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HYBRID HARMONY SEARCH-ARTIFICIAL INTELLIGENCE MODELS IN CREDIT SCORING

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By

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

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DEDICATIONS

This work is dedicated to my parents.

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

HYBRID HARMONY SEARCH-ARTIFICIAL INTELLIGENCE MODELS IN CREDIT SCORING

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September 2019

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Credit is a type of advanced lending which poses the risk of having default payments. Thus, credit scoring is important to correctly identify defaulters and non-defaulters. Statistical models are the main approaches but recently, Artificial Intelligence (AI) techniques have been popular due to their ability to account for flexible data patterns. Support Vector Machines (SVM) and Random Forest (RF) are the main focus in this study due to their competitiveness in the literature.

This study focuses to improve three main drawbacks of both AI techniques i.e. sensitivity to hyperparameters, the black-box property and increased computational effort due to hyperparameters tuning procedure. Employment of hyperparameters tuning have been a common practice for both SVM and RF in ensuring quality performance. Instead of the conventional Grid Search (GS) and manual tuning (MT) approaches, automated tuning with metaheuristics approach (MA) have also shown to be effective in this task. Genetic Algorithm (GA) has been the dominant method and other MA being attempted recently has shown the potential of MA to perform hyperparameters tuning. To the best of our knowledge, Harmony Search (HS) has yet to be utilized with SVM and RF in this domain.

To utilize the SVM credit model, features selection is conducted simultaneously with hyperparameters tuning using a HS so that the attributes can be focused down to the reduced features for explanation. For the RF credit model, a HS is hybridized with RF for hyperparameters tuning. Then, the two types of features importance computed from RF algorithm are utilized for the attributes explanation. Due to the increased computational effort from HS-SVM and HS-RF, a modified HS

(MHS) hybridized with SVM and RF are proposed in this study for an effective yet efficient search. There are four main modifications of the MHS hybrid models i.e. elitism selection instead of random selection, dynamic exploration and exploitation operators following step functions instead of a static value, replacement of the bandwidth with coefficient of variations and two additional termination criteria included. To further enhance the computational efficiency, the MHS hybrid models are parallelized.

The four hybrid models are evaluated by comparing with standard statistical models across three datasets i.e. German and Australian credit datasets from the public repository as well as a peer-to-peer (P2P) lending data from Lending Club (LC) website to account for different credit data patterns. The discussions are based on discriminating ability, model explainability and computational time.

All the hybrid models have achieved higher discriminating ability than GS-tuned models. RF hybrid models consistently show better discriminating ability compared to other methods across the three datasets. Compared to SVM hybrids, RF hybrids achieved approximately 1% improvement in German and Australian data, and around 4% improvement in LC dataset. This study also demonstrates model explainability using reduced features for MHS-SVM and features importance for MHS-RF. It is shown that these strategies are useful to obtain initial information on the attributes. For both German and Australian datasets, reduced features and features importance have directed almost the same features as 'important'. For LC dataset, end results shows only one attribute in common for both strategies. This is believed to be due to the different approaches of both classifiers in capturing data pattern for classification. In terms of computational time, compared to GS-tuned models and the respective HS hybrids, the proposed hybrid MHS-SVM and MHS-RF have reported time improvement of more than 50%, while the parallel computation have saved up approximately 80% of the computational time.

In addition, hybrid models with MHS have reduced the computational effort yet maintaining the good discriminating ability. With the parallelization of MHS hybrid models, the computational time is effectively reduced, with RF hybrid models faster than SVM hybrid models. Although statistical models are efficient as no hyperparameters tuning procedure is involved, their inferior performance compared to the AI models in this study indicates the failure to capture information from the LC dataset. In terms of model performance, explainability and computational effort, MHS-RF is the recommended credit scoring model due to its robustness in the three aspects.

