

Customer Attrition Analytics in Banking

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Abstract

In an era of mature markets and intensive competitive pressure, more and more companies realise that their most precious asset is their existing customer base. This realisation has resulted in a rise in emphasis on customer relationship management, in order to retain customers. This is a major area on which banks need to concentrate. Banks tend to be reactive to customer attrition, and many times it is too late to retain a customer. Customer attrition needs to be minimised, and loyal customers need to be rewarded.

The objective of this study to identify the factors affecting customer attrition of trust accounts for a leading American financial services company. The company realised that its trust accounts were getting closed after a period of seven to twelve years. Initially, the company tried to identify the root cause using a small set of data, but they were unable to do so. This triggered the use of analytics to build a model to predict customer churn, and come up with strategies to retain customers. This was achieved by applying data mining techniques to the transactions history of the accounts that closed down as against those that remained active.

Keywords: Customer Attrition Analytics, Customer Relationship Management, Data Mining

Introduction

Customer attrition is the phenomenon wherein a customer leaves a service provider. With the growing competition in the service sector, preventing customer attrition has become critical for sustainability, as it is well-established that retaining existing customers is more profitable than acquiring new customers (Jacob, 1994). This gives customer attrition analytics the challenging task of predicting which customers are likely to leave, and

of subsequently designing and implementing retention programmes for these customers. Customer analytics has made many strides in marketing, employer desirability, and branding.

Several statistical techniques are commonly applied for customer attrition analytics, including classification & regression trees (Gray & Fan, 2008), logistic regression (Au, Chan, & Yao, 2003), artificial neural networks (Datta, Masand, Mani, & Li, 2001), survival analysis (Ma & Li, 1994), and several other techniques (Hadden, Tiwari, Roy, & Ruta, 2006). There are mixed results concerning the most appropriate technique; however, several studies support the logistic regression model. For instance, Mozer, Wolniewicz, Grimes, Johnson, and Kaushansky (2000) and Hwang, Jung, and Suh (2004) suggested that logistic regression predicted customer attrition better than decision trees and neural networks.

The case is about an American financial services company headquartered in Dallas, Texas. It has retail-banking operations in Arizona, California and Florida, with select business operations in several other U.S. states, as well as in Canada and Mexico. It is among the twenty-five largest U.S. financial holding companies, with \$50 billion in total assets, \$35 billion in total loans, and \$40 billion in total deposits as of June 30, 2016. Its major operating units include the Business Bank, the Retail Bank, and Wealth Management. The case involves two of its trust accounts, viz. Investment Management Accounts and Revocable Living Trust accounts.

An Investment Management Account (IMA) is a flexible fund management arrangement with a financial institution that allows the customer to diversify their portfolio by gaining access to a wide range of financial instruments that span various asset types. Through an IMA account, customers can avail the wealth management services provided by fund managers under the auspices of the

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bank. The fund managers implement investment strategies to meet the individual customers' financial goals. A Revocable Living Trust account provides financial protection for the holder in case of incapacity. The bank has several other forms of trust accounts, including Marital Trust accounts, which provide lifetime financial protection for spouses, Qualified Terminable Interest Trust accounts, which balance the financial interests of spouses and children in the event of death of the holder, Gifts-to-Minors Trust accounts, which set aside funds for young children, and so on.

Customers for banking and financial services expect the pleasing, intuitive digital experiences that have become routine in many aspects of daily life. However, instead of this personalised approach attuned to their individual preferences, traditional banking has been hampered by regulatory issues and complex processes. This in turn can make offering new products and services at the speed and scale of evolving customer demands difficult. As a result, consumers often face channel experiences that reflect the isolated, siloed information that institutions have about their customers.

Analytics has been used widely by banks to ensure they remain competitive in three areas of digital disruption: the customer interface, process digitalisation and data analytics. These include activities such as strategic, advisory and management consulting across analytics and information management, business intelligence and analytics; strategic, advisory and implementation services for next-generation technologies such as big data analytics, mobile and cloud business intelligence; enterprise performance management solutions spanning business strategy and enterprise metrics definitions; and end-to-end information management services including data management, data integration, data quality and data governance.

