SOCIAL NETWORKS IN CREDIT SCORING: A MACHINE LEARNING APPROACH

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ABSTRACT

This research examines if social network tie has an incremental predictive ability for borrower default in credit scoring and the precision of effect. With advanced digital technologies and increasing availability of non-financial behaviour big data, social network data has been explored to assess consumer credit scoring in research and practice. This research uses machine learning algorithms to analyse a large dataset (loan applications and defaults) obtained from a European lender. The results show that social network data, when working together with traditional financial data, improves predictive ability of borrowers' default. A Bayesian Analysis confirms the explanatory evidence of social ties of borrowers. This research generates insights of machine learning power in analyzing imbalanced large dataset using ten different classifiers, and contributes to the theoretical debate on social capital theory as well as practical guidance of using XGBoost algorithm for lenders.

KEYWORDS

Machine Learning, Predictive Analytics, Social Networks, Credit Scoring, Financial Inclusion

1. INTRODUCTION

Credit scoring has been evolving in terms of objectives, sources, modelling, and techniques. Particularly, with big data accessibility and the advances in digital technologies, e.g. intelligent systems like artificial intelligence (AI) and machine learning (ML) in data analysis. Objectives of lenders vary from market penetration, profit maximisation (Thomas, 2009) to more socially financial inclusion and equality (McKillop, et al. 2007; Wei, et al. 2015). Financial inclusion requires provision of financial access to high calibre with thin financial files such as students, refugees (Redrup, 2017), new entrants to the job market or homestayers coming back to workforce, immigrants with high skills, craftsmen working with cash-in-hand and many other talents (McEvoy and Chakraborty, 2014). For example, the Migration Observatory at the University of Oxford reported sharp increase in unemployment rates since 2020 among migrants in the UK (Fernandez-Reino & Rienzo, 2021). Finding ways to include those who cannot access credit will reduce social inequality (Wei et al., 2015). One of the challenges, for including more borrowers, is information asymmetry, which arises when one party has limited access to information that is kept by another contracted party (Yan, et al. 2015; Ackert and Deaves, 2009).

Traditional data represented 'hard' information (Lin et al., 2013) and was retrieved from borrowers' financial history at the time of application (Leow and Crook, 2016). Such data, like average balance, past credit performance in addition to demographics dominated credit scoring for quite some time, but alternative and non-traditional data including social data has been increasingly-used by innovative lenders (Lazarow, 2017). Meanwhile, models underpinning credit scoring vary from static and parametric to dynamic and non-parametric based (Chen et al., 2018). Machine learning models are capable of learning iteratively from training datasets to classify or predict risk level of prospectus borrowers, especially when a borrower has thin financial information and face unstable circumstances.

Research into the effectiveness of non-financial data modelling and the associated techniques (ML) for credit scoring is patchy. Particularly, when referring to social network data as one of the emerging non-financial data in credit, there is a lack of precision on how social network effects credit scoring.

This research aims to examine if social network data - specifically the default tie, has an incremental predictive ability for borrower default risk in credit scoring and the precision of such an effect. The remaining sections of this paper are structured as follows. Section2 reviews credit modelling, social networks and machine learning for credit scoring. The methodology is discussed in section 3 where the dataset preparation for ML and modelling are described. The results are presented with discussion in section 4. This is followed by a conclusion and proposed future research agenda.

2. LITERATURE REVIEW

2.1 Traditional Credit Scoring Models and Data

Credit scoring professionals traditionally relied on three categories of models to estimate targeted borrowers' abilities to repay their loans. Those are Probability of default (PD), Loss given default (LGD), and Exposure at default (EAD) (Tong, et al. 2016). According to Basel II committee's definition, a default happens when, at any point of time during the loan's tenure, 90 days' worth of instalments are in arrears within a 360-day period (Puri et al., 2017). The estimated PD, usually is set for a binary target - either default or repayment in which a reject or an accept decision to be made (Gordy, 2000). LGD estimates the amounts that the lender would lose in the event of default in an estimated point of time (Schuermann, 2004). EAD is to estimate the outstanding balance of an account at any point during the life of the loan, applying to revolving credit such as credit cards and overdraft facilities (Leow and Crook, 2016). In this research, PD is used as the target variable due to the nature of the available dataset.