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

MODEL HIBRID CARIAN HARMONI-KECERDASAN BUATAN UNTUK SKOR KREDIT

Oleh

GOH RUI YING

September 2019

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Kredit merupakan sejenis peminjaman dahulu yang membawa risiko tidak mendapat pembayaran balik daripada peminjam. Oleh itu, model skor kredit penting untuk mengenal pasti peminjam yang membayar balik dan tidak membayar balik. Model statistik adalah cara utama yang digunakan, namun sejak kebelakangan ini, kaedah kecerdasan buatan menjadi popular disebabkan oleh kebolehan kaedah-kaedah ini untuk mengendalikan corak data yang bervariasi. Support Vector Machines (SVM) dan Random Forest (RF) ialah fokus utama tesis ini disebabkan oleh daya saing kedua-dua kaedah ini dalam penyelidakan lepas.

Tesis ini fokus untuk memperbaiki tiga kelemahan dua kaedah kecerdasan buatan ini, iaitu sensitif terhadap hyperparameter, model tersirat dan peningkatan masa komputasi dari prosedur pelarasan hyperparameter. Perlaksanaan pelarasan hyperparameter ialah amalan biasa untuk SVM dan RF untuk memastikan prestasi yang berkualiti. Selain daripada kaedah konvensional pencarian grid (PG) dan pelarasan manual (PM), pelarasan automatik dengan metaheuristik juga merupakan cara yang efektif untuk kerja pelarasan. Algoritma Gentik (AG) ialah cara dominan dan metaheuristik lain dalam eksperimen lalu telah menunjukkan potensi metaheuristik untuk kerja pelarasan hyperparameter. Setakat pengetahuan kita, Carian Harmoni (CH) belum pernah digunakan dengan SVM dan RF dalam domain ini.

Untuk menjelaskan model kredit SVM, proses pemilihan ciri-ciri dijalankan bersama dengan pelarasan hyperparameter dengan CH supaya ciri-ciri dapat dikurangkan dan difokuskan untuk penjelasan model. Bagi model kredit RF, CH dihibridkan dengan RF untuk pelarasan hyperparameter. Kemudian, dua jenis kepentingan ciri-ciri

yang dikira dari algoritma RF digunakan untuk penjelasan model. Disebabkan oleh peningkatan masa komputasi, kaedah modifikasi CH (MCH) dihibridkan dengan SVM dan RF untuk pencarian solusi secara efektif dan efisien. Empat modifikasi telah dilaksanakan bagi model hibrid MCH, iaitu pemilihan elit untuk menggantikan pemilihan rawak, alat eksplorasi dan eksploitasi dinamik untuk menggantikan nilai statik, penggantian nilai jalur lebar dengan koefisien variasi serta tambahan dua kriteria penamatan. Bagi memajukan efisiensi, model hibrid MCH diselarikan.

Empat model hibrid dinilai melalui perbandingan dengan model statistik menggunakan tiga data iaitu, kredit German dan Australia dari repositori awam, dan peminjaman 'peer-to-peer' (P2P) dari laman web Lending Club (LC) untuk merangkumi corak kredit data yang bervariasi. Perbincangan hasil adalah berdasarkan prestasi model, penjelasan model, dan masa komputasi model.

Semua model hibrid mencapai prestasi yang lebih baik daripada model yang dilaraskan dengan PG. Model hibrid RF menunjukkan prestasi yang lebih baik daripada kaedah lain dengan konsisten dalam ketiga-tiga data kredit. Perbandingan antara model hibrid SVM dan model hibrid RF menunjukkan model hibrid RF telah menambah baik anggaran 1% bagi data German dan Australian, dan lebih kurang 4% lebih baik bagi data LC. Tesis ini turut menunjukkan penjelasan model dengan ciri-ciri yang dipilih daripada MCH-SVM dan kepentingan ciri-ciri daripada MCH-RF. Hasil daripada kedua-dua strategi ini telah menunjukkan kepentingan strategi ini untuk memperoleh informasi awal daripada ciri-ciri data tersebut. Bagi data German and Australian, ciri-ciri yang dikurangkan dan kepentingan ciri-ciri telah melabelkan kebanyakan ciri yang sama sebagai ciri yang 'penting'. Bagi data LC, hasil eksperimen menunjukkan hanya satu ciri yang sama daripada kedua-dua strategi. Hal ini kerana pendekatan yang berbeza bagi kedua-dua model ini untuk mengendalikan corak data dalam proses klasifikasi. Bagi aspek masa komputasi, perbandingan antara model hibrid MCH dengan model yang dilaraskan dengan PG dan model hibrid CH telah menunjukkan model MCH-SVM dan MCH-RF menambah baik masa komputasi sebanyak 50% manakala model selari telah menjimatkan masa komputasi sebanyak 80%.

