Comparison of Tree-based Methods in Identifying Factors Influencing Credit Card Ownership and Prediction Accuracy

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Factors influencing credit card ownership were identified using the data from Global Financial Inclusion Index Database of The World Bank and the tree-based methods: CART, boosting, and bagging. The prediction accuracy of the methods was compared in terms of the training and test error rate. Results on the world and Philippine data were compared.

The factors influencing consumers to own a credit card are financial account ownership, highest educational attainment and age. This is the case both for the World and Philippine data. For the World data, the factors that influence credit card ownership are financial account ownership, debit card ownership, withdrawal frequency in personal account, highest educational attainment, current loan for home or apartment purchase, age, get cash in ATM and deposit cash in ATM. For the Philippine data, the influential factors to Filipino consumers are financial account ownership, age, income quintile, highest educational attainment, and deposit cash over the counter in branch of bank or financial institution.

Among the procedures, boosting has the smallest test error rate while bagging has the largest training and test error rate, both for the world and Philippine data. CART and boosting has the smallest training error rate under the world data and Philippine data respectively.

Keywords: classification and regression trees, boosting, bagging, credit card

1. Introduction

Consumer spending is a crucial part of any economy. It reflects the behaviour of the consumers and their capacity to buy goods. The banking industry has

provided different services that will make spending, buying of goods, payments, and other personal transactions convenient for consumers. One product of banks that offers this service is the use of credit cards. With credit cards, consumers can now purchase any products or services anywhere even without the availability of cash during the transaction. The hassle of carrying cash is addressed by this service. Also since credit cards have allowable credit limits in terms of spending, multiple purchases of goods and services can be made without having to worry about cash shortage.

The objective of this study is to identify the factors influencing credit card ownership using the 2011 Global Financial Inclusion Index Database or *Global Findex* of World Bank (WB). Moreover, the study also aims to determine which procedure is best in terms of predicting credit card ownership. Different tree-based methods were used specifically the classification and regression trees or CART, boosting and bagging. Results were obtained both for the world and Philippine data.

2. Review of Related Literature

The use of credit cards for consumer spending has dramaticallychanged the market landscape. This product provides convenience for consumers in terms of purchasing goods, making payments and doing other personal financial transactions.Banks are in competition with each other in terms of attracting customers and potential clients that will avail their respective credit card products and services. That is why it is of importance for banks and other financial institution to determine factors influencing consumers to own a credit card. This will be a basis for them in terms of marketing their products and capitalizing on this information that will make their product ahead of other competitors.

According to a study about the identification of factors affecting credit card ownership in Turkey, the following variables namely gender, education level and age of household head, marital status, employment of housewife, the number of people in the family with an income, usefulness of the credit card and payment of debts on time determine consumers' ownership of credit card (Yayar and Karaca, 2012). The method used in the study was Binomial Logit Model.

In the Philippines, according to the 2009 Consumer Finance Survey, a survey conducted by Bangko Sentral ng Pilipinas which captures the financial conditions of households, around 4 percent of households have credit cards. A bigger percentage of households from National Capital Region (NCR) were credit card holders which is 6.8 percent compared to those areas outside NCR which is 1.6 percent (CFS, 2009). Almost all major banks in the Philippines offer credit cards to consumers. Approval depends mainly on the income of the applicants. A lot of working professionals avail credit cards because of the convenience it brings in terms of doing personal financial transaction. Hence it is interesting to know what factors influence consumers to avail a credit card.

3. Methodology

3.1 Data source

The *Global Financial Inclusion Index Database* (Global Findex) is a survey data that contains indicators measuring how adults in 148 economies save, borrow, make payments and manage risk. The data set can be used to track the effects of financial inclusion policies globally and develop a deeper and more nuanced understanding of how people around the world manage their day-to-day finance (WB Global Findex, 2011). The survey represents 97 percent of the world's population covering around 150,000 adults. Each country is represented by almost 1000 observations.The list of variables, its description and values used in the study is shown in Table 1 of Appendix A. Most of the variables used are categorical and ordinal in nature. The dependent variable is credit card ownership with values of 'Yes' and 'No'which pertains to ownership and non-ownership respectively.