A borrower's credit score is predicted by the lender and / or external credit referencing agencies (also refers to Credit rating authority/Bureaus) (Rajan, et al., 2010). Fair Isaac Corporation (FICO) is a typical credit score using financial data - with five components: (a) payment history (0.35), amounts owed (0.30), length of credit history (0.15), credit mix (0.10), and new credit (0.10). A FICO score ranges between 300 - 850 (Wei et al., 2015).

Data sources include banking transactions, shopping data from department stores, payments of energy bills to suppliers, county court judgements, and electoral registers (Banasik et al., 1999; Kshetri, 2016). However, data used for credit scoring has been dominantly financial data (Redrup, 2017). Financial data includes, but not limited to, the number of bank accounts and credit cards held, years with bank, employment category, residency type/ownership of home, credit history, debt-to-income ratio, average account balance, maximum credit payment, number of times over credit limit, average transactions value, number of cash withdrawals, credit limit changes (Leow and Crook, 2016; Freedman and Jin, 2017; Thomas, et al. 2017).

It is argued that, despite meeting the financial criteria, abrupt incidents such as divorce, job termination, diseases can lead to unexpected financial distresses, hence, undermines the trustworthy of the financial based credit scores (Lazarow, 2017). With the scalable powers of big data analytics, machine learning and data mining, lenders are able to incorporate various sources of data that are not bound by borrowers' accounts and financial records. The sources of behavioural data include e-commerce, psychometrics tests (Arráiz, et al. 2017), social media (Guo et al., 2016; Masyutin, 2015; Rusli, 2013; Weke and Ntwiga, 2016), web analytics, mobile phones' usage (Bjorkegren and Grissen, 2015), and social network circles (Lin et al., 2013). There is an increasing tendency of adopting such behaviour data by credit agencies, online lenders and P2P lending platforms.

2.2 Social Network Models and Theories

Social data has a relational aspect (Lin et al., 2013) where the borrower is affected and influenced by the connections within a network (Wei et al., 2015). Networks can be formed based on different social connections, hence come with different purposes, structures, strength and number of ties. When it comes to strength, the more two social networks overlap, the stronger the tie between the two individuals that the networks belong to (Granovetter, 1973). Lin, et al (2013) suggested types of social networks including alumni, geographical, military, medical, demographic, hobbies, business and religion social networks. Coleman (1988) suggests that, since persons are linked in more than one context (neighbour, fellow worker, fellow parent, coreligionist, etc.), the central property of a multiplex relation is that it allows the resources of one relationship to be appropriated for use in others. According to Currier (2020), persistent connections can shape up destinies of networked people. In social network science, an influential person has a high degree of centrality.

The assumption of using social network tie for credit scoring is that people tend to associate with others who share similar features when formulating social networks. The features include demographics such as gender, race, religion, nationality, or other discrete characteristics. On the other hand, the common features can be scalar characteristics such as age or income. The notion of 'homophily' indicates that people tend to form social ties with those that are like-minded (Newman, 2010). When it comes to credit, Wei et al. (2015) and

Freedman & Jin (2017) explained that individuals form social ties with others for a social utility and a posterior credit utility. Lin et al. (2013) tested data provided by prosper.com and confirmed that having friends makes it easier for borrowers to get funded in P2P lending while enjoying lower APRs. The scholars justified their findings with the term 'social stigma', which costs borrowers when their friends default.

From a theoretical perspective, the social capital theory provides a foundation to understand the value of social networks in credit. Coleman (1988) suggests that unlike other forms of capital, social capital inheres in the structure of relations between actors and among actors (i.e. the social network). Social capital impacts on human action in two ways - facilitate or constrain actions. For example, a group within which there is extensive trustworthiness and extensive trust is able to accomplish much more than a comparable group without that trustworthiness and trust. This explains why social networks is considered a source of credit worthiness. Key form of social capital includes obligations, expectations, and trustworthiness of structures, but it is the obligations that one person owes a second in relationship X, which the second person can use to constrain the actions of the first in relationship Y. Apparently, not all social relations bear financial obligations and not only dyadic relationships influence a behavior, but also the structure and the shape of a network. For example, 'herding' behavior was defined as the socio-economic decision-making process that is influenced by other's decisions and it can be seen particularly in ego-centric networks (Pokorna & Sponer, 2016)

How social network affects credit decision remains a practical and academic challenge. Among a few limited studies, Lin et al. (2013) suggest that having friends is considered a signal of good quality in borrowers. In practice, it is reported that online lender Lenddo considers the number of personal connections a borrower has, and ask those connections to endorse the borrower (Rusli, 2013; McEvoy and Chakraborty, 2014), but differentiates two social ties: friends vs. followers, which implies that not all network ties have relevance to credit decision. The lender also measures the time social media accounts have been active in order to estimate social ties strength. Nevertheless, how the social tie data is specifically affecting the Lenddo credit score, and if the social tie data is a complementarity (work with traditional financial data), or a sole determinant in credit decision remain unknown.