Tambahan pula, model hibrid dengan MCH telah mengurangkan masa komputasi dan mengekalkan prestasi model. Dengan komputasi selari model hibrid MCH, masa komputasi dikurangkan dengan efektif, di mana model hibrid RF lebih cekap daripada model hibrid SVM. Walaupun model statistik adalah efisien disebabkan tiada hyperparameter untuk dilaraskan, kelemahan prestasi model statistik dibandingkan dengan model kecerdasan buatan menunjukkan kekurangan upaya model statistik untuk mengendalikan informasi dalam data LC. Dengan pertimbangan serentak aspek prestasi model, penjelasan model, dan masa komputasi, model MCH-RF merupakan model skor kredit yang berpotensi hasil daripada keteguhan model ini dalam ketiga-tiga aspek tersebut.

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I certify that a Thesis Examination Committee has met on 20 September 2019 to conduct the final examination of Goh Rui Ying on her thesis entitled “Hybrid Harmony Search-Artificial Intelligence Models in Credit Scoring” 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:

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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:

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Date:

Declaration by graduate student

I hereby confirm that:

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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.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
SVM	Support Vector Machines
RF	Random Forest
GS	Grid Search
MA	Metaheuristic Algorithm
HS	Harmony Search
MHS	Modified Harmony Search
LOGIT	Logistic Regression
P2P	Peer-to-peer
AUC	Area Under Receiver Operating Characteristics
ACC	accuracy
HPC	High Performance Computing
STEP	Backward Stepwise Logistic Regression
LDA	Linear Discriminant Analysis
mDA	mean decrease accuracy
mGI	mean decrease in gini impurity
AF	average frequency
AR	average rank

CHAPTER 1

INTRODUCTION

1.1 Background

"Quick to borrow is always slow to pay". In the context of credit industry, this proverb addresses defaulters that lenders always want to avoid. Credit is a type of lending to the borrowers where repayment is made in the future together with interest charged to the lenders. Since the repayment obligation is not immediate, there may be defaulting borrowers that fail to fulfil their obligations, incurring loss to financial institutions. For revolving credit services, there may be revolvers that carry balances and pay interests, posing as another group of potential customers.

As revolving credit services are a part of the overall credit services, hence, defaulters and non-defaulters are who the lenders always seek for because they account for losses to financial institutions. Being able to identify these two groups of customers is a risk management task to maximize profit and minimize cost. Thus, credit scoring stands out as a crucial tool to correctly classify customers for effective credit risk evaluation.

Before credit scoring models are developed, all credit granting decisions are purely judgemental-based. The main aspects considered by decision makers are Character, Capital, Collateral, Capacity and Condition (5Cs). The initial urge of the credit scoring model was due to the severe shortage of credit analysts that were being drafted into military services (Thomas, 2000). When credit cards started to be introduced in 1960s, the volume of applications made is necessary for credit scoring models to be developed, where a more efficient way to identify good and bad customers is considered. Thus, statistical techniques started to be introduced to form credit scoring models.

The first statistical model used to classify good and bad loans is discriminant analysis (DA) by Durand (1941). Then, another variant of DA, multiple discriminant analysis is used to predict company bankruptcy by Altman (1968). Logistic Regression is another statistical approach introduced by Ohlson (1980) to predict companies credit-worthiness. Besides, the operations research (OR) based methods are also attempted for credit scoring by Kolesar and Showers (1985) where mathematical programming is applied in credit granting decisions.