Problem Statement

Acquiring new customers is usually harder and more expensive than retaining existing customers, who already know and trust the company, and in turn the company already knows so much about them. Retaining them might be as simple as making a phone call, providing free service for some components, or some other gesture of goodwill. The key is making full use of historical data of transaction, customer behaviour, and so on to

understand what makes customers leave. Once this has been identified, the company can focus on trying to retain customers with highest value and having the highest risk of leaving.

The case concerns an American financial services company that has witnessed a 15% decline annually in revenue from its IMA trust accounts in the last four to five years. The bank realised that trust accounts were getting closed after operating for seven to twelve years, resulting in a loss in market share, declining revenue, and declining brokerage, while the cost of acquiring new customers was increasing as the bank had to spend a lot of its marketing efforts to acquire a new account; moreover, the number of accounts closed was higher than the number of new accounts acquired.

The objective of the study was to predict which IMA trust accounts were at risk of attrition. The initial hypothesis was that accounts were at risk of attrition if the sell transactions were greater than the buy transactions.

Methodology

Predictive models relate the performance or behaviour of a typical unit in a system with some known attributes or features of the unit. The objective of the model is to assess the likelihood that a similar unit in the system will exhibit similar performance or behaviour, depending on its attributes or features.

The problem addressed by the study is a classification problem: the goal is to classify whether a trust account is likely to become inoperative. The study uses logistic regression and decision tree models for this purpose. Both of these techniques employ a learning algorithm to identify a model that best fits the relationship between the attribute set and class label of the input data.

The research was conducted in four phases; viz. source data integration, exploratory data analysis, model building and validation, and finally model scoring.

Data Collection

The following data were collected as independent variables for the predictive model for customer attrition: account demographics, which gives details of the IMA and revocable account types; granular-level sell transaction details, which tell the number of sell transactions

(portfolio, bond, securities) by trust account; granular buy transaction details, i.e. details of securities or portfolio purchased; and Moody’s/ Fed’s macroeconomic data, which includes a variety of economy-wide phenomena such as as inflation, price levels, the rates of growth of national income/gross domestic product, and changes in unemployment, reflecting market sentiment. The details included under each category are presented below.

Account Demographics

Table 1 presented the data for the IMA and revocable account types. When a trust opens an account, the demographic and investment details are captured in this table. The table captures the type of account, region-branch-date opened. The table also captures the time horizon for investment made (tenure), risk tolerance and anticipated market value to achieved after tenure, from an investment perspective. The attrition model uses the account demographic data, open/close indicator, and investment objective.

Table 1: Account Demographic Variables

<i>Account Type</i>	<i>IMA or revocable account</i>
Date Opened	Account open date
Date Closed	Account closed date
Reason For Closing	Account closing reason
Risk Tolerance	Risk appetite of trust account along with horizon (closely related to investment strategy); typical values are : Balanced, Conservative Short-intermediate Conservative_Short_Intermediate Defensive_Growth_Intermediate Balanced_Intermediate Conservative_Intermediate
Investment Horizon	Total length of time that an investor expects to hold a security or a portfolio.
Investment Objective	The objective of the investment; typical values are: increase income , reduce tax liability, increase saving Minimum_Risk Moderate_No_Alt Maximum_Risk_No_Alt Moderately_Conservative_No_Alt Siadfm Camdfi Bonds_Only

Sell & Buy Transaction Tables

Table 2 captures buy/ sell activity done on behalf of the trust. Every buy/ sell transaction done by the company is recorded in this table along with security name purchased/ sold, amount of buy/ sell and the transaction fee for the company. The attrition model uses the aggregated buy/ sell amount for the last one month, three months and six months which signifies the activity levels of the trust account.

