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| **1.** | @article{Liu2019ResearchOP,  title={Research on Personal Credit Scoring Model Based on Artificial Intelligence},  author={Chengyong Liu and Huang-Chen Huang and Shangqian Lu},  journal={Application of Intelligent Systems in Multi-modal Information Analytics},  year={2019},  } | Artificial intelligence is considered to be the technological commanding height of the next era. At present, after the development of China’s artificial intelligence industry ranks in the United States, its application in the financial field is also in a new stage of rapid development, and affects many aspects of the financial industry, thus strengthening its research is of great significance. The continuous development of artificial intelligence technology has been widely used in many aspects of financial services, which is of great significance for the realization of its modeling, standardization and intelligent development. However, there are still security risks hidden in the application, which requires attention to this. aspects of the research to identify effective measures for risk prevention, this paper analyzes the application of artificial intelligence in the financial sector in the personal credit score. |
| **2.** | @article{Gahlaut2017PredictionAO,  title={Prediction analysis of risky credit using Data mining classification models},  author={Archana Gahlaut and Tushar and Prince Kumar Singh},  journal={2017 8th International Conference on Computing, Communication and Networking Technologies (ICCCNT)},  year={2017},  pages={1-7},  } | Gaining as many good credit scores are beneficial for customers in numerous ways and it also allows banks to analyse their clients and to give credit loans to them accordingly. In this paper, we look whether data mining techniques are useful to predict and classify the customer's credit score (good/bad) to overcome the future risks giving loans to clients who cannot repay. We use historical given dataset of a bank for our predictive modelling (general models), banks can use them for the better outcome of their overall credit system. For example, if a customer is assigned a bad credit score after applying these predictive classification models, then the bank will not allow giving that customer a future credit and will quickly analyse all the other risky credits. |
| **3.** | @article{Du2022ExplorationOF,  title={Exploration of Financial Market Credit Scoring and Risk Management and Prediction Using Deep Learning and Bionic Algorithm},  author={Peng Du and Hong Shu},  journal={J. Glob. Inf. Manag.},  year={2022},  volume={30},  pages={1-29},  } | The purpose is to effectively manage the financial market, comprehensive assess personal credit, reduce the risk of financial enterprises. Given the systemic risk problem caused by the lack of credit scoring in the existing financial market, a credit scoring model is put forward based on the deep learning network. The proposed model uses RNN (Recurrent Neural Network) and BRNN (Bidirectional Recurrent Neural Network) to avoid the limitations of shallow models. Afterward, to optimize path analysis, bionic optimization algorithms are introduced, and an integrated deep learning model is proposed. Finally, a financial credit risk management system using the integrated deep learning model is proposed. The probability of default or overdue customers is predicted through verification on three real credit data sets, thus realizing the credit risk management for credit customers |
| **4.** | @article{Brevoort2016CreditIA,  title={Credit Invisibles and the Unscored},  author={Kenneth P. Brevoort and Philipp H. Grimm and Michelle Kambara},  journal={Household Finance eJournal},  year={2016},  } | Having a credit record and a credit score can be an important determinant of credit access. Yet, surprisingly little is known about people who lack credit records or scores. This paper provides the first documented analysis of the characteristics of consumers without credit records, called "credit invisibles," and of consumers whose records are treated as "unscorable" by a widely used credit-scoring model. Our estimates suggest that 26 million adults, representing about 11 percent of the adult population, lack credit records. An additional 8.3 percent, or 19.6 million adults have credit records that are unscored. The incidence of having a credit record is not evenly distributed. Young, elderly, minority, and lower-income consumers are more likely to be credit invisible or have an unscored record. Additionally, our analysis finds that observable credit performance is not widely available for such consumers, which may hinder the ability of alternative data to expand credit access for these consumers. |