In order to avoid bank failures during financial crisis, Basel I accord was released on 1988 as a formal guideline for financial institutions to standardize the capital adequacy of banks to be at least 8% of the banks' risks weighted assets. Due to the expanding credit industry, Basel II accord was released in 2004 and serves as a banking regulatory to ensure financial institutions have sufficient capital requirement to deal with their exposed risk. Under credit risk, rather than the previous standardized method, Internal Rating Based (IRB) approach could be adopted by bank to compute the minimum capital requirement. Then, the economic recession in 2008 was a wake-up call for financial institutions to realize the importance of credit risk evaluation. The IRB approach allowed by Basel II together with the 2008 economic downturn have opened up a new page in the credit scoring domain as financial institutions were now able to develop and utilize internal credit models. Attempts to form sophisticated credit scoring models have been actively researched by both financial institutions as well as academic researches.

Since the final decision of credit scoring models is binary, it is equivalent to binary classification problem. Therefore, apart from statistics-based and OR-based models, different classification techniques especially Artificial Intelligence (AI) have been actively researched in credit scoring. Several comparative studies and review papers (Hand and Henley, 1997; Thomas, 2000; Baesens et al., 2003; Crook et al., 2007; Lahsasna et al., 2010; Lessmann et al., 2015; Louzada et al., 2016) have shown the shifting trend of credit models from traditional methods to AI-based methods, and currently moving towards more complex ensembles or hybrid models. As computer storage increases, financial institutions are starting to collect more and more attributes of their customers. In order to take into account for more information, the dataset available may no longer meet the required assumptions of statistical models. This is the main motivation of utilizing non-parametric AI techniques in modelling credit datasets, as they can effectively make prediction based on the different kinds of data pattern regardless of satisfying assumptions in parametric statistical models.

In the credit industry, FICO score (provided by Fair, Isaac and Company) and VantageScore (provided by Experian, TransUnion and Equifax) are the main service providers to financial institutions for credit scores. FICO and VantageScore models customers information and express their credit-worthiness in a three-digit score, where higher values indicate higher credit-worthiness and vice versa. Financial institutions purchase credit score from these service providers as a guideline for credit granting decisions. Alongside with credit scores from service providers, some financial institutions developed own internal credit scoring model tailored to their own customers database to obtain better classification. Aligned with the modelling trend captured in academic literature, FICO score, VantageScore as well as internal credit models by financial institutions have also actively involved AI techniques as a new reliable alternative.

Credit services provided by financial institutions are mainly credit cards and various types of loans. A wide coverage including retail, housing, mortgage, business, etc which are part of people's daily life, credit industry is a surging industry with expanding customer base. As online services are leading the trend in lending recently, a new type of online lending business, peer-to-peer lending has been initiated.

Increment of customers database storage and the buoyant economic situations that affect people's financial abilities urge financial institutions to self-develop internal credit scoring models that are flexible to account for various customers credit trend for different types of credit services. Hence, the types of data collected and used for credit scoring had grown beyond the common variables used in statistics-based modelling and thus assumptions needed for the modelling will not hold. Therefore, development of new credit scoring models is perceived as an essential continuous research trend.

Credit models in the literature have followed an evolving trend. It starts from purely judgemental-based, moving on to statistical modelling and shifting to the current leading AI modelling. With the flexibility of non-parametric AI models that can account for different types of data patterns, AI techniques are the focus of this study. To narrow down to the main AI techniques in this study, two remarkable comprehensive studies by Baesens et al. (2003) and Lessmann et al. (2015) on various techniques utilized in this domain are referred. Hence, Support Vector Machines (SVM) and Random Forest (RF) are the main AI-based classifiers in this research study. SVM is first attempted in building credit models by Baesens et al. (2003) and became recommendable due to its competitiveness against the other statistics-based, OR-based and AI techniques in the experiment. Thereafter, SVM has received continuous attention with competitive results in the literature. On the other hand, RF is an ensemble model which is a recent approach in this domain. As an update of Baesens et al. (2003) research, Lessmann et al. (2015) have recommended usage of RF due to the competitive results.