Table 2: Sell & Buy Transactions Variables

<i>Transaction Date</i>	<i>Date of transaction executed (sell or buy)</i>
CUSIP	Portfolio ID
Security Name	Name of the securities to purchase or sell
Security Type	Typical values are: Shares, Bonds open-end fund, Index open-end fund
Reversal	
Transaction Amount	Sell amount/purchase amount
Units	Number of units
Transaction Description	Descriptions of sell & buy transactions

Fed’s Macroeconomic Data

Fed macroeconomic data (Table 3) is generally used to understand the market. The data includes a variety of economy-wide phenomena such as price levels, inflation, national income, gross domestic product, growth rates, and changes in unemployment. The attrition model uses future oil price index, S&P 500 volatility index, consumer confidence index, and bankruptcies as external influencing factors.

Table 3: Fed's Macroeconomic Variables

FPDPGDP.US	NIPA: Chain-Type Price Index - GDP, (Index 2009=100, SA)
FYHHMEDQ.US	Median Household Income: All Races, (USD, SA)
FGDP.US	NIPA: Gross Domestic Product, (Bil. USD, SAAR)
FRGT3Y.US	Interest Rates: 3-Year Constant Maturity Securities, (% p.a., NSA)
FRILIBOR6M.US	LIBOR Rates: 6-Month U.S. Dollar Deposits, (% p.a., NSA)
FDJMIUSDDWCFTDQ.US	Dow Jones U.S. total stock market index, (USD - closing price index, NSA)
FCBC.US	Consumer Confidence Index, (Index 1985=100, SA)
FLBR.US	Household Survey: Unemployment Rate, (% SA)
FSPVOL.US	S&P 500 Volatility, (30 day MA, NSA)
FRFED.US	Interest Rates: Federal Funds Rate, (% p.a., NSA)
FEX\$.US	NIPA: Exports of Services, (Bil. Ch. 2009 USD, SAAR)
FYPSAVQ.US	Income: Personal - Saving Rate, (% SAAR)
FCPIU.US	CPI: Urban Consumer - All Items, (Index 1982-84=100, SA)
FCPWTI.US	Futures Price: NYMEX Light Sweet Crude Oil - Contract 1, (USD per bbl, NSA)
FAHETP.US	Avg. Hourly Earnings: Private - Total, (USD per hr., SA)
FHST1.US	Housing Starts: Single-Family, (Mil. #, SAAR)
FPPISP3500.US	PPI: Finished Goods less Food and Energy, (Index 1982=100, SA)
FBKPY.US	Bankruptcies: Personal - Total - Trailing 12 months, (#, SA)
FCPGASQ.US	NYMEX Natural Gas Futures Prices: Contract 1, (USD per MMBtu, NSA)
FZPAVN.US	NIPA: Profits after Tax - Dividends, (Bil. USD, SAAR)
FRFHLMCFM.US	FHLMC: 30-Year Commitment Rate - Fixed Rate - National, (% NSA)
FRPRIME.US	Interest Rates: Bank Prime Rate, (% p.a., NSA)
FRILIBOR1M.US	LIBOR Rates: 1-Month U.S. Dollar Deposits, (% p.a., NSA)
FIFNIPSQ.US	Private Fixed Investment: Nonresidential - Intellectual Property Products, (Bil. Ch. 2009 USD, SAAR)
FABABC.US	ABA Delinquency Rate: Bank Card Loans - Open End, (% of Loans 30+ Days Past Due, SA)
FMOF14TQ.US	Mortgage Originations: 1-4 Family - Total, (Bil. USD, SAAR)
FMOF14PQ.US	Mortgage Originations: 1-4 Family - Purchase, (Bil. USD, SAAR)

The dependent variables included group trust accounts that had been closed between seven to twelve years, by reasons for attrition/ closure. The specific objective was to identify trust accounts that had left and had large and/or more frequent transactions in a given month or quarter. The goal was to build an attrition model to identify high value and/or high frequency trust accounts that have high probability to closure.

