UNIVERSITI PUTRA MALAYSIA

# *MODELLING CREDIT PRODUCTS ACCEPTANCE RATE PROBABILITIES USING DYNAMIC PROGRAMMING AND CROSS TOP APPLICATION CHARACTERISTICS REMAINDER OFFER CHARACTERISTICS TREE*

TEE YA MEI

FS 2014 76

# MODELLING CREDIT PRODUCTS ACCEPTANCE RATE PROBABILITIES USING DYNAMIC PROGRAMMING AND CROSS TOP APPLICATION CHARACTERISTICS REMAINDER OFFER CHARACTERISTICS TREE

By

TEE YA MEI

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Master of Science

November 2014

## DEDICATIONS

*To My Beloved Family and Friends*

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the degree of Master of Science

**MODELLING CREDIT PRODUCTS ACCEPTANCE RATE PROBABILITIES USING DYNAMIC PROGRAMMING AND CROSS TOP APPLICATION CHARACTERISTICS REMAINDER OFFER CHARACTERISTICS TREE**

By

**TEE YA MEI**

**November 2014**

**Chair : Lee Lai Soon, PhD**

**Faculty : Science**

Credit scoring is a method of credit evaluation in the aspect of predicting credit acceptance especially in finance and banking industries. There are two types of credit scoring methods which are deductive (or judgemental) credit scoring, and empirical (or statistical) credit scoring. This thesis studies empirical credit scoring techniques, in particular, for estimating take-up probability distribution. As the market becomes saturated with many products and services, competitors are concerned about deepening the relationship with their customers. Cross-selling is the method used by plenty of competitors to achieve their purpose. It is an activity of selling multiple additional products or services to the present or existing customers. An enduring relationship between a customer and the organisation might be created by promoting to the customers the most appropriate products and explaining how the products may help them to achieve long-term financial needs. However, matching the customers with the right credit products is challenging because it involves risk on the financial provider's side while it is important to ensure the credit products offered are within the customer's purchasing power and satisfy the customer's credit eligibility. This requires financial providers to have effective credit scoring instrument which enables them to be able to make decisions effectively (easily, quickly, yet safety). The credit scoring instrument provides them with the best estimate of each customer's financial creditworthiness according to the products to be recommended. This study proposes a modified credit scoring model for credit products in cross selling. The focus of the credit scoring techniques in this thesis is on modifying a Classification and Regression Trees (CART) method, namely the Top Application characteristics Remainder Offer characteristics Trees (TAROT) and improving a dynamic programming model for predicting the best offer to be extended to the next customer. TAROT is used to classify which questions from the dataset to be asked for the purpose of cross-selling activities. The proposed dynamic programming model, with Bayesian updating to

include the probabilities of acceptance of the previous customers, is used to match a suitable product to the suitable customers for the three and four variants of the product. Both techniques, the modified TAROT and the improved dynamic programming, were attempted to estimate the acceptance rate of credit cards products. Based on the study, it has been found that there is only one switch of offer occurs regardless of number of the credit products. The number of questions to be asked can be kept as minimal as possible in the decision trees.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Sarjana Sains

**PEMODELAN KEBARANGKALIAN KADAR PENERIMAAN PRODUK KREDIT DENGAN MENGGUNAKAN PENGATURCARAAN DINAMIK DAN POKOK CIRI-CIRI PERMOHONAN ATAS CIRI-CIRI TAWARAN BAKI SILANG**

Oleh

**TEE YA MEI**

**November 2014**

**Pengerusi : Lee Lai Soon, PhD**

**Fakulti : Sains**

Skor kredit merupakan suatu kaedah penilaian kredit dalam aspek meramalkan penerimaan kredit terutamanya dalam industri kewangan dan perbankan. Terdapat dua jenis kaedah skor kredit iaitu skor kredit deduktif (atau pertimbangan) dan skor kredit empirikal (atau statistik). Tesis ini mengkaji teknik skor kredit empirikal khususnya untuk menganggarkan taburan kebarangkalian penerimaan. Disebabkan pasaran terlalu padat dengan produk dan perkhidmatan yang banyak, pesaing-pesaing lebih fokus kepada pengukuhan hubungan dengan pelanggan mereka. Jualan silang merupakan suatu kaedah yang digunakan oleh banyak pesaing untuk mencapai tujuan mereka. Ia adalah suatu aktiviti yang menjual pelbagai produk atau perkhidmatan tambahan kepada pelangan-pelangan yang sedia ada dalam satu syarikat. Hubungan yang kekal antara pelangan dengan organisasi mungkin boleh diwujudkan dengan mempromosikan kepada pelanggan dengan tawaran produk yang paling sesuai serta menerangkan bagaimana produk itu boleh membantu mereka untuk mencapai keperluan kewangan dalam jangka masa yang panjang. Walau bagaimanapun, pemadanan pelanggan-pelanggan dengan produk kredit yang betul adalah memcabar kerana ia melibatkan risiko di bahagian pembekal kewangan sementara ia adalah penting untuk memastikan produk kredit yang ditawarkan adalah dalam kuasa membeli pelanggan dan memenuhi kelayakan kredit pelanggan. Ini memerlukan pembekal kewangan mempunyai alat skor kredit yang berkesan supaya membolehkan mereka membuat keputusan yang berkesan (mudah, cepat, namun keselamatan). Alat skor kredit ini memberikan mereaka anggaran terbaik bagi nilai kredit kewangan setiap pelanggan mengikut produk yang dicadangkan. Kajian ini mencadangkan satu skor kredit yang diubahsuai untuk produk kredit dalam jualan silang. Fokus teknik skor kredit dalam tesis ini adalah untuk mengubahsuai Pokok Klasifikasi dan Regresi (PKDR) iaitu Pokok ciri-ciri Permohonan Atas ciri-ciri Tawaran Baki (TAROT) dan menambahbaik model pengaturcaraan dinamik dalam meramalkan tawaran yang terbaik bagi pelanggan yang seterusnya. TAROT digunakan untuk mengelaskan