| **5.** | @article{Burke2019CreditBO,  title={Credit Building or Credit Crumbling? A Credit Builder Loan's Effects on Consumer Behavior, Credit Scores and Their Predictive Power},  author={Jeremy Burke and Julian C. Jamison and Dean S. Karlan and Kata Mihaly and Jonathan Zinman},  journal={Household Finance eJournal},  year={2019},  } | There is little evidence on how the large market for credit score improvement products affects consumers or credit market efficiency. A randomized encouragement design on a standard credit builder loan (CBL) identifies null average effects on whether consumers have a credit score and the score itself, with important heterogeneity: those with loans outstanding at baseline fare worse, those without fare better. Selection, treatment effect, and prediction models indicate the CBL reveals valuable information to markets, inducing positive selection and making credit histories more precise, while keeping credit scores' predictive power intact. With modest targeting changes, CBLs could work as intended. |
| **6.** | @article{Herkenhoff2020TheIO,  title={The Impact of Consumer Credit Access on Self-Employment and Entrepreneurship},  author={Kyle F. Herkenhoff and G. Phillips and Ethan Cohen-Cole},  journal={Tuck School of Business at Dartmouth Research Paper Series},  year={2020},  } | Abstract We examine how consumer credit affects entrepreneurship by linking three million earnings and pass-through tax records to credit reports. In the cross-section, we show that self-employment without employees and employer firm ownership increase monotonically with credit limits and credit scores. We then isolate individuals who have had discrete increases in credit limits after the exogenous removal of bankruptcy flags to measure the effects of personal credit on entrepreneurship. Following bankruptcy flag removal, individuals are more likely to start a new employer business and borrow extensively. Those who own businesses with employees borrow $40,000 more after bankruptcy flag removal, a 33% gain relative to the sample average. |
| **7.** | @article{Herkenhoff2020TheIO,  title={The Impact of Consumer Credit Access on Self-Employment and Entrepreneurship},  author={Kyle F. Herkenhoff and G. Phillips and Ethan Cohen-Cole},  journal={Tuck School of Business at Dartmouth Research Paper Series},  year={2020},  } | Abstract We examine how consumer credit affects entrepreneurship by linking three million earnings and pass-through tax records to credit reports. In the cross-section, we show that self-employment without employees and employer firm ownership increase monotonically with credit limits and credit scores. We then isolate individuals who have had discrete increases in credit limits after the exogenous removal of bankruptcy flags to measure the effects of personal credit on entrepreneurship. Following bankruptcy flag removal, individuals are more likely to start a new employer business and borrow extensively. Those who own businesses with employees borrow $40,000 more after bankruptcy flag removal, a 33% gain relative to the sample average. |
| **8.** | @article{Wang2022ADL,  title={A Deep Learning Approach for Credit Scoring Using Feature Embedded Transformer},  author={Chongren Wang and Zhuoyi Xiao},  journal={Applied Sciences},  year={2022},  } | In this paper, we introduce a transformer into the field of credit scoring based on user online behavioral data and develop an end-to-end feature embedded transformer (FE-Transformer) credit scoring approach. The FE-Transformer neural network is composed of two parts: a wide part and a deep part. The deep part uses the transformer deep neural network. The output of the deep neural network and the feature data of the wide part are concentrated in a fusion layer. The experimental results show that the FE-Transformer deep learning model proposed in this paper outperforms the LR, XGBoost, LSTM, and AM-LSTM comparison methods in terms of area under the receiver operating characteristic curve (AUC) and the Kolmogorov–Smirnov (KS). This shows that the FE-Transformer deep learning model proposed in this paper can accurately predict user default risk. |
| **9.** | @article{Bussmann2019ExplainableML,  title={Explainable Machine Learning in Credit Risk Management},  author={Niklas Bussmann and Paolo Giudici and Dimitri Marinelli and Jochen Papenbrock},  journal={Computational Economics},  year={2019},  volume={57},  pages={203 - 216},  } | The paper proposes an explainable Artificial Intelligence model that can be used in credit risk management and, in particular, in measuring the risks that arise when credit is borrowed employing peer to peer lending platforms. The model applies correlation networks to Shapley values so that Artificial Intelligence predictions are grouped according to the similarity in the underlying explanations. The empirical analysis of 15,000 small and medium companies asking for credit reveals that both risky and not risky borrowers can be grouped according to a set of similar financial characteristics, which can be employed to explain their credit score and, therefore, to predict their future behaviour. |