The data for the study was primary data on the demographics and the transactions for a sample of 3257 unique trust accounts of the bank, collected over the two-year period 2013-15. Of the 3257 unique accounts, there were 2513 unique accounts with sell transactions data and 2543 unique accounts with buy transactions data. Further, of the 3257 unique accounts, 1648 accounts closed down during the study period, and only 1573 accounts remained open at the end of the study period. The major reasons

for closure were: customer has switched to a competitor; customer found the fees too high; customer already had established relationship with other banks; bank failed to meet customer's expectations; customer has taken advice of an external financial advisor; and several other reasons. In most cases, closure was associated with lack of communication by the bank of its updated policy and new offers; further, with respect to handling of complaints, there was a lapse on the part of the bank in understanding the customers' problems and delayed or incorrect redressal. Further, for the 1648 closed accounts, sell and buy transactions data was available for 1481 accounts. Of the 1481 closed accounts for which sell and buy transactions were available, 926 accounts had more sell transactions than buy transactions, 289 accounts had equal sell and buy transactions, and 266 accounts had more buy transactions than sell transactions.

Model Development

Exploratory data analysis was performed to summarise the main characteristics of the data sets. In this phase, data from different sources was integrated. The data was mainly primary data; only the macroeconomic data was secondary data. The data was collected from the company via a data discovery workshop in order to understand the variables and data pattern for the model development. Additionally, complaint data and relationship manager interaction data were captured to identify the reasons for closing of accounts. The sample was divided randomly,

with 70% allocated for the training set and 30% for the validation/test set.

To get better results, both logistic regression and decision tree methods have been employed for this classification problem. The model was designed and developed in R.

Variable Identification/Selection

The first filter used for selecting appropriate variables was the information values (IV) as a criterion to identify variables with high predictive power. Table 4 indicates several variables had very low IV.

Table 4: Variables Dropped with Very Low Information Value

Variable	Information Value	Strength	Variable	Information Value	Strength
Rt_CONSERVATIVE_INTERMEDIATE	0	Very weak	is_MAXIMUM_RISK_NO_ALT	0	Very weak
Rt_CONSERVATIVE_LONG	0	Very weak	is_MODERATELY_AGGRESSIVE	0	Very weak
Rt_CONSERVATIVE_NA	0	Very weak	is_MODERATELY_AGGRESSIVE_NO_ALT	0	Very weak
Rt_CONSERVATIVE_SHORT	0	Very weak	is_MODERATELY_CONSERVATIVE	0	Very weak
Rt_CONSERVATIVE_SHORT_INTERMEDIATE	0	Very weak	is_MODERATELY_CONSERVATIVE_NO_ALT	0	Very weak
Rt_D_BALANCED_LONG	0	Very weak	is_MODERATE_NO_ALT	0	Very weak
Rt_DEFENSIVE.GROWTH_INTERMEDIATE	0	Very weak	is_MUNICIPALS_ONLY	0	Very weak
Rt_DEFENSIVE.GROWTH_LONG	0	Very weak	is_NOT_APPLICABLE	0	Very weak
Rt_DEFENSIVE.GROWTH_NA	0	Very weak	is_SIADFM	0	Very weak
Rt_DEFENSIVE.GROWTH_SHORT	0	Very weak	Rt_GROWTH_NA	0	Very weak
Rt_DEFENSIVE.GROWTH_SHORT_INTERM	0	Very weak	Rt_NA_SHORT	0	Very weak
Rt_GROWTH_INTERMEDIATE	0	Very weak	Rt_AGGRESSIVE.GROWTH_INTERMEDIATE	0	Very weak
Rt_GROWTH_LONG	0	Very weak	Rt_AGGRESSIVE.GROWTH_LONG	0	Very weak
Rt_GROWTH_SHORT	0	Very weak	Rt_AGGRESSIVE.GROWTH_NA	0	Very weak
Rt_GROWTH_SHORT_INTERMEDIATE	0	Very weak	Rt_AGGRESSIVE.GROWTH_SHORT	0	Very weak
Rt_NA_INTERMEDIATE	0	Very weak	Rt_AGGRESSIVE.GROWTH_SHORT_INTERM	0	Very weak
Rt_NA_LONG	0	Very weak	Rt_BALANCED_NA	0	Very weak
Rt_NA_SHORT_INTERMEDIATE	0	Very weak	Rt_BALANCED_SHORT_INTERMEDIATE	0	Very weak
is_MODERATE	0	Very weak			
Rt_BALANCED_INTERMEDIATE	0	Very weak			
Rt_BALANCED_SHORT	0	Very weak			

As observed from Table 4, several of the investment strategy variables had very low IV, so that they were dropped from the analysis.

