PFG Bank (aka Capital One): Credit Card Design

Group 14

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Introduction:

- PFG Bank embarks on implementing an information-based strategy to redefine its credit card product offerings. This case study delves into the dynamic credit card industry, highlighting the bank's innovative approach to product design by considering critical attributes like Annual Percentage Rate (APR), annual fees, and the choice between fixed and variable rates.
- Challenge: PFG Bank faces the challenge of selecting from 12 possible product variations to maximize customer value and bank profitability. The scenario unfolds with the bank preparing for a large-scale solicitation campaign, aiming to meticulously target potential customers based on their creditworthiness, represented by their BK(Bankruptcy) scores.
- Objective: Utilize the provided data and market insights to design and execute two rounds of direct mail campaigns, aiming to maximize profitability while showcasing the power of tailored product offerings in the competitive landscape of financial services.

Descriptive Analysis of historic data

Data Collection Overview

- Collected over three months, capturing customer interactions in different economic contexts.
- Visa type and date columns excluded from analysis due to lack of relevance to credit risk assessment.
- Addressing Data Imbalance

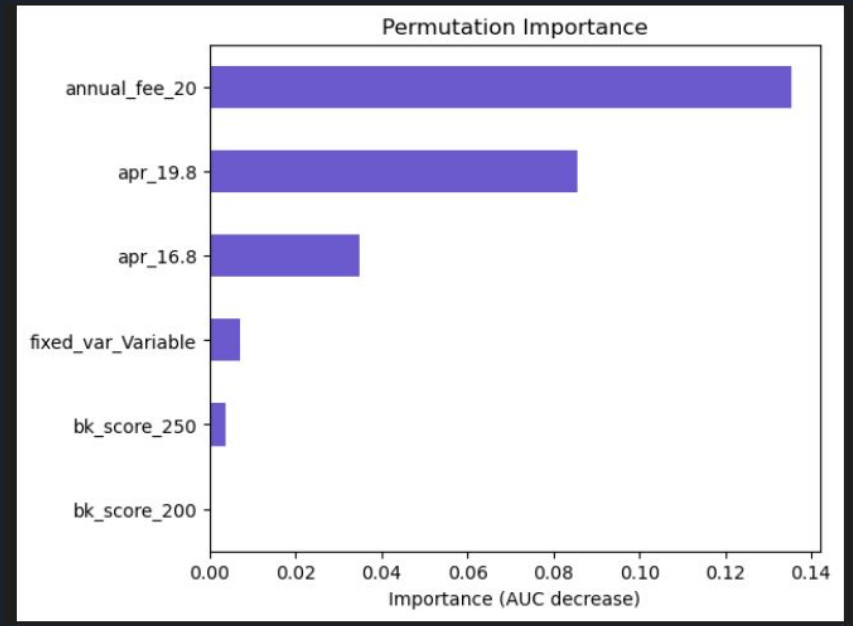
Imbalance observed with skewed email distributions, notably:

- BK score of 150 emails were exclusively sent on 19.8 and 16.8, not on 14.9.
- Fixed-rate products received 10x more emails than variable-rate products.
- Manual oversampling and undersampling techniques were employed to rectify imbalances.

Market dynamics during data collection included:

- Aggressive marketing strategies from competitors.
- New financial products such as no-fee cards influencing customer preferences.
- PFG Bank’s borrowing cost decreased by nearly 1%, impacting the interest rate environment.

Logistic regression model yielded an AUC of 0.66, signifying modest prediction strength with statistical significance ($p < 0.001$).
Neural network with a similar AUC of 0.66 suggests limited interactions between variables.



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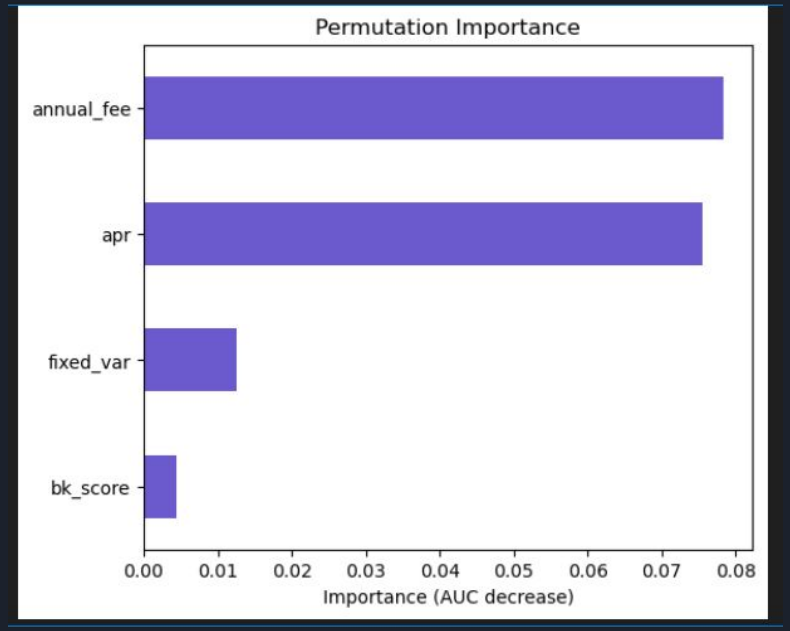