| **10.** | @article{Zeng2020OnTC,  title={On the confusion matrix in credit scoring and its analytical properties},  author={Guoping Zeng},  journal={Communications in Statistics - Theory and Methods},  year={2020},  volume={49},  pages={2080 - 2093},  } | Abstract Confusion Matrix is an important measure to evaluate the accuracy of credit scoring models. However, the literature about Confusion Matrix is limited. The analytical properties of Confusion Matrix are ignored. Moreover, the concept of Confusion Matrix is confusing. In this article, we systematically study Confusion Matrix and its analytical properties. We enumerate 16 possible variants of Confusion Matrix and show that only 8 are reasonable. We study the relationship between Confusion Matrix and 2 other performance measures: the receiver operating characteristic curve (ROC) and Kolmogorov-Smirnov statistic (KS). We show that an optimal cutoff score can be attained by KS. |
| **11.** | @article{Bhutta2021HowMD,  title={How Much Does Racial Bias Affect Mortgage Lending? Evidence from Human and Algorithmic Credit Decisions},  author={Neil Bhutta and Aurel Hizmo and Daniel R. Ringo},  journal={ERN: Microeconometric Studies of Housing Markets (Topic)},  year={2021},  } | We assess racial discrimination in mortgage approvals using new data on mortgage applications. Minority applicants tend to have significantly lower credit scores, higher leverage, and are less likely than white applicants to receive algorithmic approval from race-blind government automated underwriting systems (AUS). Observable applicant-risk factors explain most of the racial disparities in lender denials. Further, we exploit the AUS data to show there are risk factors we do not directly observe, and our analysis indicates that these factors explain at least some of the residual 1-2 percentage point denial gaps. Overall, we find that differential treatment has played a limited role in generating denial disparities in recent years. |
| **12.** | @article{Alali2012TheEO,  title={The Effect of Corporate Governance on Firm’s Credit Ratings: Further Evidence Using Governance Score in the United States},  author={Fatima Alali and Asokan Anandarajan and Wei Jiang},  journal={Auditing},  year={2012},  } | We investigate whether corporate governance affects firms’ credit ratings and whether improvement in corporate governance standards is associated with improvement in investment grade rating. We use the Gov‐score of Brown and Caylor (2006), the Gomper’s G index and an entrenchment score of Bebchuk et al. (2009) to proxy for corporate governance. Using a sample of US firms, we find that firms characterized by stronger corporate governance have a significantly higher credit rating, and that this association is accentuated for smaller firms relative to larger firms. We find that an improvement in corporate governance is associated with improvement in bond rating. |
| **13.** | @article{Hassija2020SecureLB,  title={Secure Lending: Blockchain and Prospect Theory-Based Decentralized Credit Scoring Model},  author={Vikas Hassija and Gaurang Bansal and Vinay Chamola and Neeraj Kumar and Mohsen Guizani},  journal={IEEE Transactions on Network Science and Engineering},  year={2020},  volume={7},  pages={2566-2575},  } | Credit scoring is a rigorous statistical analysis carried out by lenders and other third parties to access an individual's creditworthiness. Lenders use credit scoring to estimate the degree of risk in lending money to an individual. However, credit score evaluation is primarily based on a transaction record, payment history, professional background, etc. sourced from different credit bureaus. So, evaluating a credit score is a laborious and tedious task involving a lot of paperwork. In this paper, we propose how blockchain can provide the solution to decentralized credit scoring evaluation and reducing the amount of dependence of paperwork. Lending money is not always objective but subjective to every lender. The decision of lending involves different levels of risk and uncertainty, depending on their perspective. This paper uses the prospect theory to model the optimal investment strategy for different risk vs. return scenarios. |
| **14.** | @article{Ampountolas2021AML,  title={A Machine Learning Approach for Micro-Credit Scoring},  author={Apostolos Ampountolas and Titus Nyarko Nde and Paresh Date and Corina Constantinescu},  journal={Risks},  year={2021},  } | In micro-lending markets, lack of recorded credit history is a significant impediment to assessing individual borrowers’ creditworthiness and therefore deciding fair interest rates. This research compares various machine learning algorithms on real micro-lending data to test their efficacy at classifying borrowers into various credit categories. We demonstrate that off-the-shelf multi-class classifiers such as random forest algorithms can perform this task very well, using readily available data about customers (such as age, occupation, and location). This presents inexpensive and reliable means to micro-lending institutions around the developing world with which to assess creditworthiness in the absence of credit history or central credit databases. |
