International Journal of Scientific Engineering and Science
Volume 2, Issue 5, pp. 42-44, 2018. ISSN (Online): 2456-7361

Modeling Customer's Credit Worthiness using Machine Learning Models: A Review

Mukesh Singh[1], Gireesh Kumar Dixit[2]
[1, 2]Department of Computer Science & Engineering, Oriental Institute of Science & Technology, Bhopal, M.P., India-462021

Abstract— *The risk management for financial organizations especially banks is associated with the financial distress caused due to credit worthiness of customer. The methodology to construct models for credit scoring varies from organization to organization. The evaluation and prediction of customer's credit worthiness is a key for preventing losses in banking sector. The purpose of calculating credit scoring is to categorize the applicants into good and bad application in terms of credit worthiness. To find out such behavior can be treated as a sort of Machine Learning (ML) problem. Now, the use of ML algorithms proved its significance in solving problems of various fields including credit risk detection and prediction. At the same time, the usages of ensemble classifiers in ML showcase an imperative role in building predictive models. Several researches confirm that use of ensemble classifiers show a considerable improvement in performance of various classification techniques. In this paper, we present the survey of works undertaken by several authors for determining and predicting credit risk. The survey is presented on basis of two paradigms of ML: 1. Machine Learning approach 2. Ensemble approach. We raised some relevant research questions to be addressed. The work also aims at providing future directions for development of feasible techniques for building predictive models.*

Keywords— *Artificial Intelligence: Classification: Credit Worthiness: Credit Risk Detection: Data Mining: Financial Organization: Predictive Model: Machine Learning.*

I. INTRODUCTION

The controlled access to centralized information of bank customers is an advantage for any financial organization, as it gains and deal with customer information, to study its borrowing, buying and re-payment pattern. The financial organizations get benefitted if they share their customer information with each other in limited mode. With this data, while studying the patterns of buying, borrowing and re-payment, such organizations can discover whether the customer defaults. Besides good credit and high purchasing power of customer, a certain amount of credit risk is linked with these customer groups [1].

Historically, a bank customer is classified into the categories defined by banks (good, bad, loss, bankrupt etc.) depending on pattern of their repayment and transaction. Nowadays, Credit Scoring has become one of the basic ways for financial organization to improve cash flow, assess credit risk and to make other managerial decisions. The purpose of credit scoring is to classify the applicants into two types: applicants with good credit and applicants with bad credit. Applicants with good credit have great possibility to repay financial obligation.

With the remarkable increase of banking transactions, it is impossible to score the customers into default and non-default statistically. Here, Artificial Intelligence (AI) based Data Mining (DM) techniques comes into picture. Several financial decision-making methods based on ML now. Several classifiers based on ML are presented in this paper.

Ensemble learning is a ML paradigm where multiple classifiers are trained to solve the same problem [2]. A simple ML approach tries to learn one hypothesis from the training data whereas ensemble methods try to construct a set of hypotheses and combine them to use [3]. Learners composed of an ensemble are usually called base learners. The most popular ensemble methods are Bagging [18, 19], Boosting [20], and Stacking. This work explores various classification and ensemble based models used in building models for determining credit risk.

The paper is organized as follows: in Section 2, a brief literature of the classifiers is presented. The survey presented on ML paradigm and Ensemble approach. In Section 3, few research questions are identified. Finally, in Section 4, paper is concluded with remarks and future directions in the field.

II. LITERATURE REVIEW

The survey is presented on basis of two paradigms of ML.

A. *Machine Learning paradigm*

For ML based paradigm, refer Table I.

B. *Ensemble Approach*

For Ensemble based paradigm, refer Table II.

TABLE I. Survey based on popular machine learning approaches.

Authors	**Work / Methods undertaken**	**Dataset used**	**Tool used**
[1]	Analyses the risk linked with portfolios of higher purchasing capacity. Also proposed a predictive model based on key attributes to classify the customers in default and non-default. Three different decision tree classifiers: J48, Decision Tree and Random Tree are used.	luxurious vehicle credit range dataset	Statistical Techniques and Weka [4, 5]
[6]	Batch and incremental classifiers such as logistic regression (LR), neural networks (NN), C5, naive bayes (NB), IBk (instance-based learner, k nearest neighbour) and raced incremental logit boost is used.	Credit card dataset from banks in Malaysia.	Clementine [7] and Weka [4, 5]
[8]	Support Vector Machines with a proposed transformation method is applied for credit scoring.	Australian and German credit datasets [9]	hybrid credit scoring classifier [10]
[11]	Discriminant Analysis and Neural Network Approach	86 Tunisian companies data	MATLAB

TABLE II. Survey based on ensemble approaches.

Authors	Work / Methods undertaken	Dataset used	Tool used
[12]	Applied 15 different ML methods. All, except Naïve Bayes and Nearest Centroid, performed well and achieved accuracy between 76 – 80%. 5 features extracted but no significant impact occurred in comparison when all taken altogether. Proposed a model based on Linear Regression.	Bank Credit Card dataset [13]	Scikit-Learn [13] and MATLAB
[14]	Performance comparison of systems having ensemble of classifiers for credit scoring and bankruptcy prediction is done. Multi-layer perceptron (MLP) neural net classifier is found best. Random Subspace (RS) ensemble method performed better than other EMs.	Australian credit, German credit and Japanese credit dataset	Different suitable toolkits
[15]	To classify the risk into good and bad, authors used three Ensemble Methods namely Bagging, AdaBoost and Random Forest combined with three ML algorithms. Feature selection is applied to select the important attributes.	German credit dataset [9]	Weka [4, 5]
[16]	3 popular EMs, i.e., Boosting, Bagging, and Stacking, based on 4 basic learners: Logistic Regression, Decision Tree (DT), ANN and SVM, are compared. Performance evaluation shown that ensemble methods improve base learners. Bagging performs well with most credit datasets.	German credit and Australian credit dataset [9]	Weka toolkit [4, 5]