Further, for continuous variables, the variance inflation factor (VIF) was examined, and variables with high VIF

(i.e. $VIF > 5.0$) were dropped. In the case of categorical variables, correlation between the categorical variables was adjusted. The key variables (with and without macroeconomic variables) selected after eliminating multicollinearity (i.e. dropping variables with high VIF) are presented in Table 5.

Table 5: Variables Selected after Eliminating Multicollinearity

With Macro Economic data		Without Macro Economic data	
Variable	VIF	Variables	VIF
Futures_Price_NYMEX_Light_Sweet_Crude_Oil_diff	4.29	Sum_tran_latest_sell	2.50
Count_tran_6months_buy	3.43	Sum_tran_latest_buy	1.00
Natural_Gas_Futures_Prices_diff	3.27	Sum_tran_3months_sell	2.48
Count_tran_latest_buy	3.06	Count_tran_latest_buy	4.38
ABA_Delinquency_Rate_Bank_Card_Loans_diff	2.90	Count_tran_latest_sell	1.91
Sum_tran_latest_sell	2.50	Count_tran_3months_buy	4.72
Sum_tran_3months_sell	2.49	Count_tran_6months_sell	2.11
Count_tran_6months_sell	2.34	Tenure_month	1.06
Tenure_month	2.23		
Mortgage_Originations_Total_diff	2.09		
Count_tran_latest_sell	2.00		
Bankruptcies_diff	1.93		
Income_Personal_Saving_Rate_diff	1.87		
Consumer_Confidence_Index_diff	1.82		
SP_500_Volatility_diff	1.48		

With the inclusion of the macroeconomic data, the following variables were found to have low multicollinearity: Last Six Months Buy Transaction count, Future Prices of Crude Oil, Future Prices of Natural Gas, Delinquency rates of card loans, Mortgage Originations, Bankruptcies, S&P 500 Volatility index, and Consumer Confidence Index.

The last filter was to drop insignificant variables. Further, the results with and without macroeconomic data were compared, to see if there was any improvement in accuracy. The final set of variables (with and without macroeconomic variables) selected after eliminating insignificant variables are presented in Table 6.

Table 6: Final Set of Variables

P Values _ without Macro Data

Coefficients:	Pr(> z)	Significance level
(Intercept)	2.71E-03	**
Sell_more_than_buy6_flag1	4.38E-16	***
Count_sell_more_equal_buy_latest_flag1	2.08E-02	*
Count_sell_more_equal_buy_6_flag1	1.76E-13	***
Sum_tran_3months_sell	2.78E-05	***
Count_tran_latest_buy	<0.000000000000000002	***
Count_tran_3months_buy	<0.000000000000000002	***
Count_tran_6months_sell	2.10E-10	***
Rt_.Growth_na1	3.68E-05	***
Rt_balanced_intermediate1	0.014288	*
Rt_aggressive.Growth_intermediate1	0.005125	**
Rt_balanced.Na1	0.003631	**
Rt_defensive.Growth_short1	0.048882	*
Rt_growth_intermediate1	0.002842	**
Is_Minimum_risk1	0.010329	*
Is_aggressive1	0.031026	*
Is_bonds_only1	0.000394	***
Is_municipals_only1	0.00324	**
Is_municipals_only1	0.00324	**

P Values _ with Macro Data

Coefficients:	Pr(> z)	Significance Level
(Intercept)	3.52E-06	***
Futures_price_nymex_light_sweet_crude_oil_diff	<0.000000000000000002	***
Count_tran_6months_buy	<0.000000000000000002	***
Natural_gas_futures_prices_diff	1.34E-11	***
Count_tran_latest_buy	<0.000000000000000002	***
Sum_tran_3months_sell	0.003177	**
Count_tran_6months_sell	0.006253	**
Tenure_month	4.34E-09	***
Mortgage_originations_total_diff	<0.000000000000000002	***
Count_tran_latest_sell	0.046732	*
Bankruptcies_diff	<0.000000000000000002	***
Sp_500_volatility_diff	4.91E-05	***
Sell_more_than_buy6_flag	1.44E-12	***
Count_sell_more_equal_buy_latest_flag	1.21E-05	***
Count_sell_more_equal_buy6_flag	1.22E-11	***
Rt_growth_na	0.034466	*
Rt_balanced_na	0.003846	**
Rt_defensive_growth_short	0.014521	*
Rt_growth_intermediate	0.036489	*