soalan mana dari set data yang boleh ditanya bagi tujuan aktiviti jualan silang. Model pengaturcaraan dinamik yang dicadangkan, dengan pengemaskinian Bayesian untuk memasukan kebarangkalian penerimaan pelanggan-pelanggan yang sebelumnya, digunakan untuk memadankan produk yang sesuai kepada pelanggan yang sesuai bagi tiga dan empat produk yang berlainan. Kedua-dua teknik, pengubahsuaian TAROT dan penambahbaik pengaturcaraan dinamik, telah diusahakan untuk menganggarkan kadar penerimaan bagi kad kredit produk. Berdasarkan kajian ini, ia telah memdapati bahawa hanya ada satu penukaran tawaran berlaku tanpa mengira bilangan produk kredit. Bilangan soalan yang akan ditanya dalam pokok keputusan boleh dikekal sebagai mininum yang mungkin.

**ACKNOWLEDGEMENTS**

First and foremost, I would like to thank my mother and sisters who have given me moral support throughout the journey of my master studies. Without their love and care, I would not have completed this project successfully.

Throughout the master studies, I learnt and gained a lot of knowledge related to the field of study that is completely new to me. For this acquisition, I would like to express my sincere appreciation to my dear academic supervisor, Associate Prof. Dr. Lee Lai Soon, co-supervisor, Associate Prof. Dr. Seow Hsin-Vonn and Associate Prof. Dr. Leong Wah June for their valuable guidance, time and assistance.

Besides that, I would like to thank the School of Graduate Studies, Universiti Putra Malaysia (UPM) and Ministry of Higher Education Malaysia for the financial support throughout my study. Also, many thanks to the Department of Mathematics, Faculty of Science, UPM for providing a good research environment and equipments. Thanks to my friends and research colleagues who kindly gave me moral support and advices whenever I encountered any problems in the preparation of this thesis.

Last but not least, I am exceptionally grateful to Daran Toh for his tolerant, understanding and patience during this two years. May God grants His blessings to those who advised me in completing this research project.

I certify that a Thesis Examination Committee has met on 18 November 2014 to conduct the final examination of Tee Ya Mei on her thesis entitled “Modelling Acceptance Probabilities using Dynamic Programming and Cross TAROT” in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The committee recommends that the student be awarded the Master of Science.

Members of the Thesis Examination Committee were as follows:

Muhammad Rezal bin Kamel Ariffin, PhD
Associate Professor
Faculty of Science
Universiti Putra Malaysia
(Chairman)

Mohd Rizam bin Abu Bakar, PhD
Associate Professor
Faculty of Science
Universiti Putra Malaysia
(Internal Examiner)

Mansor bin Monsi, PhD
Faculty of Science
Universiti Putra Malaysia
(Internal Examiner)

Adibah Shuib, PhD
Associate Professor
Faculty of Computer & Mathematics Sciences
Univeisiti Teknologi Malaysia
Malaysia
(External Examiner)

ZULKARNAIN ZAINAL, PhD
Professor and Deputy Dean
School of Graduate Studies
Universiti Putra Malaysia

Date:

This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Master of Science. The members of the Supervisory Committee were as follows:

**Lee Lai Soon, PhD**
Associate Professor
Faculty of Science
Universiti Putra Malaysia
(Chairman)

**Leong Wah June, PhD**
Associate Professor
Faculty of Science
Universiti Putra Malaysia
(Internal Member)

**Seow Hsin-Vonn, PhD**
Associate Professor
Faculty of Social Science
University of Nottingham Malaysia
(External Member)

______________________________
**BUJANG BIN KIM HUAT, PhD**
Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date:

Declaration by graduate student

I hereby confirm that:

- this thesis is my original work;
- quotations, illustrations and citations have been duly referenced;
- this thesis has not been submitted previously or concurrently for any other degree at any other institutions;
- intellectual property from the thesis and copyright of thesis are fully-owned by Universiti Putra Malaysia, as according to the Universiti Putra Malaysia (Research) Rules 2012;
- written permission must be obtained from supervisor and the office of Deputy Vice-Chancellor (Research and Innovation) before thesis is published (in the formof written, printed or in electronic form) including books, journals, modules, proceedings, popular writings, seminar papers, manuscripts, posters, reports, lecture notes, learning modules or any other materials as stated in the Universiti Putra Malaysia (Research) Rules 2012;
- there is no plagiarism or data falsification/ fabrication in the thesis, and scholarly integrity is upheld as according to the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) and the Universiti Putra Malaysia (Research) Rules 2012. The thesis has undergone plagiarism detection software.

