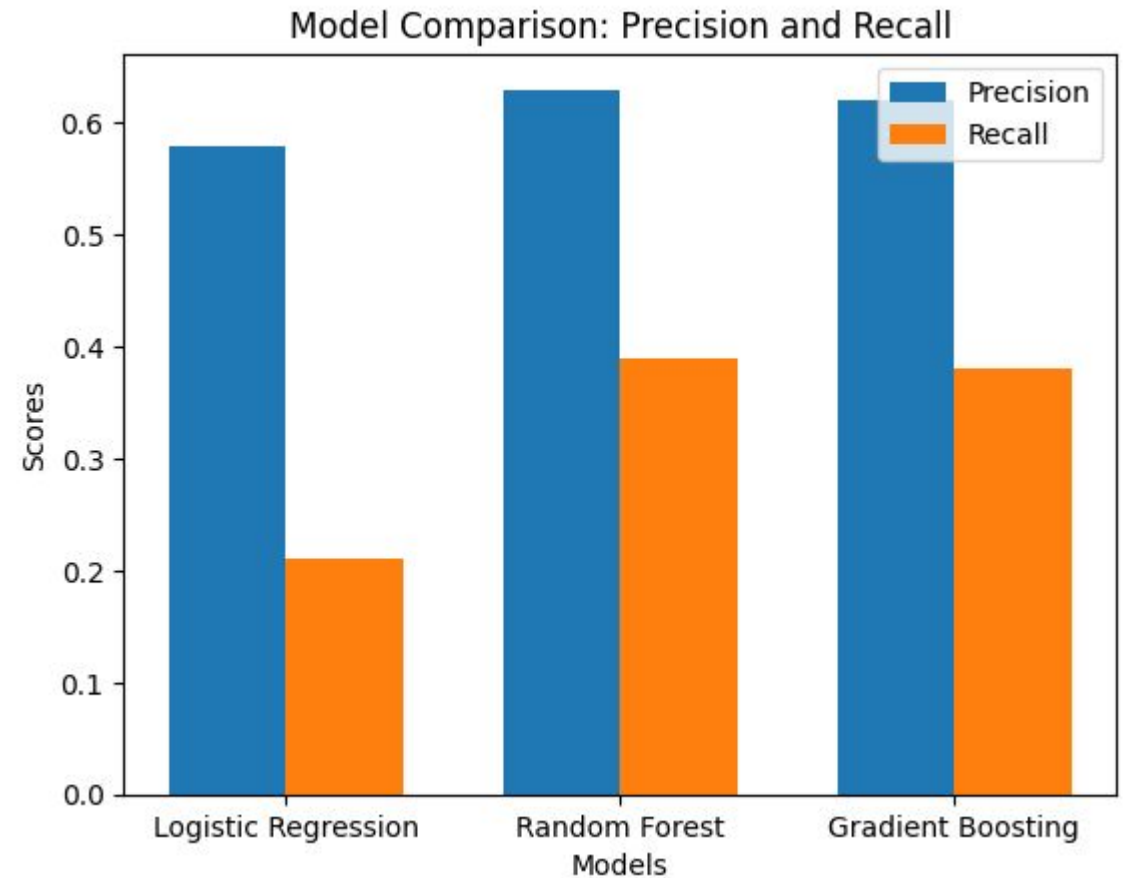
- Customize offers based on current product holdings
- Develop targeted segments by credit health
- Test engagement for at-risk defectors



Model Analysis for ABC Bank

Key Insights:

- In our analysis of predictive models for ABC Bank's term deposit marketing, we evaluated three key models: Logistic Regression, Random Forest, and Gradient Boosting. Logistic Regression, though offering high overall accuracy at 89%, showed critical limitations in identifying actual term deposit subscribers, with a recall score of just 21% for the key 'yes' class. This means that logistic regression failed to identify nearly 80% of customers who would subscribe to term deposits. Given ABC Bank's objective of precisely targeting high-potential customers, this poor recall performance renders logistic regression insufficiently effective despite stronger precision.
- By contrast, ensemble methods like Random Forest and Gradient Boosting demonstrated a markedly better balance between precision and recall - both vital metrics given the need to home in on likely subscribers. Specifically, Random Forest achieved 63% precision and 39% recall for the subscriber class. This signifies that 63% of those customers that Random Forest predicted as probable subscribers did indeed end up subscribing - a substantial improvement over logistic regression. Moreover, Random Forest doubled the recall accuracy in identifying those key potential customers correctly to 39%.
- This superior balance of precision and recall highlights Random Forest's effectiveness for ABC Bank's goals. It pointed to the right customers nearly twice as often as logistic regression. Further, 63% precision means the bank can have confidence in those identified as subscriber prospects. This combination enables more precisely targeted marketing toward promising customer segments in service of ABC Bank's aim to improve marketing efficiency and better promote term deposits to likely subscribers. Though not flawless, Random Forest notably outperformed alternatives models under consideration.