III. RESEARCH QUESTIONS

Credit and behavioral scoring are the techniques that help organizations decide whether or not to grant credit to consumers who apply [17]. Credit scoring is generally based on operational or statistical research methods. Operational methods include linear programming and Statistical techniques include linear regression and classification trees etc. The predictive models built over the concepts of DM and ML. The major questions that arise in the area of determining and forecasting financial risks are:

- How well has been this research area of forecasting credit risk?
- What are the attributes that affects the classification and scoring of customer while building model for scoring and prediction.
- How well the statistical and operational methods perform over such research problems?
- How well the statistical and operational methods scale over different data sizes.
- How accurate has been the predictive models built using ML techniques?
- Which ML model or paradigm is best suitable for analyzing financial data?
- As the volume of data growing day by day, how well the predictive models scale?
- Although ML platforms are available over cloud but what are other alternate solutions for handling future computational requirements of predictive model?
- How sampling, pre-processing and feature extraction techniques influence model building and other performance parameters?

IV. CONCLUSION AND FUTURE WORK

Research in this area is continuing but the type of impediments that occurs in predicting credit worthiness has not yet been dealt with satisfactorily. Although there are no steady conclusions that which paradigm or model performs better, recent studies suggests feature extraction and ensemble learning may bring better performance. In this work we conducted a survey of popular works in the field of predicting credit worthiness through machine learning models. The literature review also presented that which ML algorithms are suitable for studying credit dataset. Furthermore, the research questions are pointed out to motivate research in the field. In future, to predict the credit worthiness of the customer, we propose a Classification framework comprising appropriate feature extraction to derive most significant features and Ensemble based ML approach.

REFERENCES

[1] U Bhuvaneswari, P. James Daniel Paul, and Siddhant Sahu, "Financial risk modelling in vehicle credit portfolio," *IEEE International Conference on Data Mining and Intelligent Computing (ICDMIC)*, 2014.
[2] R. Polikar, "Ensemble based systems in decision making," *IEEE Circuits and Systems Magazine*, vol. 6, issue 3, pp. 21–45, 2006.
[3] Z. H. Zhou, Ensemble. In L. Liu & T. Özsu (Eds.), Encyclopedia of database systems, Berlin: Springer, 2009.
[4] http://www.cs.waikato.ac.nz/~ml/weka/index.html
[5] Weka, University of Waikato, Hamilton, New Zealand.
[6] Ling Kock Sheng and Teh Ying Wah, "A comparative study of data mining techniques in predicting consumers' credit card risk in banks," *African Journal of Business Management*, vol. 5, issue 20, pp. 8307-8312, 16 September, 2011.
[7] http://www.the-data-mine.com/Software/SPSSClementine
[8] Jingnian Chen and Li Xu, "A method of improving credit evaluation with support vector machines," *11th International Conference on Natural Computation (ICNC)*, Zhangjiajie, pp. 615-619, 2015.
[9] S. Hettich, C. L. Blake, C. J. Merz, UCI Repository of machine learning databases, Department of Information and Computer Sciences, University of California, Irvine, CA, 1998. http//www.ics.uci.edu/~mlearn/ MLRepository.html.
[10] P. Yao and Y. Lu "Neighborhood rough set and SVM based hybrid credit scoring classifier," *Expert Systems with Applications*, vol. 38, issue 9, pp. 11300–11304, 2011.
[11] Sihem Khemakhem and Younés Boujelbènea, "Credit risk prediction: A comparative study between discriminant analysis and the neural network approach", *Accounting and Management Information Systems*, vol. 14, no. 1, pp. 60-78, 2015.
[12] Regina Esi Turkson, Edward Yeallakuor Baagyere, Gideon Evans Wenya, "A machine learning approach for predicting bank credit worthiness," *IEEE International Conference on Artificial Intelligence and Pattern Recognition (AIPR)*, 2016.
[13] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.
[14] Loris Nanni and Alessandra Lumini, "An experimental comparison of ensemble of classifiers for bankruptcy prediction and credit scoring," *Expert Systems with Applications*, vol. 36, issue 2, part 2, pp. 3028–3033, 2009.
[15] C. R. Durga Devi and Dr. R. Manicka Chezian, "A relative evaluation of the performance of ensemble learning in credit scoring," *IEEE International Conference on Advances in Computer Applications (ICACA)*, 2016.
[16] Gang Wang, Jinxing Hao, Jian Mab, and Hongbing Jiang, "A comparative assessment of ensemble learning for credit scoring," *Expert Systems with Applications*, vol. 38, issue 1, pp. 223–230, 2011.

Volume 2, Issue 5, pp. 42-44, 2018. ISSN (Online): 2456-7361

[17] Lyn C. Thomas, "A survey of credit and behavioural scoring: forecasting financial risk of lending to consumers," *International Journal of Forecasting*, vol. 16, issue 2, pp. 149-172, 2000.
[18] David Opitz and Richard Maclin, "Popular ensemble methods: An empirical study," *Journal of Artificial Intelligence Research*, vol. 11, pp. 169-198, 1999.
[19] L. Breiman, "Bagging predictors," *Machine Learning*, vol. 24, issue 2, pp. 123–140, 1996.
[20] Y. Freund and R. Schapire, "Experiments with a new boosting algorithm," in *Proceedings of the Thirteenth International Conference on Machine Learning*, Bari, Italy, pp. 148–156J, 1996.