Signature: ____________________________ Date: ______________________

Name and Matric No.: Tee Ya Mei GS 32551

**Declaration by Members of Supervisory Committee**

This is to confirm that:

- the research conducted and the writing of this thesis was under our supervision;
- supervision responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) are adhered to.

| | | | |
|---|---|---|---|
| Signature: | ____________________ | Signature: | ____________________ |
| Name of Chairman of Supervisory Committee: | ____________________ | Name of Member of Supervisory Committee: | ____________________ |

| | |
|---|---|
| Signature: | ____________________ |
| Name of Member of Supervisory Committee: | ____________________ |

**TABLE OF CONTENTS**

## LIST OF TABLES

## LIST OF FIGURES

# LIST OF ABBREVIATIONS

| | |
|---|---|
| $t$ | variant number |
| $p_t$ | probability of a customer choosing variant $t$ ($t$ = 1, 2, 3, 4) |
| $P_t$ | profit to the lender if variant $t$ ($t$ = 1, 2, 3, 4) is chosen by a customer |
| $p_t\, P_t$ | maximum profit for variant $t$ |
| $u$ | worse variant |
| $v$ | better variant |
| $q_i$ | Bernoulli random variable |
| $r_t$ | number of customers that have accepted the offer $t$ ($t$ = 1, 2, 3, 4) |
| $n_t$ | number of customers who were extended offer $t$ ($t$ = 1, 2, 3, 4) |
| $m$ | size of population that has yet to be offered any financial products |
| $z$ | stage that is printed out |
| $s$ | number of customers have already been made an offer |
| $\left(\frac{r_t}{n_t}\right)$ | expectated value of accepting variant $t$ |

**Greek symbols**

| | |
|---|---|
| £ | pound sterling |
| $\beta$ | discounting factor parameter |

# CHAPTER 1

# INTRODUCTION

## 1.1 Study Background

### 1.1.1 Consumer Credit

Consumer credit is mostly known as a debt that someone (the consumer) incurs for the purpose of obtaining money, goods or service from an organisation in which both, the consumer and the organisation, have an agreement such that the consumer has to pay an extra fee or interest in the future. It began in the nineteenth century during World War II. Consumer credit is now widely spread and accepted in many societies today. The consumer consumption and the growth in home ownership would not exist without credit over the last 50 years. In credit card product, the amount of lending is increasing. Based on table 1.1, in January 2014, all plastic card spending was amounted to £46.5 billion spread over 954 million transactions from the statistical report of The UK Cards Association, which compares to the figures of £42.3 billion and 863 million transactions in 2013, respectively.

However, the debit card was calculated to £32.6 billion spread over 732 million transactions and the credit card was £13.9 billion spread over 223 million transactions, respectively. The annual growth rate in all plastic cards increased by 6.8% with debit and credit card both rising by 7.9% and 4.4%, respectively, in January 2014 (see **Table 1.1**). The trend of the consumer internet card spending was increasing obviously throughout the year from 2007 to 2012 (see **Figure 1.1**).

Credit lending was increasing. Hence, the exercise of credit scoring becomes extremely crucial to minimize loses based on decision on credit. Therefore, one must differentiate the good and bad customers, where good customer is defined as one who has the probability of default in repayment to be low while high probability of default is associated with bad customers. Scoring is a process that utilises characteristics information to form a numerical score to represent a probability of customer's paying behavior in the future. The numerical score is such as a mathematical representation of a scoring model. After the developed model has been validated, a scorecard can be produced to estimate the likelihood that the individual is good or bad customer. For more description about credit scoring, let us go back to the history of credit scoring and creditworthiness which is in the next section.

| | Total Spending (£ Billions) | | Annual Growth Rates for Spending | | Number of Purchases (Millions) | |
|---|---|---|---|---|---|---|
| | 2014 | 2013 | 2014 | 2013 | 2014 | 2013 |
| All Plastic Cards | 46.5 | 42.3 | 6.8% | 4.4% | 954 | 863 |
| Debit Cards | 32.6 | 29.5 | 7.9% | 5.8% | 732 | 662 |
| Credit Cards | 13.9 | 12.8 | 4.4% | 1.5% | 223 | 201 |