| **15.** | @article{Robb2018TestingFR,  title={Testing for racial bias in business credit scores},  author={Alicia Robb and David T. Robinson},  journal={Small Business Economics},  year={2018},  volume={50},  pages={429-443},  } | We develop a novel empirical test of racial bias based on comparisons between forward-looking, expectations-based credit scores and backward-looking, repayment-history-based credit scores. We then test for racial bias using confidential-access data from the Kauffman Firm Survey. Businesses founded by disadvantaged minorities have much lower average business credit scores, but these scores show no evidence of racial bias. If anything, forward-looking credit-score models under-predict the rate of payment delinquency among minority-owned businesses. |
| **16.** | @article{Oh2009EvaluationOC,  title={Evaluation of credit guarantee policy using propensity score matching},  author={Inha Oh and Jeong-Dong Lee and Almas Heshmati and Gyoung-Gyu Choi},  journal={Small Business Economics},  year={2009},  volume={33},  pages={335-351},  } | In this article, we evaluate the effect of the credit guarantee policy by comparing a large sample of guaranteed firms and matched non-guaranteed firms from 2000 to 2003. The sample firms are compared with respect to growth rates of different performance indicators including: productivity, sales, employment, investment, R&D, wage level, and the survival of firms in the post crisis period. In order to avoid the selectivity problem, propensity score matching methodologies are adopted. Results suggest that credit guarantees influenced significantly firms’ ability to maintain their size, and increase their survival rate, but not to increase their R&D and investment and hence, their growth in productivity. Moreover, due to the adverse selection problem, firms with lower productivity were receiving guarantees. |
| **17.** | @article{Jiang2020DecipheringBD,  title={Deciphering Big Data in Consumer Credit Evaluation},  author={Jinglin Jiang and Li Liao and Xi Lu and Zhengwei Wang and Hongyu Xiang},  journal={International Political Economy: Investment \& Finance eJournal},  year={2020},  } | Abstract This paper examines the impact of large-scale alternative data on predicting consumer delinquency. Using a proprietary double-blinded test from a traditional lender, we find that the big data credit score predicts an individual’s likelihood of defaulting on a loan with 18.4% greater accuracy than the lender’s internal score. Moreover, the impact of the big data credit score is more significant when evaluating borrowers without public credit records. We also provide evidence that big data have the potential to correct financial misreporting. |
| **18.** | @article{Puri2018OnTR,  title={On the Rise of FinTechs – Credit Scoring Using Digital Footprints},  author={Manju Puri and Tobias Berg and Valentin Burg and Ana Gombovi{\'c}},  journal={Risk Management eJournal},  year={2018},  } | We analyze the information content of a digital footprint—that is, information that users leave online simply by accessing or registering on a Web site—for predicting consumer default. We show that even simple, easily accessible variables from a digital footprint match the information content of credit bureau scores. A digital footprint complements rather than substitutes for credit bureau information and affects access to credit and reduces default rates. We discuss the implications for financial intermediaries’ business models, access to credit for the unbanked, and the behavior of consumers, firms, and regulators in the digital sphere. (JEL G20, G21, G29) |
| **19.** | @article{Addi2020AnOM,  title={An Ontology-Based Model for Credit Scoring Knowledge in Microfinance: Towards a Better Decision Making},  author={Khaoula Ben Addi and Nissrine Souissi},  journal={2020 IEEE 10th International Conference on Intelligent Systems (IS)},  year={2020},  pages={380-385},  } | In developing countries, microfinance actors mobilized during the covid-19 pandemic to support the activities of their most vulnerable clients. In this context, the main concern of microfinance institutions is to minimize credit risk by adopting the most reliable scoring system possible. There are many dimensions to consider. In the literature, credit-scoring models essentially base on the financial dimension and neglect others deemed relevant. The study presented in this paper is based on a review of several models to identify aspects related to credit score in a microfinance context, in order to build an ontological model presenting the dimensions having an impact on credit score and their interrelations. The proposed model will help these institutions in their decision-making and in particular in the evaluation of the granting of loans. |