Of the 150,526 total respondents from Global Findex data, around 18.6% owns a credit card. The figure is way lower for the Philippine data with only 4.5% of the 995 respondents owning a credit card. But this figure is a good representation of Filipino consumers owning acredit card since it is almost of the same percentage with the 2009 Consumer Finance Survey. Table 1 below shows the distribution of credit card ownership by region including the Philippines. The Philippine percentage of credit card owners is below the East Asia & Pacific region having about 8.0% but above the South Asian region having around 2.0%. The South Asian region has also the lowest percentage of credit card owners. The region with the highest percentage are the high income economies and Taiwan, with 47.6% and 48.1% credit card owners respectively.

Table 1. Credit Card Ownership by Region

Region	Credit Card		
	Yes	No	Percent
High Income Economies	18,667	20,509	47.6%
East Asia & Pacific	960	11,089	8.0%
Europe & Central Asia	3,000	20,653	12.7%
Latin America & Caribbean	2,360	16,584	12.5%
Middle East & North Africa	466	10,416	4.3%
South Asia	156	7,799	2.0%
Sub-Saharan Africa	1,844	35,029	5.0%
World	27,931	122,595	18.6%
Taiwan	478	516	48.1%
Philippines	45	950	4.5%

The number of females is slightly bigger compared to males accounting to almost 54% of the total respondents in the world data. Similar case can be observed on the Philippine data with females accounting to almost 58% of the total respondents.Table 2 below shows the distribution of gender for the Philippine and world data.

Table 2. Gender

Gender	World	Ph
Male	69,285	421
Female	81,241	574
Total	150,526	995

The five income levels are almost equally represented in the world data with each level accounting to around 20% of the total respondents. For the Philippine data, the poorest and middle 20% are around 17% and 15% respectively while the rest is a little over 20% of the total respondents. Table 3 below shows the income quintile distribution for the world and Philippine data.

Table 3. Income Quintile

Income Quintile	World	Ph
Poorest 20%	32,474	173
Second 20%	29,815	234
Middle 20%	28,967	153
Fourth 20%	29,506	224
Richest 20%	28,562	211
Total	149,324	995

3.2 Data mining methods

Tree-based methods are techniques that involve stratifying or segmenting the predictor space into a number of simple regions (James et al, 2013). It divides the feature space into a set of rectangles. A simple model is then fitted on each rectangle or space. The rectangles are formed by successive binary splits on the predictors. This is done recursively until a desired tree is grown. The most commonly used tree-based methods are CART, bagging and boosting. Bagging and boosting are a form of ensemble classification technique that aggregates predictions of multiple classifiers with the goal of improving accuracy.

Classification and regression trees

The classification and regression trees or commonly known as CART is one of the most popular tree-based methods. It is a non-parametric procedure that

uses a recursive partitioning algorithm that builds classification and regression trees for predicting categorical and continuous dependent variables. The trees are constructed by repeated binary splits of the feature space into smaller subsets. Prediction of categorical variables is used for classification while the prediction of continuous variables is used for regression.

Bagging

Bagging or bootstrap aggregation is a model averaging technique that combines predictions of multiple models. It uses different samples of observations and predictors to generate diverse classifiers. For tree-based predictions, it fits a classification and regression tree on each bootstrap sample and combined these for the purpose of improving accuracy. The predictions of the classifiers are then aggregated. Averaging is done for regression while majority voting is done for classification purposes.

Boosting

Boosting is similar to bagging except that the trees are grown sequentially wherein each tree is grown using information from previously grown trees. Boosting does not involve bootstrap sampling; instead each tree is fit on a modified version of the original data set (James et al., 2013).The motivation for boosting was a procedure that combines the outputs of many weak classifiers to produce a strong single classifier (Hastie et al., 2009).

The tree-based methods above were used in the identification of factors influencing consumers to own a credit card. The procedures were also compared in terms of prediction accuracy. Both were applied to the world and Philippine data.

4. Results and Discussion

The factors influencing credit card ownership were determined based on the results of the variable importance from each method. Consistency of the inclusion of the variables among the procedures was compared.The prediction accuracy of the tree-based methods was also compared. The dataset was divided into training and test data comprising 90% and 10% of the total observations respectively. The training data was used in model building and the misclassification rate was obtained for each method. Prediction was also done using the test data and the test error rate was obtained.Both are applied to the world and Philippine data.

4.1 Variable importance using world data

The top 10 most important variables from the three procedures were considered in identifying the factors influencing consumers to own a credit card.

Under CART, the most important variable is financial account ownership. Table 4 below shows the top 10 most important variable in CART.

Table 4. Top 10 Most Important Variable on CART

Variable	Importance
Has a Financial Account	8,343.57
Debit Card Ownership	6,073.92
Frequency of Withdrawals in Personal Account	3,138.59
Highest Educational Attainment	2,645.44
Has a current loan for home or apartment purchase	1,786.17
Age	988.10
Get cash over the counter in branch of bank or financial institution	815.61
Get cash in ATM	811.71
Income Quintile	739.41
Deposit cash in ATM	603.51

Under boosting, the top 10 most important variable is shown in Table 5. The same case with CART, most important variable in boosting is also financial account ownership which achieved 75.07% of the information gain. Eight of the most important variables in boosting are also included in CART. The important variables in boosting which are not included in CART are health/financial ownership and post office account ownership which achieved 1.26% and 0.65% information gain.

Table 5. Top 10 Most Important Variable on Boosting

Variable	Importance
Has a Financial Account	75.07
Frequency of Withdrawals in Personal Account	7.47
Debit Card Ownership	7.32
Get cash in ATM	2.19
Has a current loan for home or apartment purchase	2.01
Highest Educational Attainment	1.70
Has a health or financial insurance	1.26
Age	0.88
Deposit cash in ATM	0.76
Has Post Office Account	0.65

For bagging, the most important variable is financial account ownership which achieved 61.82 % information gain. This is also the most important variable on CART and boosting. All other important variables in bagging are also included in CART and boosting. Table 6 shows the most important variables under bagging.

Table 6. Most Important Variable on Bagging

Variable	Importance
Has a Financial Account	61.82
Frequency of Withdrawals in Personal Account	23.53
Debit Card Ownership	6.86
Has a current loan for home or apartment purchase	5.74
Highest Educational Attainment	1.47
Age	0.58

The most important variable which are consistently included in the three procedures are financial account ownership, debit card ownership, withdrawal frequency in personal account, highest educational attainment, current loan for home or apartment purchase, age, get cash in ATM and deposit cash in ATM.

The variables consistently included in the top three are financial account ownership (which also happens to be the most important variable under the three methods), debit card ownership and frequency of withdrawal in personal account.

4.2 Training and test error using world data

The prediction accuracy of the three procedures was measured in terms of the misclassification rate using the training and test data. Under the world data, CART yields a14.16 percent training error rate. Out of the 25,060 credit card owners, 11,728 were misclassified as non-owners. And of the 110,414 not owning a credit card, 7,452 were misclassified as owners. The training error rate mostly comes from misclassification of owners to non-owners. The confusion matrix for CART using the training data is shown in Appendix B: Table B.1. Using the test data, the test error rate is 14.89 percent which also mostly comes from misclassification of owners to non-owners. Out of the 2,871 credit card owners, 1,398 were misclassified as non-owners. And of the 12,181 not owning a credit card, 843 were misclassified as owners. The confusion matrix using the test data is shown in Appendix B: Table B.2.

For boosting, the training error rate is 14.24 percent.Among the credit card owners, 12,313 were misclassified as non-owners and among the non-owners, 6,979 were misclassified as owners. Also, the test error rate is 14.67 percent. The misclassification of owners to non-owners is 1,432. On the other hand, 775 non-owners were misclassified as owners. Both the training and test error rate under boosting mostly comes from misclassification of owners to non-owners. The confusion matrix under boosting using the test and training data is shown in Appendix B: Table B.3 and B.4 respectively.

For bagging, the training error rate is 18.52 percent.Owners which are misclassified to non-owners numbers to 25,038 and those consumers not owning a credit card which are misclassified as owners is 58. Also, the test error rate

is 16.36 percent. Among the credit card owners, 1,833 were misclassified as non-owners and among the non-owners, 630 were misclassified as owners. The misclassification rate under the test and training data also mostly comes from the misclassification of owners to non-owners. Appendix B: Table B.5 and B.6 shows the confusion matrix for boosting using the training and test data respectively.

Table 7. Training and Test Error Rate

	Train Error	Test Error
CART	14.16%	14.89%
Boosting	14.24%	14.66%
Bagging	18.52%	16.36%

The summary of the training and test error rate for each method is shown in Table 7. The CART has the lowest training error rate while boosting yields the lowest test error rate. Moreover, bagging has the highest training and test error rate among the three procedures.

4.3 Variable importance using Philippine data

The same case with the world data, the top 10 most important variables from the three procedures were also considered to determine the factors influencing Filipino consumers to own a credit card. The top 10 most important variable in CART is shown in Table 8. The most important variable is highest educational attainment. This is different with the result using the world data having financial account ownership as the most important variable on all three procedures. Using Philippine data, financial account ownership now becomes the fourth most important variable under CART. All of the most important variables in CART using the world data are also included in the results using the Philippine data except for the variables account used for business transactions and deposit cash over the counter in a branch of bank or financial institution.

Table 8. Top 10 Most Important Variable on CART

Variable	Importance
Highest Educational Attainment	8.44
Age	5.80
Income Quintile	4.31
Has a Financial Account	3.86
Account used for Business Transactions	3.37
Get cash in ATM	2.92
Deposit cash in ATM	2.73
Get cash over the counter in a branch	2.58
Deposit cash over the counter in branch of bank or financial institution	2.39
Debit Card Ownership	2.13

For boosting, the most important variable is age which achieved 33.20% of the information gain. This is different compared with the result using the world data having financial account ownership as the most important variable. Under boosting, all of the most important variables using the Philippine data is also included on the world data except for income quintile, deposit cash over the counter in branch of bank or financial institution, gender and frequency of deposits in personal accounts. Under the Philippine data, all of the most important variables in boosting arealso included in CART except for health/financial insurance ownership, gender, frequency of withdrawals in personal account, and frequency of deposits in personal account. Table 9 below shows the top 10 most important variable in boosting.

Table 9. Top 10 Most Important Variable on Boosting

Variable	Importance
Age	33.20
Has a Financial Account	9.73
Income Quintile	8.92
Highest Educational Attainment	8.21
Deposit cash over the counter in branch of bank or financial institution	6.87
Has a health or financial insurance	4.57
Gender	3.78
Frequency of Withdrawals in Personal Account	3.44
Debit Card Ownership	3.32
Frequency of Deposits in Personal Accounts	2.95

For bagging, the most important variable is highest educational attainment which achieved for 23.57% of the information gain. This is again different compared with the result using the world data. The most important variables under bagging in the Philippine data which are also included in the results of the world data are financial account ownership, highest educational attainment and age.Under the Philippine data, all of the variables in bagging are also included in CART except for health/financial insurance ownership. Moreover, comparing it with boosting, all of the variables are also the same except for account used for business transactions, get cash in ATM, deposit cash in ATM and get cash over the counter in branch of bank or financial institution. Table 10 shows the top 10 most important variable under bagging.

Under the Philippine data, the most important variable which are consistently included in the threeprocedures are financial account ownership, age, income quintile, highest educational attainment, and deposit cash over the counter in branch of bank or financial institution. Moreover, the variables consistently included in the top four most important are highest educational attainment, age, income quintile and financial account ownership.

Table 10. Top 10 Most Important Variable on Bagging

Variable	Importance
Highest Educational Attainment	23.57
Age	18.00
Has a Financial Account	17.16
Income Quintile	9.97
Has a health or financial insurance	7.03
Account used for Business Transactions	5.78
Get cash in ATM	4.10
Deposit cash in ATM	3.56
Deposit cash over the counter in branch of bank or financial institution	2.64
Get cash over the counter in a branch	1.87

Under the Philippine data, the most important variable which are consistently included in the three procedures are financial account ownership, age, income quintile, highest educational attainment, and deposit cash over the counter in branch of bank or financial institution. Moreover, the variables consistently included in the top four most important are highest educational attainment, age, income quintile and financial account ownership.

Comparing with the results of the world data, the variables financial account ownership, highest educational attainment and age, are the common factors influencing consumers to own a credit card.

4.4 Training and test error using Philippine data

Under the Philippine data, the training error rate using CART is 3.01 percent. Out of the 40 credit card owners, 24 were misclassified as non-owners. Of the 856 not owning a credit card, 3 were misclassified as owners. The confusion matrix using the training data is shown in Appendix C: Table 1. Moreover, the test error rate is 6.06 percent. Out of the 5 credit card owners under the test data, 5 were misclassified as non-owners. Of the 94 not owning a credit card, 1 was misclassified as an owner. The confusion matrix using the test data is shown in Appendix C: Table C.2. The misclassification rate under the training and test data mostly comes from the misclassification of owners to non-owner.

For boosting, no credit card owners were misclassified yielding a zero percent training error rate. All of the 40 credit card owners were correctly classified as owners. Same with non-owners, all 856 were correctly classified as non-owners. On the other hand, the test error rate is 5.05 percent. Among the credit card owners, 4 were misclassified as non-owners and among the non-owners, 1 was misclassified as an owner. The confusion matrix using the training and test data is shown in Appendix C: Table C.3 and C.4 respectively. Large part of the test error rate was due mostly from the misclassification of owners to non-owners.

For bagging, the training error rate is 4.46 percent. All of the 40 credit card owners were misclassified as non-owners while all of the 856 non-owners were correctly classified. Hence the training error rate was all due to misclassification of owners to non-owners. The test error rate is 7.07 percent. All of the 5 credit card owners were misclassified as non-owners. Of the 94 not owning a credit card, 2 were misclassified as owners. The test error rate mostly comes fromthe misclassification of owners to non-owners. The confusion matrix using the test and training data is shown in Appendix C: Table C.5 and C.6 respectively.

Table 11. Training and Test Error per Method

	Train Error	Test Error
CART	3.01%	6.06%
Boosting	0.00%	5.05%
Bagging	4.46%	7.07%

The summary of the training and test error rate for each method is shown in Table 11. Boosting has the smallest training and test error rate while bagging has the largest training and test error rate among the three procedures.

5. Conclusion

The factors influencing consumers to own a credit card was identified using the Global Financial Inclusion Index Database by World Bank. Results using the world and Philippine data were compared. The CART, boosting and bagging are the tree-based methods used in the study. The prediction accuracy of the methods was also measured to determine which procedure best predicts credit card ownership.

The most important variables that influenceconsumers to own a credit card are financial account ownership, highest educational attainment and age. This is true both for the world and Philippine data.

Under the world data, the variables which are consistently included in the three methods are financial account ownership, debit card ownership, withdrawal frequency in personal account, highest educational attainment, current loan for home or apartment purchase, age, get cash in ATM and deposit cash in ATM. For the Philippine data on the other hand, the most important variablesthat influence credit card ownership are financial account ownership, age, income quintile, highest educational attainment, and deposit cash over the counter in branch of bank or financial institution.

Among the three procedures, boosting has the smallest test error rate both for the world and Philippine data.Using the world data, CART has the smallest training error rate while under the Philippine data, boosting has the smallest training error rate. Also, among the three methods, bagging has the worst

prediction performance having the largest training and test error rate, both for the world and Philippine data.

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APPENDIX A

Table A.1. List of Variables

Variable Name	Description	Values
credit_card	Credit Card Ownership	1=Yes, 0=No
Gender	Gender	1=Male, 0=Female
Age	Age	Number of Years
Educ	Highest Educational Attainment	1=Completed Primary or less, 2=Secondary, 3=Completed Tertiary or more
inc_quintile	Income Quintile	1=Poorest 20%, 2=Second 20%, 3=Middle 20%, 4-Fourth 20%, 5=Richest 20%
debit_card	Debit Card Ownership	1=Yes, 0=No
acct_FI	Has a Financial Account	1=Yes, 0=No
acct_PO	Has Post Office Account	1=Yes, 0=No
trans_person	Account used for Personal Transactions	1=Yes, 0=No
trans_bus	Account used for Business Transactions	1=Yes, 0=No
deposit_freq	Frequency of Deposits in Personal Accounts	Count
withdraw_freq	Frequency of Withdrawals in Personal Account	Count
getcash_atm	Get cash in ATM	1=Yes, 0=No
getcash_branch	Get cash over the counter in branch of bank or financial institution	1=Yes, 0=No
getcash_retail	Get cash over the counter at a retail store	1=Yes, 0=No
getcash_person	Get cash from some other person associated in a financial institution	1=Yes, 0=No
getcash_donot	Do not withdraw cash	1=Yes, 0=No
putcash_atm	Deposit cash in ATM	1=Yes, 0=No
putcash_branch	Deposit cash over the counter in branch of bank or financial institution	1=Yes, 0=No
putcash_retail	Deposit cash over the counter at retail store	1=Yes, 0=No
putcash_person	Deposit cash using some other person associated with a financial institution	1=Yes, 0=No
putcash_donot	Do not deposit cash	1=Yes, 0=No
loan_home	Has a current loan for home or apartment purchase	1=Yes, 0=No
loan_homecons	Has a current loan for home or apartment cosntruction	1=Yes, 0=No
loan_school	Has a current loan for school/education fees	1=Yes, 0=No
loan_ehealth	Has a current loan for emergency/health purposes	1=Yes, 0=No
loan_funwed	Has a current loan for funerfals or weddings	1=Yes, 0=No
insurance	Has a health or financial insurance	1=Yes, 0=No

APPENDIX B (Results on World Data)

Table B.1 Prediction of Credit Card ownership using CART - Training Data

	Predicted		
Observed	Yes	No	Total
Yes	13,332	11,728	25,060
No	7,452	102,962	110,414
Total	20,784	114,690	135,474

Table B.2 Prediction of Credit Card ownership using CART - Test Data

	Predicted		
Observed	Yes	No	Total
Yes	1,473	1,398	2,871
No	843	11,338	12,181
Total	2,316	12,736	15,052

Table B.3 Prediction of Credit Card ownership using Boosting - Training Data

	Predicted		
Observed	Yes	No	Total
Yes	12,747	12,313	25,060
No	6,976	103,438	110,414
Total	19,723	115,751	135,474

Table B.4 Prediction of Credit Card ownership using Boosting - Test Data

	Predicted		
Observed	Yes	No	Total
Yes	1,439	1,432	2,871
No	775	11,406	12,181
Total	2,214	12,838	15,052

Table B.5 Prediction of Credit Card ownership using Bagging - Training Data

	Predicted		
Observed	Yes	No	Total
Yes	22	25,038	25,060
No	58	110,356	110,414
Total	80	135,394	135,474

Table B.6 Prediction of Credit Card ownership using Bagging - Test Data

	Predicted		
Observed	Yes	No	Total
Yes	1,038	1,833	2,871
No	630	11,551	12,181
Total	1,668	13,384	15,052

APPENDIX C (Results on Philippine Data)

Table C.1 Prediction of Credit Card ownership using CART using Training Data

	Predicted		
Observed	Yes	No	Total
Yes	16	24	40
No	3	853	856
Total	19	877	896

Table C.2 Prediction of Credit Card ownership using CART using Test Data

	Predicted		
Observed	Yes	No	Total
Yes	0	5	5
No	1	93	94
Total	1	98	99

Table C.3 Prediction of Credit Card ownership using CART using Training Data

	Predicted		
Observed	Yes	No	Total
Yes	40	0	40
No	0	856	856
Total	40	856	896

Table C.4 Prediction of Credit Card ownership using CART using Test Data

	Predicted		
Observed	Yes	No	Total
Yes	1	4	5
No	1	93	94
Total	2	97	99

Table C.5 Prediction of Credit Card ownership using CART using Training Data

	Predicted		
Observed	Yes	No	Total
Yes	0	40	40
No	0	856	856
Total	0	896	896

Table C.6 Prediction of Credit Card ownership using CART using Test Data

	Predicted		
Observed	Yes	No	Total
Yes	0	5	5
No	2	92	94
Total	2	97	99