There are risks associated with using social networks for credit assessment, for example, social network members can deliberately falsify lenders (Wei, et al. 2015) by forming false association, because connections to individuals with high type signals (good borrowers) have an overall positive impact. Whereas individuals with low type signals (e.g. with default history) may be difficult to associate with or being endorsed by good borrowers, hence, exacerbate social exclusion problem. This is an important issue to pursue, however is beyond the scope of the current study.

In summary, despite a few limited studies on social networks' inference on credit scores, the results are largely inconclusive, and specifically lack of necessary precision as to the extent of social network tie impact. This gap is fulfilled by this study using a machine leaning approach on a large loan dataset that includes information about social ties of existing borrowers.

2.3 Machine Learning Models in Credit

The introduction of machine learning (ML) was prominent in last two decades. Dash et al. (2017) assert that machine learning and deep learning algorithms can make better and faster underwriting decisions in credit. Along similar lines, many researchers argued the superior suitability of ML models that would analyse and learn iteratively from both financial and non-financial data to predict credit scores (Turner & McBurnett, 2019; West, 2000).

The normal procedure in machine learning is to split the dataset into a large part (70-80%) of training set then test the model on the remaining (20-30%) holdout part (Han, Pei, & Kamber, 2011), using either supervised or unsupervised learning. A large literature review on ML models shows a tendency of using ML models, although traditional parametric models remain prevalent all the time including Discriminant Analysis (linear), Logistic Regression, Decision / Classification Trees, Linear Programming. On the non-parametric models, Neural Networks is dominating, this is followed (in popularity order) by K-Nearest Neighbors (West, 2000; Lee et al. 2002; Baesens et al. 2003; Chen and Li, 2010; Brown and Mues, 2012), Support Vector Machines (Bellotti and Crook, 2009; Huang, et al. 2007; Yang, 2007), Random Forests (Kruppa et al. 2013; Malekipirbazari and Aksakalli, 2015), Gradient Boosting (Fahner, 2018), Naïve Bayes (Kou and Wu, 2014), Genetic Algorithms (Huang et al. 2007).

The reported model accuracy from these studies has been moderately high in the range of 0.70-0.80 with some outliers. For probability default (PD) estimation, Yang (2007) suggests that logistic regression (LR) and linear discriminant analysis (LDA) have been the most commonly-used models, which supports the finding from our literature review. All the models mentioned above have been used to examine their suitability for the dataset, as well as their predictive ability as a PD ML module.

3. METHODOLOGY

In this research, we use a large dataset of loan by individual barrowers obtained from a European lender through an online repository. The dataset is large enough for the intent of this research. It contains a total of 307,511 borrowers data described in 120 variables representing the columns. In addition to that, the outcome of loans was available in binary setting – default or repaid. This enables supervised machine learning to be performed. The dataset covers dominantly financial and behavior data, with two columns of relevant social network data.

The process of the analysis is conducted in two stages - a) data preparation and b) fitting a machine learning model on the dataset for predictability.

3.1 The Dataset and Preparation

Within the total 307,511 distinct borrowers load data, 282,686 loans were repaid and the remaining 24,825 were not (default). The 120 columns cover wide range of attributes, which were classified into three main categories: financial, behavioural, and social attributes. For simplicity, behavioural and social data will be considered as non-traditional. Traditional attributes are those provided from the financial banking systems such as types of loans, which are classified into tenured loan with a maturity repayment date (e.g. car loan, mortgage, microloan loan, cash loan, etc.), and revolving loans indicating a credit limit that renews periodically whenever a borrower settles the outstanding (e.g. credit card).

In pre-processing, a number of steps were followed including data cleaning, data extraction, attribute construction, data aggregation, and loading (ETL). Missing values were treated by replacing with either mode, median or mean (based on variables' types and distributions) using the fillna() function in Python 3. Some observations with majority of their fields being missing were deleted. Also, attributes with many possible outcomes were aggregated in smaller number of categories. The dataset was loaded onto a virtual environment where a high processing unit that is set on a super computer node was used to run the models. Finally, the algorithm was run on a clean data made of 304,427 borrowers described in 48 variables. The new dataset included 279,767 repaid and 24,660 default cases. It is worthy to note the two social network attributes. One is a delinquent type – indicating friends of arears within 30 days and another defaulting type – network friends of actual default of the loan.