Logistic Regression

Evaluating CLV and CAV

- The logistic regression model helped in calculating and contrasting potential Customer Lifetime Value (CLV) and Customer Acquisition Value (CAV).
- Insights from this analysis informed the credit card offer strategies.

Profit Optimization via Experimental Design

- Initiated 12-trial partial factorial experiments based on logistic model findings.
- Aimed to determine the optimal product mix for maximizing initial phase profit.

Testing: DOE

Focus on three primary variables: apr, annual_fee, fixed_var, plus an additional variable, bk_score, for comprehensive analysis

The inclusion was based on its significant impact on response outcomes, influenced by both the BK score of individuals and the product characteristics.

The objective was to find a design configuration requiring the fewest trials but achieving a D-efficiency score above 0.8.

Evaluation of 20 different designs, each with 12 trials, using an algorithm to forecast potential earnings from balanced historical data.

apr	annual_fee	fixed_var	bk_score
16.8	20	Fixed	250
16.8	20	Variable	200
16.8	0	Fixed	150
16.8	0	Variable	250
19.8	20	Fixed	200
19.8	20	Variable	150
19.8	0	Fixed	250
19.8	0	Variable	150
14.2	20	Fixed	150
14.2	20	Variable	250
14.2	0	Fixed	200
14.2	0	Variable	200

Modelling for Round 2

Trained a model using results of round 1

Compared the Customer Lifetime Value (CLV) to the Customer Acquisition Cost (CAC) and determine the CLV/CAC ratio, then estimate potential earnings from sending mail to an individual customer.

For each group, dataframes were sorted by the CLV/CAC ratio, selecting the top 3 products

apr	annual_fee	fixed_var	clv/cac_150	clv/cac_200	clv/cac_250
14.9	0	Fixed	4.244452	3.086478	0.249151
14.9	0	Variable	5.086701	4.071659	1.502416
14.9	20	Fixed	1.681201	1.516729	1.037630
14.9	20	Variable	1.893748	1.766785	1.359195
16.8	0	Fixed	2.143795	1.838597	1.014166
16.8	0	Variable	2.454434	2.203713	1.482872
16.8	20	Fixed	0.745890	0.715287	0.597971
16.8	20	Variable	0.822676	0.805743	0.714583
19.8	0	Fixed	2.246336	2.135499	1.742467
19.8	0	Variable	2.484062	2.415139	2.101970
19.8	20	Fixed	0.713698	0.719789	0.687881
19.8	20	Variable	0.772284	0.788826	0.776929

Conclusion

- Total campaign costs: $393,600
  - Solicitation development: $17,000
  - Mailing costs: $1,600
  - Cost of mailing pieces: $375,000
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Round 1 Results			
Solicitation Development	$17,000	Round 1 Number Sent	48,000
Mailing Costs	$800	Round 1 Number of Responses	855
Cost of Pieces Mailed	$24,000	Total Response Value	$36,895
Total Cost of Mailing	$41,800		
		Total Profit	-$4,905

Round 2 Results			
		Round 2 Number Sent	702,000
Mailing Costs	$800	Round 2 Number of Responses	22,687
Cost of Pieces Mailed	$351,000	Total Response Value	$1,056,848
Total Cost of Mailing	$351,800		
		Total Profit	$705,048

Cumulative Results			
Solicitation Development	$17,000	Round 1 Number of Responses	855
Mailing Costs	$1,600	Round 2 Number of Responses	22,687
Cost of Pieces Mailed	$375,000	Total Response Value	$1,093,743
Total Cost of Mailing	$393,600		
		Total Profit	$700,143

- Two-round campaign:
  - Round 1: 48,000 pieces mailed, 855 responses, $36,895 total response value, $4,905 loss
  - Round 2: 702,000 pieces mailed, 22,687 responses, $1,056,848 total response value, $705,048 profit
- Cumulative results:
  - 23,542 total responses
  - $1,093,743 total response value
  - $700,143 total profit
- Round 2 significantly outperformed Round 1 due to higher mailing quantity and response rate
- Scaling up the mailing in Round 2 led to a highly profitable campaign overall, despite the initial loss in Round 1
- Results showcase the potential effectiveness of this direct mail approach when executed at a larger scale.