



University of Technology, Sydney

Fuzzy Transfer Learning for Financial Early Warning System

A Thesis Submitted for the Degree of
Doctor of Philosophy

By

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CERTIFICATE OF AUTHORSHIP/ORIGINALITY

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DEDICATION

To my beloved Mother, for her prayers for me.

To the soul of my Father, the first to teach me.

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ABSTRACT

Financial early warning system aims to warn of the impending critical financial status of an organization. A financial early warning system is more than a classical prediction model and should provide an explanatory analysis to describe the reasons behind the failure; the explanatory ability of a system is as important as its predictive accuracy. In addition, failure prediction is intrinsically a class imbalance problem in which the number of failed cases is much less than the number of survived cases. Also, the vagueness in the value of predictors is an inevitable problem which has emerged in the uncertain environment of the finance industry. Scarcity of training data is another critical problem in finance industry; a new type of financial early warning system, which can be transferred and modified for different domains to transfer knowledge to new prediction domain, is highly desirable in practical applications because it is easy to install and cheap to setup.

To achieve the aforementioned properties, this study develops algorithms, methods and approaches in the case of bank failure prediction. First, a novel parametric adaptive inference-based fuzzy neural network approach is devised to predict financial status accurately and generate valuable knowledge for decision making. It handles the imbalance problem and the vagueness in features' value using parametric learning and rule generation algorithms. Second, a fuzzy domain adaptation method is developed to transfer knowledge from a related old problem to the problem under consideration and the labels are then predicted with a high level of accuracy. This method handles the data scarcity problem and enables the financial early warning system to be transferrable between prediction domains which are different in data distribution. Third, a fuzzy cross-domain adaptation approach is proposed to make the financial early warning system transferable from different but related domains to the current domain. This approach handles the problem in which the feature spaces of

prediction domains are different and have vague value. This approach selects the significant fuzzy predictors in the current prediction domain by transferring knowledge from the related prediction domains.

The proposed algorithms, methods and approaches are validated and benchmarked in each step of development using experiments performed on real world data. The results show that this study significantly enhances predictive accuracy at different stages of development. Finally a case study is performed to integrate and validate the proposed methods and approaches using Australian banking system data. The results demonstrate that this study successfully solves the abovementioned problems and significantly outperforms existing methods.