Preface

Credit risk evaluation is one of the most important topics in the field of financial risk management. Due to recent financial crises and regulatory concern of Basel II, credit risk analysis and assessment have been a major focus of financial and banking industry. Especially for many credit-granting institutions such as commercial banks and credit companies, the ability to discriminate good customers from bad ones is crucial to success of their business. The need for reliable quantitative models that predict defaults accurately is imperative so that the interested parties can take either preventive or corrective actions. Hence, credit risk modeling and analysis become very important for sustainability and profit of enterprises. Furthermore, an accurate prediction of credit risk could be transformed into a more efficient use of economic capital in business. Therefore, credit risk modeling and analysis have become an important issue in both academic and industrial communities.

In this monograph, the authors try to integrate recent emerging support vector machines (SVM) and other computational intelligence techniques that replicate the principles of bio-inspired information processing for credit risk modeling and analysis. Selecting SVM for credit risk modeling analysis is due to its unique features and powerful pattern recognition capability of SVM. Unlike most of the traditional statistical models, SVM is a class of data-driven, self-adaptive, and nonlinear methods that do not require specific assumptions (e.g., normal distribution in statistics) on the underlying data generating process. This feature is particularly appealing for practical business situations where data are abundant or easily available, even though the theoretical model or the underlying relationship is unknown. Secondly, SVM performs a nonlinear mapping from an original input space into a high dimensional feature space, in which it can construct a linear discriminant function to replace the nonlinear function in the original low dimensional input space. This characteristic also solves the dimension disaster problem because its computational complexity is not dependent on the sample dimension. Thirdly, SVM implements structural risk minimization strategy instead of empirical risk minimization strategy in artificial neural networks (ANN) to separate hyperplanes by using margin maximization principle, therefore possessing good generalization ability. This feature directly helps SVM escape local minima, which are often occurred in the training of ANNs. Furthermore, SVM has been successfully applied to a wide range of practical problems in almost all areas of business, industry and science. In some sense, SVM has some distinct advantages in comparison with the traditional statistical techniques and ANN models when analyzing credit risk.

The main purpose of this monograph is to develop some new models and techniques to evaluate credit risk and meantime to report some recent progress in credit risk modeling via SVM and other computational intelligence techniques, as well as to present a comprehensive survey of the past researches in the area of credit risk modeling for academic researchers and business practitioners. Therefore, some most important advancements in the field of credit risk modeling with SVM are presented. The book contains 4 parts with a total of 11 chapters which are briefly described below.

Part I presents an analytical survey on computational intelligence in credit risk modeling and analysis. Particularly, this survey discusses the factors of affecting credit risk classification capability with SVM. Through a literature review and analysis, some important implications and future research directions are pointed out. According to the results and implications of this survey, the sequel chapters will discuss these new research directions and provide the corresponding solutions.

In terms of non-optimal parameter selection problem in SVM learning algorithm shown in the existing studies, Part II mainly develops two unitary SVM models with optimal parameter selection to evaluate credit risk. In the first unitary SVM model presented in Chapter 2, a design of experiment (DOE) method is used to determine the optimal parameters of the SVM model and simultaneously a nearest point algorithm (NPA) is used to obtain quickly the solutions of the SVM model with optimal parameters. In the second unitary SVM model given in Chapter 3, its parameters are determined by a direct search (DS) algorithm. Meantime, some other parameter selection methods, such as genetic algorithm (GA), grid search (GS) algorithm, and design of experiment (DOE), are also conducted to compare the performance of different parameter selection methods when the proposed unitary SVM models with optimal parameter are applied to credit risk evaluation and analysis.

In accordance with the previous analysis in the survey, the hybrid and ensemble models usually achieve better classification performance than the unitary SVM models. For this purpose, Part III and Part IV present four hybrid models and four ensemble models, respectively.

In the first hybrid model of Part III, rough set theory (RST) and SVM are hybridized into a synergetic model for credit risk classification and analysis. Different from the existing hybrid approach integrating RST and

SVM, SVM is used for feature selection and then RST is used to generate classification rules for credit risk evaluation in the proposed hybrid model. In terms of computational complexity problem of SVM, the second hybrid model incorporates fuzzy set theory (FST) and least squares SVM (LSSVM) to create a least squares fuzzy SVM (LS-FSVM) for credit risk assessment. Subsequently, a bilateral-weighted fuzzy SVM (FSVM) model hybridizing SVM and FST is proposed for credit risk assessment in the third hybrid model. In the new fuzzy SVM model, we treat every sample as both positive and negative classes, but with different memberships, which is generated by fuzzy set theory. This model is applied to three typical credit datasets and obtains good classification performance. Finally, an evolving LSSVM model based on genetic algorithm (GA) is proposed for credit risk analysis and evaluation. This model consists of two main evolutions: input feature evolution and parameter evolution. On one hand, a standard GA is first used to search the possible combination of input features. The input features selected with GA are used to train LSSVM. On the other hand, another GA is used to optimize parameter of LSSVM using the feature evolved LSSVM. For the purpose of verification, three different credit datasets are used and accordingly satisfied classification results are reported.

In the four ensemble models of Part IV, the first model presents a multistage ensemble framework to formulate an SVM ensemble learning approach for credit risk evaluation. The second ensemble model introduces a metalearning strategy to construct a SVM-based metamodeling ensemble method. In a sense, the proposed SVM ensemble model is actually an SVM metamodel. In the third ensemble model, an evolutionary programming (EP) based knowledge ensemble model is proposed for credit risk evaluation and analysis. In the last chapter of Part IV, a novel intelligent-agent-based multicriteria fuzzy GDM model is proposed as a multicriteria decision-making (MCDM) tool to support credit risk assessment. Different from the commonly used "one-member-one-vote" or the "majority-voting-rule" ensemble models, the novel fuzzy GDM model first uses several intelligent agents to evaluate the customers over a number of criteria, then the evaluation results are fuzzified into some fuzzy judgments, and finally these fuzzy judgments are aggregated and defuzzified into a group consensus as a final group decision measurement.

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Lean YU
Institute of Systems Science
Academy of Mathematics and Systems Science
Chinese Academy of Sciences
Beijing, 100190, China
Email: yulean@amss.ac.cn

Shouyang WANG
Institute of Systems Science
Academy of Mathematics and Systems Science
Chinese Academy of Sciences
Beijing, 100190, China
Email: sywang@amss.ac.cn

Kin Keung LAI
Department of Management Sciences
City University of Hong Kong
83 Tat Chee Avenue, Kowloon, Hong Kong
Email: mskklai@cityu.edu.hk

Ligang ZHOU
Department of Management Sciences
City University of Hong Kong
83 Tat Chee Avenue, Kowloon, Hong Kong
Email: mszhoulg@cityu.edu.hk

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