1.2 Definition of Credit Scoring

According to Abdou and Pointon (2011), the credit industry has been around for a long time but the credit scoring history is shorter as it has just gained its popularity around the late 20th century. Therefore, proper definitions of credit scoring are only available thereafter.

Several proper definitions of credit scoring are from (Hand and Henley, 1997; Thomas, 2000; Anderson, 2007). Hand and Henley (1997) defined credit scoring as "the term used to describe formal statistical methods used for classifying applicants for credit into 'good' and 'bad' risk classes". Thomas (2000) explained credit scoring as the technique that helps organizations decide whether or not to grant credit to consumers who apply them. To describe credit scoring, Anderson (2007) divided the term into *credit* and *scoring*. The first term 'credit' originates from the Latin word 'credo', carrying the meaning of I trust or I believe. The second term 'scoring' indicates usage of numerical tool to rank order cases to discriminate between good and bad qualities. Joining both terms, Anderson (2007) defined credit scoring as "the use of statistical models to transform relevant data into numerical measures that guide credit decisions".

Abdou and Pointon (2011) viewed credit scoring as an important kit to classify customers for credit evaluation to reduce the risk of bad credit customers. Baesens et al. (2003) and Lessmann et al. (2015) also provided their views on credit scoring in their comprehensive review. Baesens et al. (2003) stated that developing models to distinguish good applicants from bad is the main aim of credit scoring while Lessmann et al. (2015) described credit score as "a model-based estimate of the probability that borrower will show some undesirable behaviour in the future".

In view of the various perspectives from researchers to the term *credit scoring*, it can be summarized that credit scoring is a risk evaluation model that effectively classify customers into defaulters and non-defaulters to identify potential profit and loss. Since risk management is a crucial routine for financial institutions, credit scoring is thus regarded as the main tool to carry out this task.

1.3 Problem Statement

AI techniques to model for credit domain has been promising with competitive or even outstanding results compared with the others statistical models (Baesens et al., 2003; Crook et al., 2007; Boughaci and Alkhawaldeh, 2009; Louzada et al., 2016). The main focus in this study, SVM and RF have also shown their great potential among AI techniques. However, as compared to the standard statistical models, both SVM and RF pose two main drawbacks i.e. sensitive to hyperparameters settings and black-box property.

Standard statistical models quantify customers attributes by parameters estimation during the model training process to do classification. In contrast, AI models have hyperparameters to be pre-determined before the model training process to effectively capture the data pattern to do the classification. Inappropriate hyperparameters setting will result in failure of the AI models to perform well. Therefore, careful hyperparameters tuning have to be conducted. For SVM, the exhaustive Grid Search (GS) along a recommended range (Hsu et al., 2003) has always been the common approach. Apart from GS, metaheuristics approach (MA) to tune hyperparameters have been a recent trend. Genetic Algorithm (GA) has been the most popular to be hybridized with SVM for hyperparameters tuning (Huang et al., 2007; Zhou et al., 2009a,b; Yu et al., 2011), followed by few attempts using Particle Swarm Optimization (PSO) (Danenas et al., 2011; Danenas and Garsva, 2012; Garsva and Danenas, 2014) and Artificial Bee Colony (ABC) (Chen et al., 2013; Hsu et al., 2018). For RF, manual tuning through repeated experiments of trial-and-error have been the usual method used by past researchers. Being a relatively new AI method that has just recently been considered in credit scoring, there is only one attempt from He et al. (2018) utilizing PSO to tune the hyperparameters.