3.2 Machine Learning Models

Python 3 was used to perform machine learning on the full dataset. The functions that built our machine learning classifiers in the designed Python 3 algorithm are:

- *LabelEconder( )* to transform all categorical variables into numbers (encoding).
- *StandardScalar( )* to standardize all numeric variables within attributes.
- *fit( )* to initiate the model on the training sample set.
- *predict( )* to create a y_predict (y') object, which is compared to the corresponding y_test (actual loan outcome) to measure performance.
- *accuracy_score( )* to calculate each one of the classifiers' accuracy using the formula: (TP+TN)/(N_test)
- *log_loss()* is the function that computes the logarithmic loss which penalises false classifications during the iteration process of the machine learning classifier. The lower its value, the better. A log loss value of zero means that the model is perfectly classifying cases.
- *KNeighborsClassifier(), SVC(), NuSVC(), DecisionTreeClassifier(), RandomForestClassifier(), AdaBoostClassifier(), GradientBoostingClassifier(), GaussianNB(), LinearDiscriminantAnalysis(), QuadraticDiscriminantAnalysis()* are the machine learning classifiers. Algorithms trained on 70 per cent of the sample dataset and they were tested on the remaining 30 per cent.

To overcome the data imbalance class problem explained by Zięba et al. (2016), a balanced dataset is created to include all 24,660 default cases, and an equal sampled set from the class of repaying borrowers (24,660). This makes a total of 49,320 loans applications sample frame for the regress analysis. The target variable (loan outcome) was isolated in Y object. The X object contained different variations of attributes. The design is to examine the accuracy and precision of the bad social network tie impact on the default risks.

4. RESULTS AND DISCUSSION

The ML classification results are presented in the sub sections below.

4.1 Bayesian Analysis

Table 1 shows the default network ties and the associated metrics derived from posterior probability (Bayesian) analysis using proportionate figures.

Table 1. Profile of defaulting social tie from Bayesian analysis

Number of defaulting social ties	Repay	Default	Odds	Probability of repay	Probability of default	Information odds	Weight of evidence
0	248,523	20,989	11.84	0.92	0.08	1.04	0.04
1	25,276	2,862	8.83	0.90	0.10	0.78	- 0.25
2	4,667	616	7.58	0.88	0.12	0.67	- 0.40
3	1,032	150	6.88	0.87	0.13	0.61	- 0.50
4	214	34	6.29	0.86	0.14	0.55	- 0.59
5	48	8	6.00	0.86	0.14	0.53	- 0.64
6	7	1	7.00	0.87	0.13	0.62	- 0.48

The analysis indicates that a borrower, who has no defaulting ties (0) demonstrates 4% more evidence to being a good borrower. Conversely, a borrower with 1 - 6 defaulting social ties indicate a negative repayment effect.

4.2 Machine Learning Results

ML algorithms are run on both datasets (financial and full dataset). The results below (see Table 2) highlight the performance of the ten classifiers where those were measured by both accuracy and logarithmic (log) loss.

Table 2. Predictability of Machine Learning Classifier on PD

	Financial		Full dataset		Difference
ML Classifier	Accuracy	Log Loss	Accuracy	Log Loss	In accuracy
K-Nearest Neighbors	0.607	4.408	0.591	4.451	-0.016
Support Vector Machine	0.664	0.614	0.668	0.609	0.004
Nu-Support Vector Machine	0.613	0.673	0.636	0.643	0.023
Decision Trees	0.581	14.46	0.583	14.405	0.002
Random Forests	0.634	0.952	0.636	0.824	0.002
AdaBoost	0.668	0.689	0.673	0.689	0.005
Extreme Gradient (XGBoost)	0.676	0.604	0.680	0.599	0.004
Naïve Bayes (Gaussian)	0.604	0.914	0.635	1.316	**0.031**
Linear Discriminant Analysis	0.667	0.613	0.677	0.604	0.01
Quadratic Discriminant Analysis	0.583	0.907	0.535	10.159	-0.048