| **20.** | @article{Addi2020AnOM,  title={An Ontology-Based Model for Credit Scoring Knowledge in Microfinance: Towards a Better Decision Making},  author={Khaoula Ben Addi and Nissrine Souissi},  journal={2020 IEEE 10th International Conference on Intelligent Systems (IS)},  year={2020},  pages={380-385},  } | In developing countries, microfinance actors mobilized during the covid-19 pandemic to support the activities of their most vulnerable clients. In this context, the main concern of microfinance institutions is to minimize credit risk by adopting the most reliable scoring system possible. There are many dimensions to consider. In the literature, credit-scoring models essentially base on the financial dimension and neglect others deemed relevant. The study presented in this paper is based on a review of several models to identify aspects related to credit score in a microfinance context, in order to build an ontological model presenting the dimensions having an impact on credit score and their interrelations. The proposed model will help these institutions in their decision-making and in particular in the evaluation of the granting of loans. |
| **21.** | @article{Qi2021ApplicationOE,  title={Application of explainable machine learning based on Catboost in credit scoring},  author={Ji Qi and Ruicheng Yang and Pucong Wang},  journal={Journal of Physics: Conference Series},  year={2021},  volume={1955},  } | Credit scoring is the core part of an institution’s lending. As artificial intelligence is used in various fields, credit rating is also under the same topic of accepting technological changes. Combining credit evaluation and machine learning can incorporate relatively comprehensive features into the credit evaluation process. Through the excellent performance of Catboost, while ensuring accuracy, it demonstrates the explainability of the model as much as possible, avoiding the traditional trust problem of the black-box model. Explainability is proposed to the machine learning model, which reduces the difficulty of processing large amounts of data and the threshold for non-professionals to understand the model. In this article, the dataset is the personal loan data of LendingClub obtained through python. By analyzing the data through Catboost, we can derive excellent results in applying the explainability of machine learning in personal credit evaluation. |
| **22.** | @article{Kyeong2021CanSL,  title={Can System Logs Enhance the Performance of Credit Scoring? – Evidence from an Internet Bank in Korea},  author={Sunghyun Kyeong and Daehee Kim and Jinho Shin},  journal={Sustainability},  year={2021},  } | This study is the first to examine whether the performance of credit rating, one of the most important data-based decision-making of banks, can be improved by using banking system log data that is extensively accumulated inside the bank for system operation. This study uses the log data recorded for the mobile app system of Kakaobank, a leading internet bank used by more than 14 million people in Korea. After generating candidate variables from Kakaobank's vast log data, we develop a credit scoring model by utilizing variables with high information values. Consequently, the discrimination power of the new model compared to the credit bureau grades was significantly improved by 1.84% points based on the Kolmogorov–Smirnov statistics. Therefore, the results of this study imply that if a bank utilizes its log data that have already been extensively accumulated inside the bank, decision-making systems, including credit scoring, can be efficiently improved at a low cost. |
| **23.** | @article{Njuguna2021PosterAS,  title={Poster: A Scoping Review of Alternative Credit Scoring Literature},  author={Rebecca G Njuguna and Karen Sowon},  journal={ACM SIGCAS Conference on Computing and Sustainable Societies},  year={2021},  } | This paper covers a scoping review to establish the breadth of alternative credit scoring literature. The field is nascent and gaining popularity due to the crucial role alternative data is playing to accelerate financial inclusion. Historically, evaluating creditworthiness required availability of past financial activity such as loan repayment. Such stringent requirements rendered people with little or no financial history ‘credit invisible’. Advancements in Artificial Intelligence and Machine Learning have enabled scoring algorithms to work with non-financial data such as digital footprints from mobile devices and psychometric data to compute credit scores. Although the largest portion of ‘credit invisibles’ are in developing economies, research in the area is predominantly originating from developed economies and most alternative credit scoring models are trained with data from developed economies. There is need for more research from developing contexts and utilization of alternative data from populations with a smaller digital footprint. |