The following variables were found to be significant predictors after including macroeconomic data: Last Six Months Buy Transaction Count, Last Month Sell Transaction Count, Tenure, Futures Crude Oil, Futures Natural Gas, Mortgage Originations, Bankruptcies, and S&P 500 Volatility Index.

The models were compared on the basis of sensitivity, i.e. the proportion of actual positive cases (attrition customers) that were correctly identified, and specificity,

i.e. the proportion of actual negative cases (non-attrition customers) that were correctly identified. The model results are summarized in the tables below. To check for robustness, the models were compared with decision tree models using the same underlying variables. The classification results for the test data set are presented in Table 7.

Table 7: Classification Results for the Test Data**Logistic Model – Without Macro data**

Sensitivity	0.84
Specificity	0.69
Accuracy of the Model	0.77

Logistic Model – With Macro data

Sensitivity	0.83
Specificity	0.82
Accuracy of the Model	0.83

Key Insights:

- Accuracy of the Logistic Model has been increased by 6% after including Macro Data
- Sensitivity is decreased by 1 % and specificity increased by 13 % with Macro Data

Decision Tree – Without Macro data

Sensitivity	0.85
Specificity	0.78
Accuracy of the Model	0.82

Decision Tree – With Macro data

Sensitivity	0.91
Specificity	0.92
Accuracy of the Model	0.92

Key Insights:

- Accuracy of the Dtree Model has been increased by 10% after including Macro Data
- Sensitivity and specificity increased by 6 % and 14% respectively with Macro Data.

The classification results show that the decision tree model performs better than the logistic regression model in predicting both customer attrition and retention, particularly with the macroeconomic data. The final model was found to be quite accurate, i.e. 91% sensitivity and 92% specificity.

Conclusion

Predictive analytics can be a powerful tool for customer retention. There are many predictive techniques that can help reduce customer attrition. In fact, this approach can also be used to predict other aspects of accounts behaviour, such as when a trust account will sell the portfolio, when a trust account will buy the portfolio, whether a customer is committing a financial crime, and so on. Banks and financial institutions can also use predictive techniques to improve marketing strategies for acquiring new customers.

In the current case, data mining was performed on past accounts, and it was observed that closed accounts have larger sell transactions than buy transactions for the last three to six months. By introducing macroeconomic data from the Fed, the final model was able to identify six/seven variables that were key predictors of account closure, with high accuracy in the model, viz. 92%.

The results of the study suggest that decision tree methods may be more appropriate than logistic regression methods in customer attrition analysis. Thus finding is contrary to that of Mozer *et al.* (2000) and Hwang *et al.* (2004), who suggested that logistic regression was better than the decision tree model for predicting customer attrition. In the current case, decision tree model is perhaps more appropriate, as it is the event that sell transactions exceed buy transactions that predicts attrition, rather than the extent of the difference. It would be interesting to review the results of earlier studies with this additional insight.

The results of the study also suggest that macroeconomic variables play a significant role in customer attrition. Macroeconomic indicators clearly provide a stimulus for investment behaviour. The results of the study suggest that the relevant macroeconomic indicators for customer attrition are oil prices, natural gas prices, bankruptcies, and stock market volatility. The model suggests that there are threshold levels for each of these variables beyond which investors are more likely to exit the market.

The study contributes to the literature of customer attrition analytics by indicating that decision tree models may be more appropriate in some contexts of customer attrition, and by indicating that macroeconomic variables may play a significant role in customer attrition modelling. There is great scope for extending the study in other customer attrition contexts.

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