Identification of important customers attributes is a plus point for a good credit scoring model. Statistical models can identify statistical significance of the attributes but both SVM and RF have complex model building procedure that leads to the black-box property which is unable to provide information on attributes of customers. For SVM, there have been hybrid MA-SVM models to do features selection. Features selection task does not aim to solve the black box model, but it is able to provide an easier explanation with a reduced subset. To perform features selection, wrapper model with GA is a well-known approach (Jadhav et al., 2018; Wang et al., 2018) with some conducting simultaneous hyperparameters tuning and features selection with GA (Huang et al., 2007; Zhou et al., 2009a). For RF, it poses a great advantage on the second drawback as it computes the features importance of every attribute. The features importance is a useful measure to provide insights to end users on the customers attributes. Hence, RF can utilize these features importance to explain the features. Research on developing hybrid MA-SVM and MA-RF in the literature are indications of the potential ability of MA to improve these AI models. MA is perceived as a suitable tool to be hybridized with SVM and RF to improve the models' performance. From the literature, GA is the most commonly used method. To the best of our knowledge, Harmony Search (HS) which is also a type of MA has yet to be hybridized with SVM and RF.

In consideration of the two drawbacks of the AI models, there are two additional issues to be addressed to form a good credit scoring model i.e. low computational effort and robust across different types of datasets. Utilizing the MA approach to seek for quality solutions as the input of AI models may be time consuming because the search space has to be fully explored. The search process using MA has to be properly developed for efficient modelling. In addition, hybridizing the AI models with MA eventually form an automated credit model where the input of AI models is the MA solutions from the automated search process. Thus, the model development has to ensure the MA solutions from the automated search process will allow the AI models to be robust in handling different patterns of datasets.

1.4 Research Motivation

With the tremendous growth of credit industry and the need for a risk evaluation tool, credit scoring models become important. The main motivation of this study is to improve AI techniques with MA. There are several motivations for the conduct of this research study focusing on hybrid MA-AI models:

i. The growth of credit industry together with computer storages have altogether results in wider variety of datasets pattern. AI techniques are the current state-of-the-art and proven to be potential classifiers for credit modelling due to their flexibility in capturing data patterns.

ii. There are two benchmark studies by Baesens et al. (2003) and Lessmann et al. (2015) in this domain. Although no obvious winners are reported from their experiments, SVM (Baesens et al., 2003) and RF (Lessmann et al., 2015) are the recommended potential AI techniques for credit scoring. Thereafter, successful applications of these two models have further validated their potential. Thus, both models are worth to be considered for new hybrid model development.

iii. Hybrid MA-SVM can perform simultaneous hyperparameters tuning and features selection. Numerous past research have shown the MA approach to conduct these two tasks are effective to improve SVM performance; where appropriate settings of hyperparameters can ensure stable model performance and features selection can enhance model explainability with the reduced features.

iv. Hybrid MA-RF perform hyperparameters tuning solely because the computed features importance is an useful measure for model explainability. As a relatively new ensembles that just received attention lately in this domain, RF hyperparameters tuning has only one research to tune hyperparameters with MA approach with good performance. This is perceived as a prospective new page for automated process of tuning RF hyperparameters in place of manual repeat trial-and-error.

v. GA is the most popular MA to be hybridized for model improvement. Despite its successful performance, GA has complex structure for implementation with a number of operators that control the automated search process. In contrast, HS has simpler structure with fewer operators to be adjusted. Thus, HS is believed to have easier implementation and more flexible to be modified to achieve effective and efficient search process.

1.5 Scope and Limitations

The scope of this study with the corresponding limitations are as follows:

i. The role of HS and MHS in hybridizing with SVM is to perform simultaneous hyperparameters tuning and features selection. The automated search process of the hyperparameters and features subset is not expected to find the best solution for SVM, but the solution is expected to be a ‘satisfactory’ one. This is because the search process is based on a validation set and the solution from HS is expected to have good generalization ability on any unseen test sets. Besides, hybrid HS-SVM and MHS-SVM only enhance model explainability using the reduced features subset, but it does not solve the complex internal structure of SVM to make it a transparent model.

ii. The role of HS and MHS in hybridizing with RF is only focused on hyperparameters tuning as the features importance is already useful to solve model explainability problem. Hence, both hybrid models handle black-box property of RF via the attributes explanation approach instead of directly solving the black-box structure. Since the main aim is to introduce an automated tuning of RF using HS, unlike SVM that has recommended search range in the literature, the RF search range in this study is considered as a reasonable one which is decided based on past works. The hybrid HS-RF is focused to tune RF with good generalization ability instead of finding the 'best' hyperparameters on a particular dataset.