4.3 Discussion

The key points emerged from the findings are summarized below:

i. The results confirm that the ten ML classifiers yields average over 0.6 accuracy in predicting PD, with behavior and social network tie data, the accuracy improves particularly for Naïve Bayes, Nu-Support Vector Machine, AdaBoost, Extreme Gradient (XGBoost) models.

ii. The Naïve Bayesian machine learning algorithm improved significantly when adding social variables, which is consistent with the initial Bayesian analysis done in Table 1. That analysis demonstrated the weight of evidence added to the loan outcome when knowing in advanced the number of defaulting social ties a borrower has.

iii. The Extreme Gradient Boosting (XGBoost) algorithm achieved the highest accuracy while suffering the lowest log loss confirming that the said algorithm predicts the binary targets closest to their real values.

iv. It is believed that XGBoost algorithm outperformed other classifiers because, as heterogeneous behavioural data accumulate, a fast and parallel processing is needed. This is consistent with XGBoost with its ability to build decision trees (that are the basis for a simple credit scoring method) in a series of parallel analyses while minimizing its objective function (Dastile et al., 2020).

The findings of this study partially confirm the social capital theory that the default social tie does have a negative impact on other's credit scoring, other side of the social capital theory - the scalar homophily and its positive association with credit risks has not been examined in this study due to the aforementioned limitation of the dataset. We argue that the specific network ties pose impact on one's credit score. Whether or not the network size matter in effecting other's credit scoring deserve further investigation.

The machine learning approaches experienced in this study proves that the ML classification algorithms can uncover the potential trustworthiness of borrowers with thin financial files. Nevertheless, this research raises more questions than offering specific answer, for example:

1) Given the social networks data role in credit scoring, what types of social ties should be collected and how?
2) How such social network data shall be collected with necessary consideration of privacy, ethics and governance issues?
3) How to monitor and track the changing dynamics of such social network ties, so as to ensure a true dynamic credit assessment? i.e. moving from looking backwards of the history/current to forward prediction?
4) How to ensure healthy or defaulting network ties not exacerbate social exclusion and digital gaps in societies?
5) How to detect/ eliminate / counter fight social networks behaviour that intentionally falsify lenders?

5. CONCLUSION

It is concluded that default social tie has a negative influence on borrower's credit scoring, but the size seems not significant. Machine learning models overall are effective in analyzing and predicting probability default, but the accuracy and precision can vary from one model to another, this depends on the nature and classes of the dataset. The social capital theory on homophily and obligations within social relations need further examination and validation.

Analysing borrowers' social circles and network types may not be useful in classifying default risk, unless as revealed in this study, the very specific type of network tie – either with default association, or financial homophily can be identified. The main challenges, however, are to determine the relevant criteria of the social networks by the lenders and credit agencies, and overcome privacy and ethical concerns raised by regulators and data subjects. There are also needs to examine changes in social networks over time as well as the network attributes – the network nodes, edges, centrality, size, distance, layers, etc.. This can advance not only credit scoring research, but also the areas of customer relationship management and business intelligence. This study raised an important question addressing financial exclusion problem if social networks data are not fairly used by lenders and effectively governed for social equality and inclusion.

REFERENCES

Ackert, L., & Deaves, R. (2009). *Behavioral finance: Psychology, decision-making, and markets.* Cengage Learning.

Arráiz, I., Bruhn, M., & Stucchi, R. (2017). Psychometrics as a tool to improve credit information. *The World Bank Economic Review*, *30* (Supplement_1), S67-S76.

Banasik, J., Crook, J. N., & Thomas, L. C. (1999). Not if but when will borrowers default. *Journal of the Operational Research Society*, 1185-1190.

Bjorkegren, D., & Grissen, D. (2015). Behavior revealed in mobile phone usage predicts loan repayment. *Social Science Research Network (SSRN)*, *2611775*, 1-10.

Chen, C., Lin, K., Rudin, C., Shaposhnik, Y., Wang, S., & Wang, T. (2018). An interpretable model with globally consistent explanations for credit risk. arXiv preprint arXiv:1811.12615.

Coleman, James S. (1988) Social Capital in the Creation of Human Capital. *The American Journal of Sociology*, Vol. 94, Supplement: Organizations and Institutions: Sociological and Economic Approaches to the Analysis of Social Structure (1988), pp. 95-120 URL: http://www.jstor.org/stable/2780243

Currier, J. (2020). Revealing the Unseen Forces That Guide Your Life. Your Life and Network Effects. Retrieved from https://www.nfx.com/post/your-life-network-effects/

Dastile, X., Celik, T., & Potsane, M. (2020). Statistical and machine learning models in credit scoring: A systematic literature survey. *Applied Soft Computing*, *91*, 106263.