Why Random Forest Is Ideal for ABC Bank

Key Insights:

- With a 39% recall rate for identifying subscribers, Random Forest doubles the effectiveness of Logistic Regression (21% recall), substantially improving targeting of high-potential customers. This directly enables more efficient promotions.
- Precision of 63% means over 3 in 5 Random Forest subscriber predictions convert, giving the bank confidence in acting on identified prospects.
- Balancing strong recall and precision is crucial for ABC Bank's goals, and Random Forest provides the optimal trade-off versus alternatives.
- Random Forests mitigate overfitting through bootstrap aggregation, where each decision tree trains on random data samples. This maintains performance integrity across new data like ABC Bank's evolving customer pool.
- The algorithm handles intricate variable interactions well. Financial behaviors have nonlinear relationships and nuanced drivers - no single factor dominates. Random Forest excels in modeling these complex patterns.
- The model remains robust and accurate despite ABC Bank's data diversity - customer demographics, products held, campaign contacts, economic trends, and more. Avoiding overfit is key with such varied data.
- As an ensemble technique combining many decision trees, Random Forest brings stability. Individual trees can have high variance but are smoothed across the "forest".

RANDOM FOREST

Random Forest Advantages

01

It produces a highly accurate classifier and learning is fast.

02

It runs efficiently on large databases.

03

It can handle thousands of input variables without variable deletion.

04

It computes proximities between pairs of cases that can be used in clustering, locating outliers, or give interesting views of the data.

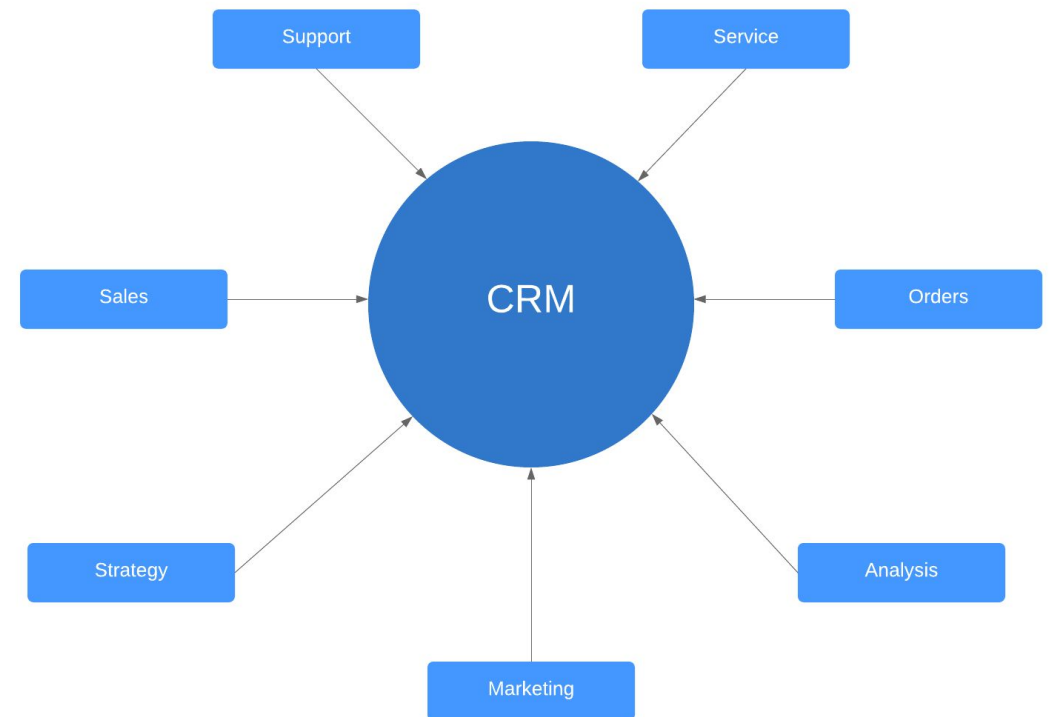
05

It offers an experimental method for detecting variable interactions.