iii. The AI models focused in this study are only SVM and RF, where the evaluation of the proposed hybrid models are only compared with these two. Other AI models are not studied since they required cautious tuning of the hyperparameters which will require further investigations.

iv. HS is the main technique for automated tuning process. Although some studies have treated other MA techniques as a standard to be overcome, we do not include them in our comparative studies because utilizing MA requires presetting of the parameters, and detailed experimentations are required for these settings.

v. Application scoring is the main credit domain being focused in this study. Hence, the classifications are based on applicants information instead of their payment behaviours as in behavioural scoring.

vi. Predictive modelling that formulates credit models with good predictive ability is the main study focus. Thus, formulation of descriptive models that study the relationships of the attributes would require additional research efforts.

1.6 Research Objectives

The main objective of this research is to form credit scoring model that incorporates HS algorithm with AI techniques. The specific objectives are:

1. to develop a hybrid HS-SVM with HS to conduct simultaneous features selection and hyperparameters tuning for SVM, then enhance model explainability with the reduced features subset.
2. to develop a hybrid HS-RF with HS to conduct hyperparameters tuning for RF, then enhance model explainability with the features importance computed from RF.
3. to develop hybrid models with modified HS (MHS), forming MHS-SVM and MHS-RF together with parallel computing that provide comparable solutions as HS hybrids with lower computational effort.
4. to validate the model performances by internal benchmarking with standard credit models across three credit datasets of different natures i.e. loan application, credit card application and peer-to-peer lending as well as external benchmarking with past literature studies.

1.7 Thesis Organization

The content of this thesis are organized in five chapters. The current chapter provides a general background and definition of credit scoring leading to the problem statement and research motivation. The scope and limitations and research objectives are outlined.

Chapter 2 studies the background and literature review of credit scoring, particularly on SVM, RF and MA. A general trend is outlined, followed by a general overview of credit models based on the three techniques before funneling down to the comprehensive review on hyperparameters tuning and model explainability issues. Several research gaps from past researches are also addressed.

Chapter 3 shows the detailed formulation of the proposed hybrid models. The standard SVM, RF and HS are explained. MHS for effective and efficient search is presented. Then, the hybridization of both HS and MHS with the two AI techniques i.e. SVM and RF are elaborated accordingly to show how the model development solved the hyperparameters tuning and model explainability problems. Lastly, the parallelization procedure is described.

Chapter 4 describes the experimental setup procedures starting from the credit datasets preparation to the computational experiments of the proposed models together with other benchmark models. Then, the results are reported and discussed based on three aspects i.e. model performances, model explainability and computational time.

Chapter 5 summarizes and concludes the research findings based on results and discussions to answer the research objectives in Chapter 1. Then, possible future works are pointed out.

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BIODATA OF STUDENT

The student, Goh Rui Ying, was born in September 1993. She received the Bachelor Degree in Statistics from Universiti Putra Malaysia, in 2017. Currently, she is pursuing her masters degree in Universiti Putra Malaysia. Her research interest is artificial intelligence and data mining focusing in credit scoring.

LIST OF PUBLICATIONS

The following are the list of publications that arise from this study.

Goh, R. Y. & Lee, L. S. (2019). Credit scoring: A review on support vector machines and metaheuristic approaches. *Advances in Operations Research*. *https://doi.org/10.1155/2019/1974794*. (Published)

Goh, R. Y., Lee, L. S. & Adam M. B. Hyperparameters tuning of random forest with harmony search in credit scoring. *ASM Science Journal*. (Accepted).

Goh, R. Y. & Lee, L. S. Hybrid harmony search-artificial intelligence models in credit scoring. *Journal of Credit Risk*. (under review).

Goh, R. Y. & Lee, L. S. Random forest as the future credit scoring model? *Journal of Analysis and Applications*. (under review).

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