**Table 1.1: Card Expenditure Statistics - January 2014**
Source: The UK Cards Association (2014)

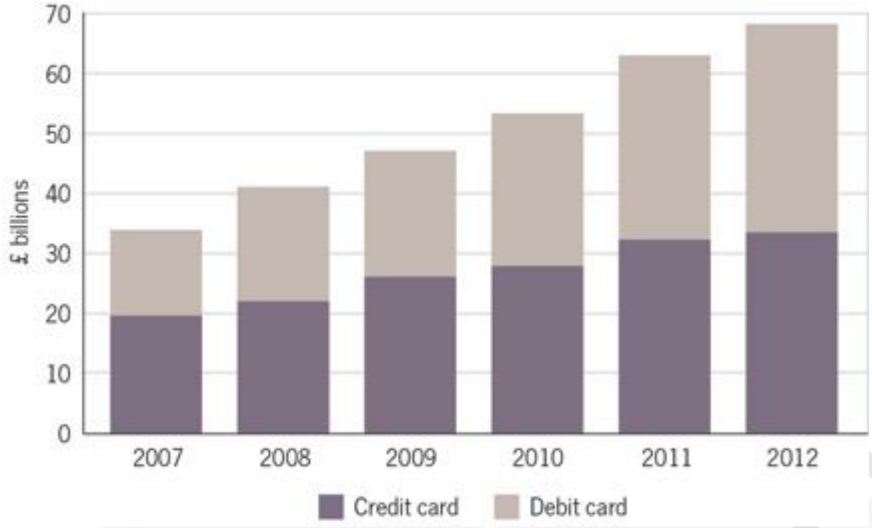


**Figure 1.1: Internet Card Use - Consumer Internet Card Spending**
Source: The UK Cards Association (2014)

### 1.1.2 History of Credit Scoring and Creditworthiness

Credit scoring is a method of credit evaluation. It is one of the most successful applications of statistical and operations research modeling in finance and banking and the number of scoring analysts in the credit industry has increased constantly (Lewis, 1992). Credit score is always affected by the FICO score. FICO is an acronym for Fair Isaac Corporation, which was established in the year 2003. It was rebranded in the year 2009 as FICO. Besides the credit bureau and Fair Credit Reporting Act (FCRA), FICO is one of the companies that provides credit scoring models for some financial institutions to support the decision on granting loans. Nowadays, credit score plays an important role in a consumer's personal financial.

The first application of credit scoring dated back to Durand (1941), who classified good and bad loans. However, the first consultancy using credit scoring was formed in San Francisco by Bill Fair and Earl Isaac in the early 1950s. According to Thomas et al. (2002), the set of decision models and their underlying techniques that aid lenders in the granting of consumer credit is credit scoring.

According to Lewis (1992), credit scoring is a way to study the creditworthiness of an individual applicant who wants to obtain money, goods or services in any form of business or commercial activities with the promise to repay the debt with interest in the future. Credit scoring can be used to measure the creditworthiness of an individual's characteristic by converting the information of a credit applicant into numbers to form a numerical score (Lewis, 1992). The credit grantors normally depend on applicant's characteristics, called the Three C's of credit, which are Character, Capacity, and Collateral, to determine whether the applicant has the ability to pay off the debts in the stated period. As stated by Lewis, the history of credit scoring maybe considered short and the literature is limited, but, nevertheless, the credit scoring methodologies have been used since 1950s.

Creditworthiness is based on the likelihood that someone will repay the credit they are extended with. It also looks at the customer's behaviour so that there is an opportunity to cross-sell another products or services and a potential for revenue to be generated. In other words, a creditworthy customer generates profit to an organisation while an un-creditworthy customer generates a loss. However, creditworthiness is defined differently by each company. For example, a company may implement different software such as Credit Tip-Off Service (CTOS) to determine whether the new customer is entitled to receive credit from the company. Different software can generate different cut off point. Hence, how creditworthy of each person is dependent on the company itself. One of the basic tasks which any of the company or lenders must deal with is to predict the risk level of the credit takers in order to minimize the credit risk.

### 1.1.3 Credit Risk and Evaluation

Credit risk can be defined as "the probability of the loss (due to non-recovery) emanating from the credit extension, as a result of the non-fulfillment of contractual obligations arising from the unwillingness or inability of the counter-party or for any other reason (Joseph, 2006)." In other words, credit risk exists whenever credit is extended to the customer. Credit scoring is essentially a tool to evaluate the credit risk. The evaluation is primary based on how likelihood the customer going to default. To manage the credit defaulter in recent years, various credit scoring techniques have been developed to assess the credit risk (Harris, 2013).

Nowadays, online shopping is booming. One has to pay the fee when buying items online. Some of the organisations allow the consumers to pay the fee when the goods arrived at their home like Zalora and certain companies deals on Groupon. However, some might ask " What is the risk involved?", if the consumer mis-sold the goods in the stated period or consumers fail to pay when the goods arrived. All these business deals have no credit risk evaluation tools usually. Nevertheless, the loss faced by the consumer is limited to the goods' value and the delivery fees. As claimed in Lewis (1992), how good the company depends on how good the company can estimate the credit risk.

Another benefit of credit risk estimation by using credit scoring system is its capability to generate positive profit to an organisation. However, the customer needs to accept the product in order to contribute profit to the organisation. Hence, this thesis studies credit scoring techniques, that is dynamic programming as well as Classification and Regression Tree (CART), in particular, for estimating acceptance probability.

### 1.1.4 Acceptance Scoring

In credit scoring, consumers can be classified as default and a non-default categories. One of the classification purposes is to estimate the offer of credit acceptance by consuming in a non-default category. In this saturated market for personal financial product, banks have to fight for sales in a highly competitive market in order to gain profit. Before bank can fight for this competitive market, the bank needs to identify the characteristic or preference of the customers so as to customize a product which gains highest profit to suit these customers. One can use credit scoring techniques to model from historical consumer data. The aim is then to predict the acceptance rate of the potential customers from analyzing the said data.

