Executive Summary

The results of this thesis can be classified into several main points:

- it presents the main machine learning methods used in credit scoring,
- reviews the corresponding literature, and
- introduces a new artificial credit risk market, allowing for a more profound assessment of machine learning based score models compared to the traditional methods.

We start by introducing credit risk management in general, explaining the approaches in credit rating, credit scoring, as well as giving some regulatory background. We further provide a literature review on machine learning methods in credit scoring, putting emphasis on the assessment methods. We also review several master and doctoral theses on this topic.

A lot of room is devoted to a detailed explanation of the basic machine learning methods used in our work: logistic regression, linear discriminant analysis, support vector machine, neural networks, classification and regression trees, and random forest.

In the main part of the thesis we present three crucial building blocks on which we build our new model. We introduce the Blöchlinger-Leippold (2006) credit market model, which is used as a basis of our market model. Then we discuss the construction of artificial credit risk data proposed by Kennedy (2003), which we further formalize and simplify. We give an overview of agent based modeling in computational economics, since this is exactly where our model can be naturally classified. Finally, we introduce our artificial credit market, by giving a detailed description of its R-implementation and presenting simulation results.

The main contribution of our work is therefore the introduction of this new artificial market. It allows us to assess credit scoring models from a new perspective. Instead of comparing models by testing them separately on the same data, we let the models compete for clients in a realistic market environment. We show that big discrepancies can occur in comparison with the traditional static assessment methods, such as AUC. We observe that peculiarities of a concrete market implementation may be equally relevant for the performance of an algorithm as its AUC power. The fact that a high-AUC algorithm can perform worse than a low-AUC algorithm we explain by introducing the term

"masking", which refers to the fact that under informational asymmetry parts of the client market may remain masked for certain banks. Finally, as a by-product, we are able to model dynamically credit interest rate within our model.