| **24.** | @article{Levinger2011TheCO,  title={The Cost of Not Knowing the Score: Self-Estimated Credit Scores and Financial Outcomes},  author={Benjamin Levinger and Marques Benton and Stephan Meier},  journal={Journal of Family and Economic Issues},  year={2011},  volume={32},  pages={566-585},  } | This study analyzes consumers’ knowledge of their own credit situation and tests whether a lack of knowledge affects financial outcomes. The unique dataset from survey and credit report data includes self-estimates of credit scores and actual scores from a low-to-moderate income sample. We argue and show empirically that many respondents don’t know their credit score and generally underestimate their creditworthiness. Furthermore, our evidence suggests that this biased self-assessment may explain differences in perceived credit constraints and credit contracts, specifically credit card interest rates. Our research suggests that an important aspect of financial literacy is self-assessment, and that it is important to encourage consumers to regularly check their credit reports and scores so as to better understand their actual creditworthiness. |
| **25.** | @article{Anderson2021RetailC,  title={Retail Credit},  author={Raymond A. Anderson},  journal={Credit Intelligence \& Modelling},  year={2021},  } | This chapter covers retail credit, which has different data and modelling needs than wholesale. (1) Scorecard terminology—presented is a points-based model (other forms are acknowledged). The goal is to identify rare events, e.g. loan defaults, liquidations, bankruptcies or other undesirable outcomes. (2) Retail models—types across the credit cycle {solicitation, origination, collection, recovery, fraud}, what is being measured {risk, response, retention, revenue}, whose data is used {bespoke, generic, pooled, borrowed} and how it is done {empirical, hybrid, expert judgment}. (3) Data sources—focus is on credit bureaux and credit registries, their spread across various countries, ownership types of credit bureaux and some behind their establishment and spread. (4) Risk indicators—presentation of scores to end-users or downstream processes, as distinct from risk grades. (5) FICO scores—provided by major credit bureaux, with details of different versions and types, plus an imperfect formula for converting their scores into probabilities. |
| **26.** | @article{Stango2016BorrowingHV,  title={Borrowing High versus Borrowing Higher: Price Dispersion and Shopping Behavior in the U.S. Credit Card Market},  author={Victor Stango and Jonathan Zinman},  journal={Review of Financial Studies},  year={2016},  volume={29},  pages={979-1006},  } | We document substantial cross-individual dispersion in U.S. credit card borrowing costs, even after controlling for borrower risk and card characteristics. That remaining dispersion arises because cross-lender pricing heterogeneity generates dispersion in annual percentage rate (APR) offers to borrowers, and borrowers vary in shopping intensity. Our empirics match administrative data to self-reported card shopping intensity and use instruments suggested by fair lending law to account for the endogeneity between APRs and search. The results show that shoppers versus nonshoppers pay APRs as different as those paid by borrowers in the best versus worst credit score deciles. We discuss implications for policy and practice. Received August 2, 2014; accepted July 7, 2015 by Editor Philip Strahan. |
| **27.** | @article{Giudici2020NetworkBC,  title={Network based credit risk models},  author={Paolo Giudici and Branka Hadji-Misheva and Alessandro Spelta},  journal={Quality Engineering},  year={2020},  volume={32},  pages={199 - 211},  } | Abstract Peer-to-Peer lending platforms may lead to cost reduction, and to an improved user experience. These improvements may come at the price of inaccurate credit risk measurements, which can hamper lenders and endanger the stability of a financial system. In the article, we propose how to improve credit risk accuracy of peer to peer platforms and, specifically, of those who lend to small and medium enterprises. To achieve this goal, we propose to augment traditional credit scoring methods with “alternative data” that consist of centrality measures derived from similarity networks among borrowers, deduced from their financial ratios. Our empirical findings suggest that the proposed approach improves predictive accuracy as well as model explainability. |
