ABT Case Analysis for XYZ Bank

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Part-1

Abstract:

This investigation endeavors to optimize the categorization of bank customers through data analysis. The primary focus is on constructing an Analytics Base Table (ABT) from a spectrum of data types to comprehensively comprehend customer behavior. This comprehensive understanding facilitates refined segmentation and strategy formulation to enhance customer satisfaction and retention.

Introduction:

Effective customer categorization stands as a fundamental strategy in banking to cater to diverse customer needs. The creation of an ABT, utilizing various data types, serves as a critical tool to scrutinize customer behavior. This paper elucidates the foundational processes involved in ABT construction, functioning as a cornerstone for strategic planning aimed at improving customer engagement and loyalty.

Methodology:

The initial phase involved identifying fundamental raw data concerning customer transactions, demographics, channel interactions, and account engagement. This raw data formed the basis for subsequent feature engineering. Techniques such as aggregation, flagging, ratio analysis, and mapping were employed to derive insights into customer behavior, providing a deeper understanding and valuable insights for segmentation and strategy development.

Feature Engineering and ABT Development:

Bank XYZ is facing a significant challenge with customer churn, where a notable percentage of its customer base is closing accounts or ceasing to use their services. This churn is impacting the bank's revenue and market share, despite their current efforts to retain customers and acquire new ones. In this situation, I was appointed as the analyst of the bank and my responsibility was to create a model that would predict Customer Churn and improve the overall situation of the Bank.

To find out the reasons for Customer churn, I have gone through customer feedback, complaints, and reviews and identified some of the main reasons below:

- 1. Poor Customer Service
- 2. High Fees or Charges
- 3. Lack of Personalization
- 4. Better Offers Elsewhere
- 5. Convenience and Accessibility
- 6. Trust and Reputation
- 7. Life Changes
- 8. Unsatisfactory Products or Services
- 9. Communication and Transparency
- 10. Long Processes and Red Tape

These also helped me to understand the current situational fluency of the XYZ bank.

After understanding XYZ bank's business process and capacity, I have suggested the below models to predict customer churn, which are:

1. Churn Prediction Model:

- Data Requirement: Utilizes various customer-related data such as transaction history,
 account activity, demographic information, customer service interactions, and behavioral patterns.
- Capacity Requirement: The bank might need to invest in data management and data science capabilities to maximize the use of these insights.

2. Customer Segmentation and Behavior Analysis:

- Data Requirement: Involves segmenting the customer base and analyzing behavior patterns.
- Capacity Requirement: Utilizing the insights from customer segmentation and behavior
 analysis might be less resource-intensive compared to predicting individual churn, thus
 requiring fewer resources for implementation.

3. Churn Risk Assessment and Mitigation Strategies:

- Data Requirement: Analyzing historical data and patterns related to customer churn.
- Capacity Requirement: Utilizing this model requires the ability to translate historical insights into actionable strategies.

Model Selection and Rationale:

Among the proposed analytics solutions, the Customer Segmentation and Behavior Analysis model might be the most feasible option for Bank XYZ due to the following reasons:

- Data Accessibility: This model may require relatively less complex data aggregation compared to
 predicting individual customer churn. Segmenting customers based on behavior might utilize more
 generalized patterns rather than individual transactional data, potentially overcoming privacy
 concerns.
- 2. **Capacity Requirement:** Implementing customer segmentation and behavior analysis may demand fewer resources compared to the other models. It could be more straightforward to integrate these insights into existing strategies and requires less data science expertise to implement effectively.

Raw Data Sources for Customer Segmentation and Behavior Analysis:

1. Transactional Data:

- Transaction Records: Details of every financial transaction, including date, amount, type
 (withdrawal, deposit), and transaction channel (online, ATM, in-branch).
- Transaction Logs: Time-stamped logs recording each transaction event and associated metadata.

2. Customer Profile Data:

- Customer Information: Demographic details such as age, gender, contact information, and identification documents.
- Account Information: Details related to account types, account opening date, and current status.

3. Interaction and Service Data:

- Customer Service Interactions: Records of customer support inquiries, complaints, feedback, and their resolutions.
- Service Utilization Data: Information about the usage of various banking services, like loan
 applications, card activations, and account inquiries.

4. Digital Interaction Data:

- Online and Mobile Banking Logs: Details of login times, session duration, features
 accessed, and frequency of use.
- Mobile App Usage: Information on features used within the mobile banking application.

5. Marketing and Campaign Data:

- Response to Offers: Records of customers' responses to marketing campaigns, promotions, and special offers.
- Campaign Engagement Data: Data about customer participation and responses to marketing initiatives.

6. Behavioral Data:

- Usage Patterns: Patterns in the frequency and types of transactions, the channels used, and the time of activity.
- Customer Behavior Analytics: Analytics on customer behavior within the bank's premises
 or digital channels.