Fernandez-Reino, M., & Rienzo, C. (2021). *Migrants in the UK labour market: An overview*. Migration Observatory-University of Oxford.

Freedman, S., & Jin, G. Z. (2017). The information value of online social networks: lessons from peer-to-peer lending. *International Journal of Industrial Organization,* 51, 185-222.

Gordy, M. B. (2000). A comparative anatomy of credit risk models. *Journal of Banking & Finance*, 24(1-2), 119-149.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360-1380.

Guo, G., Zhu, F., Chen, E., Liu, Q., Wu, L., & Guan, C. (2016). From footprint to evidence: an exploratory study of mining social data for credit scoring. *ACM Transactions on the Web* (TWEB), 10(4), 1-38.

Han, J., Pei, J., & Kamber, M. (2011). *Data mining: concepts and techniques*: Elsevier.

Lazarow, A. (2017). What do emerging market consumers expect from InsureTech? Retrieved from https://medium.com/omidyar-network/what-do-emerging-market-consumers-expect-from-insuretech-e439b894b2c5

Leow, M., & Crook, J. (2016). A new Mixture model for the estimation of credit card Exposure at Default. *European Journal of Operational Research*, 249(2), 487-497.

Lin, M., Prabhala, N. R., & Viswanathan, S. (2013). Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. *Management Science*, 59(1), 17-35.

Masyutin, A. (2015). Credit scoring based on social network data. *Бизнес-информатика*(3 (33)).

McEvoy, M. J., & Chakraborty, T. (2014). Enabling financial inclusion through “alternative data”. *Mastercard Advisors: Bentonville, AR, USA*.

McKillop, D. G., Ward, A.-M., & Wilson, J. O. (2007). The development of credit unions and their role in tackling financial exclusion. *Public money and management*, 27(1), 37-44.

Newman, M. (2010). *Networks: an introduction*: Oxford University Press, Oxford.

Pokorná, M., & Sponer, M. (2016). Social Lending and Its Risks. *Procedia - Social and Behavioral Sciences*, 220, 330-337. doi:10.1016/j.sbspro.2016.05.506

Puri, M., Rocholl, J., & Steffen, S. (2017). What do a million observations have to say about loan defaults? Opening the black box of relationships. *Journal of Financial Intermediation*, 31, 1-15.

Redrup, Y. (2017). How email and smartphone data could help you get a loan. Technology. Retrieved from http://www.afr.com/technology/how-email-and-smartphone-data-could-help-you-get-a-loan-20171212-h02zi0#ixzz534zFfQmg

Rusli, E. M. (2013). Bad credit? Start tweeting. *WALL ST. J.*, Apr, 1.

Schuermann, T. (2004). What do we know about loss given default?

Sullivan L. (2022) Nonparametric Tests. Retrieved 2022 from http://sphweb.bumc.bu.edu/otlt/MPH-Modules/BS/BS704_Nonparametric/BS704_Nonparametric_print.html

Thomas, L., Banasik, J., & Crook, J. (2001). Recalibrating scorecards. *Journal of the Operational Research Society*, 52(9), 981-988.

Thomas, L. C. (2009). *Consumer Credit Models: Pricing, Profit and Portfolios.* OUP Oxford.

Thomas, L. C., Edelman, D. B., & Crook, J. N. (2017). *Credit scoring and its applications (Second edition. ed.)*: Society for Industrial and Applied Mathematics.

Tong, E. N., Mues, C., Brown, I., & Thomas, L. C. (2016). Exposure at default models with and without the credit conversion factor. *European Journal of Operational Research*, 252(3), 910-920.

Turner, M., & McBurnett, M. (2019). Optimizing neural networks for risk assessment: Google Patents.

Wei, Y., Yildirim, P., Van den Bulte, C., & Dellarocas, C. (2015). Credit scoring with social network data. *Marketing Science*, 35(2), 234-258.

West, D. (2000). Neural network credit scoring models. *Computers & Operations Research*, 27(11), 1131-1152.

What's in my FICO scores. Retrieved from http://www.myfico.com/credit-education/whats-in-your-credit-score/

Yan, J., Yu, W., & Zhao, J. L. (2015). How signaling and search costs affect information asymmetry in P2P lending: the economics of big data. *Financial Innovation*, 1(1), 1.