| **28.** | @article{Agarwal2019FinancialIA,  title={Financial Inclusion and Alternate Credit Scoring: Role of Big Data and Machine Learning in Fintech},  author={Sumit Agarwal and Shashwat Alok and Pulak Ghosh and Sudip Gupta},  journal={FEN: Behavioral Finance (Topic)},  year={2019},  } | We use unique and proprietary data from a large Fintech lender to analyze whether alternative data captured from an individual’s mobile phone (mobile/social footprint) can substitute for traditional credit bureau scores. Variables that measure a borrowers’ digital presence, such as the number and types of apps installed, crude measures of social connections, and measures of borrowers’ “deep social footprints” based on call logs, significantly improve default prediction and outperform the credit bureau score. Using machine learning-based prediction counterfactual analysis, we show that alternate credit scoring based on the mobile and social footprints can expand credit access for individuals who lack credit scores without adversely impacting the default outcomes. Our analysis suggests that the marginal benefit of using alternative data for credit decisions are likely to be higher for borrowers with low levels of income and education, as well as borrowers residing in regions with low levels of financial inclusion. |
| **29.** | @article{Jang2020ESGSA,  title={ESG Scores and the Credit Market},  author={Ga‐Young Jang and Hyoung-Goo Kang and Ju-Yeong Lee and Kyounghun Bae},  journal={Sustainability},  year={2020},  } | This study analyzes the relationship between Environmental, Social and Governance (ESG) scores and bond returns using the corporate bond data in Korea during the period of 2010 to 2015. We find that ESG scores include valuable information about the downside risk of firms. This effect is particularly salient for the firms with high information asymmetry such as small firms. Interestingly, of the three ESG criteria, only environmental scores show a significant impact on bond returns when interacted with the firm size, suggesting that high environmental scores lower the cost of debt financing for small firms. Finally, ESG is complementary to credit ratings in assessing credit quality as credit ratings cannot explain away ESG effects in predicting future bond returns. This result suggests that credit rating agencies should either integrate ESG scores into their current rating process or produce separate ESG scores which bond investors integrate with the existing credit ratings by themselves. |
| **30.** | @article{Smith2010StabilityIC,  title={Stability in Consumer Credit Scores: Level and Direction of FICO Score Drift as a Precursor to Mortgage Default and Prepayment},  author={Brent C. Smith},  journal={LSN: Other Consumer Reporting (Sub-Topic)},  year={2010},  } | This article represents an extension of the expansive credit risk and credit migration literature, prominent in the corporate bond and securities risk pricing literature, to an analysis of the drift of consumer credit scores. A rich data set of residential mortgages is used to observe credit score migration post loan origination and in a test of the ability of credit score transition to serve as a precursor to potential default and prepayment. The results indicate credit scores provide signals and information to investors and servicing agents in a fashion similar to credit ratings on commercial paper as to default potential. |

Giới Thiệu

Trí tuệ nhân tạo được coi là đỉnh cao chỉ huy công nghệ của kỷ nguyên tiếp theo. Hiện tại, sau sự phát triển của ngành công nghiệp trí tuệ nhân tạo của Trung Quốc ở Hoa Kỳ, ứng dụng của nó trong lĩnh vực tài chính cũng đang ở giai đoạn phát triển nhanh chóng mới và ảnh hưởng đến nhiều khía cạnh của ngành tài chính, do đó việc tăng cường nghiên cứu của nó có ý nghĩa rất lớn. . Sự phát triển không ngừng của công nghệ trí tuệ nhân tạo đã được sử dụng rộng rãi trong nhiều khía cạnh của dịch vụ tài chính, điều này có ý nghĩa to lớn đối với việc hiện thực hóa mô hình hóa, tiêu chuẩn hóa và phát triển thông minh của nó. Tuy nhiên, vẫn có những rủi ro bảo mật tiềm ẩn trong ứng dụng, cần phải chú ý đến điều này. khía cạnh nghiên cứu nhằm xác định các biện pháp phòng ngừa rủi ro hiệu quả, bài viết này phân tích việc ứng dụng trí tuệ nhân tạo trong lĩnh vực tài chính trong việc chấm điểm tín dụng cá nhân [1] Đạt được càng nhiều điểm tín dụng tốt sẽ có lợi cho khách hàng theo nhiều cách và nó cũng cho phép các ngân hàng phân tích khách hàng của họ và cấp các khoản vay tín dụng cho họ phù hợp. Trong bài viết này, chúng tôi xem xét liệu các kỹ thuật khai thác dữ liệu có hữu ích trong việc dự đoán và phân loại điểm tín dụng của khách hàng (tốt/xấu) nhằm khắc phục những rủi ro trong tương lai khi cho những khách hàng không có khả năng trả nợ vay hay không. Chúng tôi sử dụng tập dữ liệu lịch sử đã cho của một ngân hàng cho mô hình dự đoán của mình (mô hình chung), các ngân hàng có thể sử dụng chúng để mang lại kết quả tốt hơn cho hệ thống tín dụng tổng thể của họ. Ví dụ: nếu một khách hàng bị xếp hạng tín dụng xấu sau khi áp dụng các mô hình phân loại dự đoán này, thì ngân hàng sẽ không cho phép cấp tín dụng trong tương lai cho khách hàng đó và sẽ nhanh chóng phân tích tất cả các khoản tín dụng rủi ro khác [2]. Mục đích nhằm quản lý hiệu quả thị trường tài chính, đánh giá toàn diện tín dụng cá nhân, giảm thiểu rủi ro cho doanh nghiệp tài chính. Trước vấn đề rủi ro hệ thống do thiếu điểm tín dụng trên thị trường tài chính hiện tại, một mô hình chấm điểm tín dụng được đưa ra dựa trên mạng học sâu. Mô hình đề xuất sử dụng RNN (Mạng thần kinh tái phát) và BRNN (Mạng thần kinh tái phát hai chiều) để tránh những hạn chế của các mô hình nông. Sau đó, để tối ưu hóa việc phân tích đường dẫn, các thuật toán tối ưu hóa sinh học được giới thiệu và mô hình học sâu tích hợp được đề xuất. Cuối cùng, một hệ thống quản lý rủi ro tín dụng tài chính sử dụng mô hình deep learning tích hợp được đề xuất. Xác suất khách hàng vỡ nợ hoặc quá hạn được dự đoán thông qua xác minh trên ba bộ dữ liệu tín dụng thực tế, từ đó hiện thực hóa việc quản lý rủi ro tín dụng cho khách hàng tín dụng [3]. Có hồ sơ tín dụng và điểm tín dụng có thể là yếu tố quyết định quan trọng trong việc tiếp cận tín dụng. Tuy nhiên, điều đáng ngạc nhiên là rất ít thông tin về những người thiếu hồ sơ hoặc điểm tín dụng. Bài viết này cung cấp phân tích tài liệu đầu tiên về đặc điểm của người tiêu dùng không có hồ sơ tín dụng, được gọi là "tín dụng vô hình" và của người tiêu dùng có hồ sơ được coi là "không thể tính điểm" bằng mô hình chấm điểm tín dụng được sử dụng rộng rãi [4]. Hiện chưa có nhiều bằng chứng về cách thị trường lớn về sản phẩm cải thiện Credit score ảnh hưởng đến người tiêu dùng hay hiệu suất thị trường tín dụng. Một nghiên cứu ngẫu nhiên sử dụng mô hình khuyến nghị trên một khoản vay xây dựng Credit score tiêu chuẩn (CBL) xác định không có tác động trung bình vào việc người tiêu dùng có Credit score hay không và điểm số chính nó, tuy nhiên có sự khác biệt quan trọng: những người có khoản vay còn tồn đọng từ trước thì kém hơn, còn những người không có vay thì tốt hơn. Các mô hình lựa chọn, tác động điều trị và dự đoán cho thấy CBL cung cấp thông tin quý giá cho thị trường, tạo ra sự lựa chọn tích cực và làm cho lịch sử tín dụng chính xác hơn, trong khi vẫn giữ nguyên khả năng dự đoán của Credit score. Với những thay đổi nhẹ trong việc định hướng, CBL có thể hoạt động như ý định [5]. Tóm tắt Chúng tôi xem xét tín dụng tiêu dùng ảnh hưởng như thế nào đến hoạt động kinh doanh bằng cách liên kết ba triệu thu nhập và hồ sơ thuế chuyển tiếp với các báo cáo tín dụng. Trong phần cắt ngang, chúng tôi cho thấy rằng việc tự kinh doanh không có nhân viên và quyền sở hữu công ty của người sử dụng lao động tăng đơn điệu với giới hạn tín dụng và điểm tín dụng. Sau đó, chúng tôi tách biệt những cá nhân đã tăng giới hạn tín dụng một cách riêng biệt sau khi loại bỏ các dấu hiệu phá sản ngoại sinh để đo lường tác động của tín dụng cá nhân đối với hoạt động kinh doanh. Sau khi dỡ bỏ cờ phá sản, các cá nhân có nhiều khả năng bắt đầu kinh doanh với chủ lao động mới và vay mượn nhiều hơn. Những người sở hữu doanh nghiệp có nhân viên vay thêm 40.000 USD sau khi gỡ bỏ cờ phá sản, mức tăng 33% so với mức trung bình của mẫu[6].

Credit score classification là quá trình phân loại đánh giá rủi ro tín dụng của khách hàng dựa trên các thông tin tài chính và hành vi tín dụng. Credit score, hay còn gọi là điểm tín dụng, đánh giá khả năng của người vay trả nợ và xác định mức rủi ro mà họ mang lại cho ngân hàng hoặc tổ chức tín dụng.

Quá trình phân loại Credit score bao gồm việc xây dựng mô hình dự đoán sử dụng các phương pháp thống kê và học máy. Các yếu tố quan trọng được sử dụng để tính toán Credit score bao gồm lịch sử thanh toán, tổng số tiền vay, tỷ lệ nợ, tỷ lệ sử dụng tín dụng, thời gian sử dụng tín dụng và nhiều yếu tố khác.

Mô hình Credit score được huấn luyện trên một tập dữ liệu lớn chứa thông tin tài chính của khách hàng và kết quả thanh toán trước đây. Các thuật toán phân loại được áp dụng để đưa ra dự đoán về khả năng trả nợ của khách hàng và xếp hạng họ vào các nhóm rủi ro khác nhau.

Quá trình phân loại Credit score có ứng dụng rộng rãi trong ngành ngân hàng và tài chính, giúp các tổ chức đánh giá rủi ro tín dụng và đưa ra quyết định về việc cấp cho vay, xác định mức lãi suất và hạn mức tín dụng. Nó cũng hỗ trợ người vay trong việc xây dựng và cải thiện Credit score của họ, từ đó tăng cơ hội được vay vốn và có điều kiện tài chính tốt hơn.

Trong tình hình kinh tế hiện nay, Credit score classification đóng vai trò quan trọng trong việc đảm bảo tính bền vững của hệ thống tài chính và xây dựng một môi trường tín dụng an toàn và minh bạch cho tất cả các bên liên quan.