7. External Data Sources:

- **Economic Indicators:** External economic data that might influence customer behavior, such as interest rates, economic conditions, etc.
- Geographic Data: Data related to the location of customers and its economic, social, or demographic characteristics.

8. Compliance and Regulatory Data:

- Compliance Records: Data related to adherence to regulatory and compliance requirements.
- Audit Trails: Records of compliance-related activities and audit findings.

9. Feedback and Surveys:

 Customer Feedback and Surveys: Surveys, feedback, or ratings given by customers for their experience with the bank's services.

10. Historical Data:

 Historical Transaction Data: Past transaction records that provide insights into long-term behavioral patterns.

Feature Engineering for Customer Segmentation and Behavior Analysis:

Raw Features:

Transaction Behavior:

- Total Transaction Count
- Average Transaction Amount
- Transaction Frequency

Demographic Profile:

- Age
- Gender
- Location

Channel Interaction:

- Total Online Interactions
- Total In-Person Visits

Account Engagement:

- Average Account Balance
- Logins per Week

Derived Features using Feature Engineering Techniques:

1. Aggregate Features:

- Total Interaction Count: Aggregate of total online interactions and total in-person visits.
- **Total Transactions:** Aggregation of the total transaction count.

2. Flags:

- High Online Interaction Flag: Binary flag indicating if a customer has a high number of online interactions.
- Regular User Flag: Binary flag identifying customers who log in frequently.

3. Ratios:

- Ratio of Transactions to Age: Calculation of the total transaction count divided by the customer's age.
- Ratio of Online Interactions to In-Person Visits: Division of online interactions by in-person visit count.

4. Mapping:

 Mapping Location to Urban/Suburban/Rural: Categorization of the location variable into urban, suburban, and rural areas based on predefined mapping rules.

Explanation of Derived Features:

1. Aggregate Features:

 Aggregating data helps to summarize and condense multiple data points into singular meaningful statistics, such as summarizing interactions or transactions.

2. Flags:

Flags are binary indicators that signal the presence or absence of a specific behavior,
 enabling easy categorization of customers based on certain characteristics.

3. Ratios:

 Calculating ratios allows for a relative assessment of different raw features, providing normalized insights. For instance, the ratio of transactions to age indicates how active a customer is relative to their age.

4. Mapping:

 Mapping involves transforming one set of values into another for easier categorization or analysis. In this case, converting the location variable into broader categories facilitates segmentation based on geographical characteristics.

These derived features add depth to the analysis by offering additional perspectives on customer behavior and characteristics.

Customer Segmentation and Behavior Analysis - Analytics Base Table (ABT):

Here's an outline of what the ABT might look like based on the suggested features:

ABT Structure:

Customer	Age	Gender	Location	Total	Avg.	Transactio	Total	Total	Average	Logins	Total	Total	High	Regular	Ratio of	Ratio of
ID				Transactions	Transaction	n	Online	In-	Account	per	Interac	Trans	Online	User	Transacti	Online
					Amount	Frequency	Interactio	Person	Balance	Week	tion	action	Interactio	Flag	ons to	Interactions
							ns	Visits			Count	s	n Flag		Age	to In-Person
																Visits
001	35	Male	Urban	300	\$150	High	50	5	\$5000	10	55	300	1	1	8.57	10
002	28	Female	Suburban	150	\$200	Medium	30	3	\$3000	5	33	150	0	0	5.36	10
003	45	Male	Rural	500	\$100	High	80	8	\$8000	15	88	500	1	1	11.11	10

Descriptive Variables:

- Raw Features: These include individual transaction details, demographics, interaction counts, and engagement statistics. They describe fundamental characteristics of each customer.
- Derived Features: Such as ratios, aggregates, and flags, providing nuanced insights into behavior relative to age, interactions, and patterns. They offer a more comprehensive understanding of customer behavior.

Target Feature:

Segmentation Group (Potential): If the analysis aims to segment customers, the target feature
might be the specific group or cluster assigned to each customer based on behavior and profile
attributes.

Explanation:

- Descriptive Variables: Provide detailed customer-specific information used to understand behavior and characteristics, crucial for segmentation and tailored strategy development.
- Target Feature (Segmentation Group): This is the output or the outcome variable from segmentation models, categorizing customers into distinct groups based on behavior and profile similarities.