Implementing the Random Forest Model

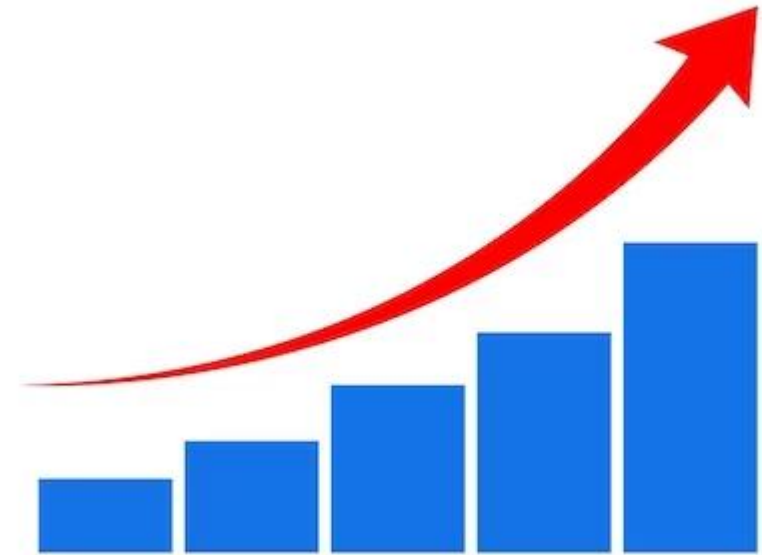
Strategy:

- Fully integrate the subscriber prediction model into ABC Bank's customer relationship management system (CRM) to enable practical usage across marketing. Embed into workflows.
- Connect the model to existing databases of customer information – demographics, products held, campaign interactions, payments made, previous subscriptions etc. This data feeds predictions.
- As new customer data streams into the CRM, the Random Forest model will ingest it and score each individual with an estimated probability that they will subscribe to a term deposit.
- The marketing team utilizes these subscriber probability scores to precisely target customers and personalize the content and offers sent via campaigns across channels like email, digital ads, direct mail and telephony. Focus on high probability strata.
- Continuously update Random Forest model by feeding newer chunks of customer data on an ongoing basis. This allows predictions to stay relevant to latest trends as the customer pool evolves over time.
- As model ingests new data reflecting changes in broader economy or bank offerings, subscription probability predictions become more accurate, further improving campaign targeting.
- Establish a bi-annual model performance review. Check precision and recall – if metrics dip, re-tune model hyperparameters to regain effectiveness.
- Take the subscriber probability scores generated by the model and make them available across all marketing channels to enable personalized messages tailored to the likelihood of response.



Future Outlook Using Random Forest at ABC Bank

- Integrating Random Forest's personalized predictive intelligence directly enables more relevant, targeted campaigns. Messaging can be tailored based on a customer's estimated propensity to subscribe. This amplifies engagement.
- More personalized promotions based on subscription likelihoods convert at higher rates. This directly lifts sales growth trajectory over years as compounding continues.
- With higher converting campaigns, ABC Bank grows revenues efficiently. The model optimization prevents wasted spend by honing in on receptive customers.
- Continually feeding the Random Forest model new customer data allows it's accuracy at predicting potential subscribers to incrementally improve over months and years.
- As prediction precision improves, ABC Bank can double down on the most high-potential customer segments surfaced by the model for specialized products. Maximizing wallet share.
- Ongoing advances in AI may lend themselves to integration with Random Forest to further boost predictiveness. For example, neural approaches unpack deeper subtle patterns.
- Could implement pilot tests blending Neural Nets with Random Forest trees to quantify if performance gains justify additional complexity in production.
- Keeping cutting edge model optimization as a priority sustains ABC Bank's competitive edge in the market. Personalization drives long-term loyalty.



Conclusion

In closing, ABC Bank stands ready to revolutionize its marketing approach through data intelligence and predictive modeling. By assimilating the Random Forest model into existing CRM infrastructure, the bank can precisely target high-potential customer groups, tailor messaging, and realize expanded marketing return on investment.

Going forward, ABC Bank is dedicated to perpetually optimizing this modernized, insight-led marketing methodology. Through ever-closer harmony with emergent customer preferences and behaviors, new value can bloom - for both clients and the bank alike.

By binding advanced analysis to human needs, ABC Bank is pioneering a higher order of banking - one built upon the bedrocks of trust and excellence. We remain devoted to this vision and appreciate your partnership on the journey. The future is bright, and we welcome you to build it with us.



Thank You



Data Glacier

Your Deep Learning Partner