In this thesis, we deal with two scenarios. One of the scenarios is when there is no publicly data available. We suggest solving this by using the dynamic programming model with Bayesian updating so as to include the previous response for better estimate of the acceptance probability. This model allows the learning on how to promote the next product for better acceptance.

In the other scenario, we use the Fantasy Student Account data set, which is available in a web page of the University of Southampton. The credit scoring techniques which is used to analyze this data is the modified CART. We call it cross TAROT.

## 1.2 Problem Statement

Good customers generate profit to the organisations like banks, credit unions and other financial organisations if they are willing to accept the product offer. So, the organisations would try hard to encourage customers to accept their offer. There are several ways to encourage a customer to accept an offer. One of them is the lender must gather the information on customer's preferences in order to know which type of offer the customers may have interest on. The lenders must "learn" about the customers' preferences after the information is obtained. They need to decide what offer to make by looking at which type of products might be accepted by different type of customers. This acceptance model is described as a Markov Decision Process under uncertainty. Information acquisition is based on the response of previous question to determine what the offer to be made to the next customer. This sequential process would aid in achieving high take-up probability.

Customer preference shed light on the new trend in lifestyle which can have a significant impact on selecting a question to be asked. It is strongly related to the number of questions asked, given what we know so far about the preference of the customer. So, if the questions prepared for customers are too long or too many, the customers may quickly get bored when answering the questions. On the other hand, if customers feel attacked by a lot of questions, they will take a lot of time to answer and this might cause them to reject the products offered. So, it is strongly suggested that the number of questions asked is as few as possible in order to get the relevant information to match with the existing range of products. Interactive forms of communications channels like the internet and telephone are popular. These tools were used to connect with the customers dynamically (Gooley and Latin, 1998), which means that the current decision was guided by the previous decision. Such an interactive tool can be used to lighten daily paper works.

After selecting the questions, the applicant is given an offer. Offer that maximises profit and acceptance probability is preferable. However, the problems faced in selecting questions and subsequently grant credit or not are:

1. Which questions to ask to get information on customer preference to estimate acceptance probability?

2. What method should be used in selecting questions?
3. How to determine whether the applicant is profitable?
4. Which product to offer them next if they are profitable to the bank?

## 1.3 Motivation of the Work

The motivation to conduct this research is guided by the work of Seow and Thomas (2006). Their research was on credit scoring for estimating take-up probability where they applied a dynamic programming with Bayesian updating to estimate take-up probability for two or many variants of products. In this work, we are interested in using dynamic programming to ensure acceptance rate by predicting profit for three and four variants of products. Based on another paper of Seow and Thomas (2007), this study intends to work on a modified CART namely the Top Application characteristics Remainder Offer characteristics Tree (TAROT). TAROT is used to identify which questions to ask the customers so that the likehood to accept the product is high. Hence, a desire occurred which is to help banks increase their profit by using cross TAROT tree for cross-selling.

## 1.4 Objectives of the Research

The main objective of the research is to estimate take-up probability in order to obtain a high acceptance rate probabilities for many different variants of credit card products. The specific objectives of the research are as the following:

1. to propose a modified TAROT called cross TAROT to classify which questions from the dataset to be asked for the purpose of cross-selling.
2. to proposed a dynamic programming model with Bayesian updating to include the probabilities of acceptance of the previous customers in order to match a product to the suitable customers for three and four variants of a product.

## 1.5 Scope and Limitations

This thesis will focus on both the cross TAROT and the dynamic programming model. The cross TAROT is based on decision trees of the CART. The method for building decision trees, that is, SAS *Enterprise Miner 7.1*, will be implemented in this thesis. Four decision trees will be built based on a combination of one question and one offer, a combination of two questions and one offer, combination of one question and two offers and combination of two questions and one offer. Starting from the root node, a decision tree will perform several manual splitting until the final leaf node is achieved. The final leaf gives an offer to extend to customers based on the question asked in the upper part of the trees. The second approach is a dynamic programming with Bayesian updating which is used to determine which offer to be made based on the predicted profit. The significance of Bayesian updating in this approach is it includes the previous responses in the decision process to ensure a better estimation of the take-up probability distribution. The dynamic programming in this thesis is conducted by using C language.

Dynamic programming can be applied to any problem that observes the *principle of optimality*. This means that partial solutions can be optimally extended with regard to the state after the partial solution instead of the partial solution itself. Future decisions will be made based on the consequences of previous decisions, not the actual decisions themselves. The biggest limitation on using dynamic programming is the number of partial solutions. The partial solutions can be completely described by specifying the stopping places in the input. This is because the combinatorial objects being worked on (array, strings and numerical sequences) all have an implicit order defined upon their elements. This order cannot be scrambled without completely changing the problem. Once the order is fixed, there are relatively few possible stopping places or states, so efficient algorithms will be obtained. If the objects are not firmly ordered, however, we have an exponential number of possible partial solutions and are doomed to need an infeasible amount of memory. Hence, the limitation of this research is the array in C has its own limitations. For example, in six dimensional array, the maximum value can be stored in the array is 25 for each dimension. It is not big enough to store such a big amount of data. As a result, there is a need to modify the program into parallel processing such as parallel programming or Structured Query Language (SQL) in order to solve the problem. However, the modified program does not solve the problem entirely due to the limitation of the dynamic programming. The calculation in this study will stop at the maximum figure that can be afforded by the memory of the computer.

## 1.6 Summary of the Thesis

Given the objectives and scope of the study as highlighted in this chapter, the following four chapters present the research with the conclusion in the last chapter. Chapter 2 present the literature review of work related to this study. The basic areas reviewed cover credit scoring techniques and acceptance scoring with sub-sections profit scoring and cross-selling. Chapter 3 describes the development of the acceptance model by using dynamic programming with Bayesian updating to include the previous response for learning purpose. The results have been presented and discussed in this chapter. Chapter 4 presents the basic theory of CART and the process on how CART has been modified to TAROT by using the Fantasy Student Account data. The interpretation of the results are discussed in this chapter as well. Chapter 5 presents the process of building the modified TAROT namely cross TAROT to deal with the issue of cross-selling. The results are discussed.

## REFERENCES


Abdou, H. A. and Pointon, J. 2011. Credit Scoring, Statistical Techniques and Evaluation Criteria: A Review of the Literature. *Intelligent Systems in Accounting Finance & Management*. 18: 59 – 88.

Abrahams, C. R. and Zhang, M. 2009. Fair Lending Compliance: Intelligence and Implications for Credit Risk Management. Hoboken, New Jersey: John Wiley & Sons, Inc.

Ahn, H., Ahn, J. J., Oh, K. J., and Kim, D. H. 2011. Facilitating cross-selling in a mobile telecom market to develop customer classification model based on hybrid data mining techniques. *Expert Systems with Applications.* 38: 5005 – 5012.

Andreeva, G., Ansell, J. and Crook, J. 2007. Modelling Profitability using Survival Combination Scores. *European Journal of Operational Research.* 183: 1537 – 1549.

Baesens, B., Gestel, T.V., Viaene, S., Stepanova, M., Suykens, J. and Vanthienen, J. 2003. Benchmarking State-of-the-Art Classification Algorithms for Credit Scoring. *Journal of the Operational Research Society.* 54: 627 – 635.

Banasik, J., Crook, J.N. and Thomas, L.C. 1999. Not if but when will Borrowers Default. *Journal of the Operational Research Society.* 50: 1185 – 1190.

Bellman, R. 1957. Dynamic Programming. Princeton, NJ: Princeton University Press.

Bierman, H. JR. and Hausman, W. H. 1970. The credit granting decision. *Manegement Science.* 16: B519 – B532.

Bijak, K, and Thomas, L. C. 2012. Does segmentation always improve model performance in credit scoring?. *Expert System with Applications*. 39: 2433 – 2442.

Breiman, L., Friedman, J., Olshen, R. and Stone, C. 1984. Classification and Regression Trees. Wadsworth, California: Wadsworth International Group.

Burrows, W. R., Benjamin, M., Beauchamp, S., Lord, E. R., Mccollor, D., and Thomson, B. 1995. CART Decision-Tree Statistical Analysis and Prediction of Summer Season Maximum Surface Ozone for the Vancouver, Montreal, and Atlantic Regions of Canada. *Journal of Applied Meteorology*. 34: 1848 – 1862.

Cai, W., Lin, X., Huang, X., and Zhong, H. 2009. A genetic algorithm model for personal credit scoring. In: *Proceedings of the International Conference on Computational Intelligence and Software Engineering*. 1 - 4.

Cyert, R.M., Davidson, H.J. and Thompson, G.L. 1962. Estimation of the Allowance for Doubtful Accounts by Markov Chains. *Manegement Science.* 8: 287 –303.

Davis, R. H., Edelman, D. B. and Gammerman, A. J. 1992. Machine-learning algorithms for credit card applications. *IMA Journal of Mathematics Applied in Business & Industry.* 4: 43 –51.

Durand, D. 1941. Risk Elements in Consumer Instalment Financing, Studies in Consumer Instalment Financing. New York: National Bureau of Economic Resesarch.

Finlay, S. 2008. Towards Profitability: A Utility Approach to the Credit Scoring Problem. *The Journal of Operational Research Society*. 59: 921 – 931.

Finlay, S. 2010. Credit scoring for profitability objectives. *European Journal of Operational Research.* 202: 528 –537.

Fisher, R.A. 1936. The Use of Multiple Measurements in Taxonomic Problems. Annals of Eugenics 7 (2): 179 –188.

Freixas, X. and Rochet, J-C. 1997. Microeconomics of Banking, Cambridge, MA: The MIT Press.

Genc, T. S., Reynolds, S. S., and Sen, S. 2007. Dynamic Oligopolistic Games under Uncertainty: A Stochastic Programming Apporoach. *Journal of Economic Dynamics and Control.* 31: 55 – 80.

Gittins, J. C. 1979. Bandit Processes and Dynamic Allocation Indices. *Journal of the Royal Statistical Society*. 41: 148 – 177.

Gooley, C.G. and Lattin, J.M., 1998. Dynamic Customization of Marketing Messages in Interactive Media. *Working Paper, Standford University*.

Grodzicki, D. 2013. The Evolution of Competition in the Credit Card Market. *mimeo*.

Hand, D.J. and Henley, W.E. 1997. Statistical Classification Methods in Consumer Credit Scoring: A Review. *Journal of the Royal Statistical Society. Series A (Statistics in Society).* 160: 523-541.

Harper, P.R. and Winslett, D.J. 2006. Classification trees: A possible method for maternity risk grouping. *European Journal of Operational Research.* 169: 146 – 156.

Harper, P.R., Sayyad, M.G., Senna, V.de., Shahani, A.K., Yajnik, C.S., and Shelgikar, K.M., 2003. A systems modelling approach for the prevention and treatment of diabetic retinopathy. *European Journal of Operational Research.* 150: 81 – 91.

Harris, T. 2013. Quantitative Credit Risk Assessment using Support Vector Machines: Board versus Narrow Default Definitions. *Expert Systems with Applications.* 40: 4404 – 4413.

Haughton, D. and Oulabi, S. 1997. Direct Marketing Modeling with CART and CHAID. *Journal of Direct Marketing.* 11: 42 – 52.

Heilman, C. M., Kaefer, F. and Ramenofsky, S. D. 2003. Determining the appropriate amount of data for classifying consumers for direct marketing purposes. *Journal of Interactive Marketing.* 17(3): 5 – 28.

Joseph, C. 2006. Credit Risk Analysis. New Delhi: Tata McGraw-Hill.

Kaishev, V. K. , Nielsen, J. P. and Thuring, F. 2013. Optimal customer selection for cross-selling of financial services products. *Expert Systems with Applications.* 40: 1748 – 1757.

Kamakura, W. A., Ramaswami , S. and Srivastava, R. 1991. Applying latent trait analysis in the evaluation of prospects for cross-selling of financial services. *International Journal of Research in Marketing*. 8: 329 – 349.

Keeney, R. L. and Oliver, R. M. 2005. Designing Win-Win Financial Loan Products for Consumers and Business. *The Journal of the Operational Research Society*. 56(9): 1030 – 1040.

Knott, A., Hayes, A. and Neslin, S. A. 2002. Next-Product-To-Buy Models for Cross-selling Applications. *Journal of Interactive Marketing*. 16: 59 – 75.

Larivière, B. and Van den Poel, D. 2004. Investigating the role of product features in preventing customer churn, by using survival analysis and choice modeling: The case of financial services. *Expert Systems with Applications*. 27(2): 277 – 285.

Lewis, E. M. 1992. An Introduction to Credit Scoring. California: Fair, Isaac & Co., Inc.

Li, H.G. and Hand, D.J. 2002. Direct versus Indirect Credit Scoring Classifications. *The Journal of the Operational Research Society.* 53: 647 – 654.

Li, S., Sun, B. and Wilcox, R. T. 2005. Cross-Selling Sequentially Ordered Products: An Application to Consumer Banking Services. *Journal of Marketing Research.* 42(2): 233 – 239.

Liebman, L. H., 1972. A Markov decision model for selecting credit control policies. *Management Science.* 18: B519 – B525.

Ma, P., Crook, J. and Ansell, J. 2010. Modelling Take-Up and Profitability. *Journal of the Operational Research Society.* 61: 430 – 442.

Marqués, A. I., Garcia, V. and Sánchez, J. S. 2013. A literature review on the application of evolutionary computing to credit scoring. *Journal of the Operational Research Society.* 64: 1384 – 1399.

Maskin, E. and J. Tirole. 2001. Markov Perfect Equilibrium: I. Observable Actions. *Journal of Economic Theory*. 100: 191 – 219.

Montgomery, A. L. 2001. Applying Quantitative Marketing Techniques to the Internet. *Interfaces 31*. 2: 90 – 108.

Myers, J. H. and Forgy, E. W. 1963. The Development of Numerical Credit Evaluation Systems. *Journal of the American Statistical Association*. 58: 799 – 806.

Narain, B. 1992. Survival analysis and the credit granting decision. *Credit Scoring and Credit Control.* (L.C. Thomas, J.N. Crook and D.B. Edelman, eds). Oxford University Press. 109 – 122.

Netzer, O., Lattin, J. M. and Srinivasan, V. 2008. A Hidden Markov Model of Customer Relationship Dynamics. *Marketing Science*. 27(2): 185 – 204.

Ohlson, J. A. 1980. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research.* 18: 109 – 131.

Orgler, Y. E. 1970. A credit scoring model for commercial loans. *Journal of Money, Credit and Banking II.* 4: 435 – 445.

Pakes, A. and McGuire, P. 1994. Computing Markov-Perfect Nash Equilibria: Numerical Implications of a Dynamic Differentiated Product Model. *RAND Journal of Economics*. 25: 555 – 589.

Puterman, M. L. 1994. Markov Decision Process: Discrete Stochastic Dynamic Programming, United States of America: John Wiley & Sons, Inc.

Raghu, T. S., Kannan, P. K., Rao, H. R., and Whinston, A. B. 2001. Dynamic profiling of consumers for customized offerings over the internet: a model and analysis. *Decision Support Systems*. 32: 117 – 134.

Raiffa, H. and Schlaifer, R. 1961. Applied Statistical Decision Theory. Colonial Press, Mass.

Rosenberg, E., and Gleit, A. 1994. Quantitative Methods in Credit Management: A Survey. *Operations Research*. 42: 589 – 613.

Rossi, P. E., McCulloch, R. E. and Allenby, G. M. 1996. The value of purchase history data in target marketing. *Marketing Science.* 15(4): 321 – 340.

Sadatrasoul, S. M., Gholamian, M. R., Siami, M. and Hajimohammadi, Z. 2013. Credit scoring in banks and financial institutions via data mining techniques: A literature review. *Journal of AI and Data Mining*. 1: 119 – 129.

Sara, V. and Ali, Y. 2008. Cross-selling: The power of embodied interactions. *Journal of Retailing and Consumer Services*. 15: 480 – 490.

Seow Hsin-Vonn. PhD Thesis. Using Adaptive Learning in Credit Scoring to Estimate Acceptance Probability Distribution. University of Southampton, 2006.

Seow, H.-V. 2010. Question selection responding to information on customers from heterogeneous populations to select offers that maximize expected profit. *Journal of Operational Research Society.* 61: 443 – 454.

Seow, H.-V. and Thomas, L.C. 2006. Using adaptive learning in credit scoring to estimate take-up probability distribution. *European Journal of Operational Research.* 173: 880 – 892.

Seow, H.-V. and Thomas, L.C. 2007. To ask or not to ask, that is the question. *European Journal of Operational Research.* 183(3): 1513 – 1520.

Smith, D. K. 2007. Dynamic Programming and Board Games: A Survey. *European Journal of Operational Research.* 176: 1299 – 1318.

So, M. M. C. and Thomas, L.C. 2011. Modelling the Profitability of Credit Cards by Markov Decision Processes. *European Journal of Operational Research.* 212: 123 – 130.

Stepanova, M. and Thomas, L.C. 1999. Survival Analysis Methods for Personal Loan Data. *Operational Research.* 50: 277 – 289.

Stepanova, M. and Thomas, L.C. 2001. PHAB scores: proportional hazards analysis behavioural scores. *Journal of the Operational Research Society.* 52: 1007 – 1016.

Stepanova, M. and Thomas, L.C. 2002. Survival Analysis Methods for Personal Loan Data. *Operational Research.* 50: 277 – 289.

The UK Cards Association Card Expenditure Statistics. January 2014 (http://www.theukcardsassociation.org.uk/2012factsfigures/internet_card_use_2012.asp). Retrieved 21 April 2014

The UK Cards Association Card Expenditure Statistics. January 2014 (http://www.theukcardsassociation.org.uk/wm_documents/January%202014%281%29.pdf). Retrieved 21 April 2014

Thomas, L. C., Edelman, D. B. and Crook, J. N. 2004. Readings in Credit Scoring: recent developments, advances, and aims. New York: Oxford University Press.

Thomas, L. C., Edelman, D. B., and Crook, J. N. 2002. Credit Scoring and its applications. Philadelphia: SIAM

Thomas, L. C., Ho, J. and Scherer, W. T. 2001. Time will Tell: Behavioural Scoring and the Dynamics of Consumer Credit Assessment. *IMA Journal of Management Mathematics*. 12: 89 – 103.

Thomas, L.C. 1994. Applications and solution algorithms for dynamic programming. *Bulletin of the IMA.* 30: 116 – 122.

Thomas, L.C. 2000. A survey of credit and behavioural scoring: Forecasting financial risk of lending to customers. *International Journal of Forecasting.* 16: 149 – 172.

Thomas, L.C., Jung, K. M., Thomas, S. D. and Wu, Y. 2006. Modeling consumer acceptance probabilities. *Expert Systems with Applications.* 30: 499 – 506.

Thomas, L.C., Oliver, R. W., and Hand, D. J. 2005. A survey of the issues in consumer credit modeling research. *Journal of the Operational Research Society*. 56: 1006 – 1015.

Thuring, F., Nielsen, J. P., Guillén, M. and Bolancé, C. 2012. Selecting Prospects for Cross-Selling Financial Products using Multivariate Credibility. *Expert Systems with Applications.* 39: 8809 – 8816.

Värlander, S. and Yakhlef, A. 2008. Cross-selling: The power of embodied interactions. *Journal of Retailing and Consumer Services*. 15: 480 – 490.

Wong, W. K., Leung, S.Y.S., Guo, Z. X., Zeng, X. H. and Mok, P. Y. 2012. Intelligent Product Cross-selling System with Radio Frequency Identification Technology for Retailling. *Int. J. Production Economics*. 135: 308 – 319.

Yang, X.-C., Wu, J., Zhang, X.-H. and Lu, T.-J. 2008. Using decision tree and association rules to predict cross selling opportunities. in *Machine Learning and Cybernetics*, *Kunming*, Proceedings of the Seventh International Conference, 12 – 15.

Yeh, H.C., Yang, M.L. and Lee, L.C. 2007. An Empirical Study of Credit Scoring Model for Credit Card. *International Conference on Innovative Computing, Information and Control City*. 216.