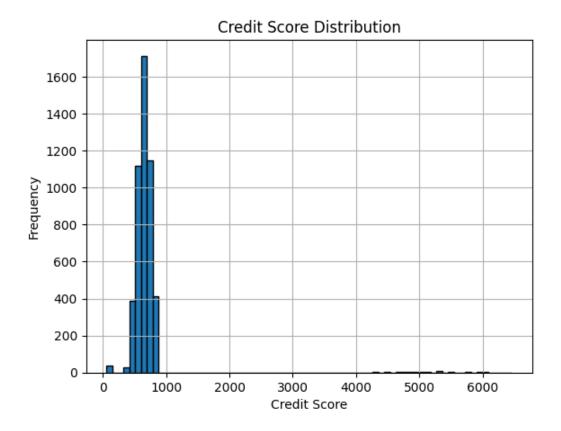
Conclusion:

The developed ABT stands as a foundational asset for banking institutions, offering a structured representation of customer behavior. The method employed in feature engineering and ABT development proves instrumental in generating insights for targeted customer segmentation. Further research and implementation of predictive models using this ABT can lead to enhanced customer engagement and retention strategies.

Part-2
Continuous Feature - Credit Score:

a) Continues Features

Feature	Count	%	Card.	Min.	1 st	Mean	Median	3 rd	Max.	Std.
		Miss.			Qrt.			Qrt		Dev.
CreditScore	5000	1.94	539	56.123	583	699.67	652	719	6456	499.86

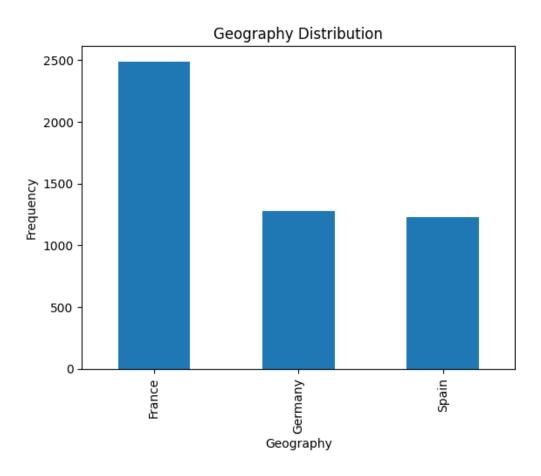


- Count: The count of available credit scores is 5000.
- Percentage of Missing Values (% Miss.): This shows the percentage of missing or null values in the dataset for credit scores, which stands at 1.94%.
- Cardinality (%): Cardinality is the percentage of unique values within the dataset. The observed high cardinality within credit scores signifies a substantial diversity in the spectrum of credit ratings among the customer demographic, denoting a wide array of financial statuses and creditworthiness distributed among individuals.
- Descriptive Statistics: This includes various statistical measures such as minimum, 1st quartile, mean, median, 3rd quartile, maximum, and standard deviation. These values give insights into the distribution and central tendencies of credit scores among customers.

Categorical Feature - Geography:

b) Categorical Feature

Feature	Count	%	Card.	Mode	Mode	Mode	2 nd	2 nd	2 nd
		Miss.			Freq.	%	Mode	Mode	Mode
								Freq.	%
Geography	5000	0	3	France	2490	49.8	Germany	1280	25.6



- **Count:** There are 5000 entries in the dataset for the geography feature.
- Percentage of Missing Values (% Miss.): Indicates the percentage of missing values, which, in this
 dataset, is 0% for the geography category.
- Cardinality (%): The geographic feature displays low cardinality as it has only three unique regions: France, Germany, and Spain region.

• Mode and Mode Percentage: The mode represents the most frequently occurring category within the data, which, in this case, is 'France' with 49.8%. The second most common region is 'Germany' with 25.6%.

Linking Insights to Customer Churn Context:

- **Geographic Insight:** A high percentage of customers are from France (49.8%), followed by Germany (25.6%). If a substantial portion of customers at risk of churn are concentrated in a specific region, it could imply geographic segmentation for targeted retention strategies.
- Strategies for Addressing Churn: If a significant number of customers at risk of churn are from a
 particular region, the bank could implement location-specific strategies. For instance, targeted
 marketing campaigns, personalized offers, or enhanced customer support tailored to the needs or
 preferences of customers in those regions could be employed to improve customer satisfaction and
 reduce churn.

Managing Missing Values and Outliers:

Ninety-seven (97) instances of missing data are identified in the "CreditScore" column, constituting 1.94% of the dataset. Addressing these missing values can be achieved through Imputation or Deletion, given the relatively low percentage of missing data. Moreover, the "CreditScore" column has been subjected to a clipping technique to confine values within predetermined lower and upper bounds, effectively managing potential outliers.

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Predictive Analytics. (n.d.). Retrieved October 30, 2023, from https://learningspace.myucw.ca/d2l/le/content/12127/viewContent/334151/View

Know Your Data Data Exploration. (n.d.). Retrieved October 30, 2023, from https://learningspace.myucw.ca/d2l/le/content/12127/viewContent/339208/View

Proof of Algarism:

