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Application of Decision Tree Model in Personal Credit Scoring and Its Fairness Optimization

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Abstract: Credit scoring is an essential tool for assessing borrower risk in the financial industry. Traditional credit scoring methods often fail to maintain high accuracy and flexibility in the face of complex financial data. In contrast, decision tree modeling is an effective tool for improving the accuracy of credit scoring due to its simplicity and ability to handle complex data. However, decision tree models may also amplify biases in the data, leading to unfair treatment of certain groups in scoring. This paper explores several fairness optimization methods, such as data preprocessing, fairness constraints in model training, and post-processing adjustments to address this issue.It proposes a framework for balancing fairness, accuracy, and efficiency. Although these methods reduce bias to a certain extent, none of them deal with the issue of how to ensure fairness with high precision, so future research should focus on developing optimization algorithms adapted to dynamic environments, balancing multiple objectives, and improving fairness assessment criteria to achieve a fairer and more efficient credit scoring model that will promote the continued development of the financial industry and contribute to the sustainable development of society.

Keywords: Decision Tree Model, Financial Credit Scoring, Data Bias, Fairness Optimization.

1. Introduction

Credit scoring is an essential tool in the modern financial industry to measure the credit risk of the borrower to solve the loan approval, credit limit, and loan interest rate setting, which is regarded as a key evaluation index in almost all processes related to financial decision-making and is widely used [1]. Most of the traditional numerical methods for credit scoring are based on statistical models (mainly logistic regression models), which have been the preferred method for financial institutions because of their simplicity and ease of understanding. However, with the rapid development of the financial market, the amount of data collected is becoming huge, and the characteristics of the data are becoming more and more complex; the disadvantages of the traditional credit scoring methods in the face of non-linear and complex data of increasing scale are becoming apparent, especially the prediction accuracy is not in line with the current market demand for more and more complicated financial affairs [2].

To solve these problems, more and more financial institutions and scholars have started to adopt machine learning and data science techniques, especially decision tree modeling. Here, we can regard the decision tree model as a “yes” and “no” selection process, it will constantly divide the data into different groups. Each time it groups the data, it relies on only one of the most essential features to

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make a decision, ultimately resulting in one prediction for each group. In this way, the decision tree model identifies complex connections between the data and automatically filters out the features that impact the outcome most. This feature has led to the widespread use of decision trees in finance, especially in personal credit scoring. Compared with traditional models, decision tree models can handle more complex data and find the patterns inherent in the data, thus assessing credit more accurately. Another advantage is that it is highly interpretable, as the output of a decision tree model is presented as a clear tree diagram, where the basis for each step of the decision is visualized. This is especially important for financial decision-making, as it is directly related to customers' economic interests and social well-being [3].

While decision tree modeling has improved predictive accuracy and interpretability, its fairness issues cannot be ignored. When used for personal credit scoring, it has been found that if there is bias in the training data, the decision tree model amplifies this bias, which can disadvantage certain groups. These groups are not adequately evaluated in the model and naturally find it difficult to obtain loans or lower interest rates [4]. This phenomenon can exacerbate social inequality and raise legal and ethical issues. Therefore, optimizing the fairness of decision tree models as much as possible to ensure their predictions are accurate becomes an urgent problem in academia and finance. Current research in this area focuses on the following two directions: first, they explore the advantages and disadvantages of the decision tree model itself. Second, they investigated how to incorporate fairness optimization measures into the models. Kamiran and Calders proposed a data preprocessing method to remove bias from the data, and they reduced the bias of the model by adjusting the distribution of the data, and Chouldechova added fairness constraints into the training of the model, and they devised a new type of loss function that allows the model to maintain prediction accuracy while reducing the variance between groups, Lipton et al. proposed a post-processing approach after model training, where they adjusted the decision results to make the ratings of the groups more balanced [5-7]. These methods reduce the group bias in the decision tree model to some extent, but how to balance the accuracy and fairness of the decision tree model is still a challenge.

This paper outlines the application of decision tree models in personal credit scoring. It discusses fairness optimization methods, such as adding fairness constraints to model training and data preprocessing to remove bias. Although each method has its advantages and disadvantages, all of them can ensure fairness while improving prediction accuracy. The optimized decision tree model can give a fairer and more transparent credit assessment and avoid the legal and ethical issues caused by bias. The paper aims to provide ideas for the financial industry in balancing fairness and accuracy, to promote fairness improvement, and to facilitate financial institutions to fulfill their social responsibilities better.

2. Fundamentals of Decision Tree Modeling and Application to Personal Credit Scoring

2.1. Fundamentals and Advantages and Disadvantages of Decision Tree Modeling

A decision tree model can be viewed as a recursive classification process that progressively splits the data set through a series of conditional judgments, eventually forming a tree-like structure. In each split, the model decides the direction of branching by selecting the variables that will most influence the prediction based on the importance of the features. For example, the model might first make decisions based on features such as income and credit history. A decision tree can be compared to a tree, with the root representing the initial decision starting point, equivalent to the trunk. At this stage, the model asks the first key question:"Does the applicant have a regular income?" If the answer is "yes," the model will continue to analyze along one branch; if the answer is "no," the model will analyze along another branch. This process is repeated, repeatedly by progressively breaking down the data, eventually reaching leaf nodes that give predictions. For example, the final leaf node may

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determine “whether the customer will likely default on the loan.” Due to the straightforward structure and path of the decision tree, all decision-making processes can be easily tracked and understood, ensuring the model’s transparency and interpretability.

Decision tree modeling has many advantages, which is one of the reasons why it is so widely used. The most obvious one is that it is very easy to understand [8]. The entire decision tree model can be viewed as a step-by-step decision-making process, with each branch representing an explicit judgment node. For example, the model may determine, “Does the customer have a stable income?” If the answer is “yes,” the model continues to the next step of the analysis by asking, “What is the credit history?” Ultimately, the model will draw clear conclusions based on this set of judgments, such as “This customer has a low risk of default. This transparent decision-making process provides the final prediction and clearly demonstrates the result’s rationale, making the model's reasoning easy to understand and trace. For the financial sector, this is critical. Internally, clients, regulators, and firms want the model's reasoning to be clear and understandable. In addition to being transparent and understandable, a decision tree model is also very good at handling complex relationships [9]. It can automatically pick out the factors most important to the outcome and simply ignore those irrelevant. This is particularly useful when dealing with large-scale data. Compared with the traditional logistic regression model, which must first standardize and normalize the data, the decision tree model is not so “picky” about the data, greatly reducing the trouble of preliminary data processing. Of course, the decision tree model also has some shortcomings. A big problem is that it is easy to “remember too much,” that is, overfitting [10]. Especially when the training data is relatively small or noisy, the decision tree model may “remember” some irrelevant details. As a result, although it performs well on the training data, it is easy to make mistakes when facing new data. This problem is severe if the tree is too deep, as the model becomes too dependent on every little detail of the training data. Coupled with the fact that the decision tree is also sensitive to data changes, as long as the training data is slightly different, the generated tree may change completely, which leads to a less stable performance of the model [11]. However, these problems are not without a solution, by combining multiple decision trees can significantly improve the model effect. For example, Random Forest and Gradient Boosting Tree are typical examples of “many hands make light work” [12,13]. Allowing multiple trees to make decisions together greatly enhances the performance of the model. This approach also makes decision trees more powerful in practical applications and allows them to continue to play an important role in finance, healthcare, and other fields (All of the above can be seen in Figure 1).

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Figure 1: Decision tree model.

2.2. Typical Application of Decision Tree Modeling in Personal Credit Scoring

Decision tree modeling is widely used in personal credit scoring and is crucial in the financial industry. First, it is commonly used to predict credit risk. Banks will use decision tree models to predict whether a borrower will likely default on a loan. By analyzing information such as a borrower's past credit history, income status, and indebtedness, the model can predict the probability of a borrower defaulting on a loan in a future period. Assuming that a borrower has made late payments and has a high debt ratio, the decision tree model may assess that he has a high risk of default and therefore advise the bank to reject the borrower's loan application or reduce his loan amount. In this way, financial institutions can identify high-risk customers early and thus minimize losses. Second, decision tree modeling is important in loan approval and credit line management. Financial institutions will use decision tree modeling to decide whether to approve a customer's loan request and how much credit should be given. For example, suppose a customer applies for a large loan. In that case, the decision tree model will decide based on information such as the customer's credit score,

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job stability, income level, and debt ratio. If the customer has a high credit score and a stable income with low debt, the decision tree model may approve the loan and give a higher amount; on the contrary, if the customer has high debt or bad credit history, the model may reject the loan application or limit the loan amount. In addition, decision tree models are widely used for customer segmentation and credit rating. Banks use decision tree models to segment customers to provide differentiated financial services to customers with different risk levels. For example, banks classify customers into high-risk, medium-risk, and low-risk categories based on their spending behavior, repayment history, and account balance. For high-risk customers, banks may adjust credit card limits or adopt stricter loan vetting policies, while for low-risk customers, banks may offer more credit limits or favorable loan interest rates. This kind of personalized service improves customer satisfaction, and the bank can also use the decision tree model to adjust its resource allocation. It can be seen that the decision tree model is highly operable, practical, and convenient, has high decision-making efficiency, and is a powerful tool for banks to make loan approvals and business decisions.

3. Analysis and Optimization Methods for Fairness Problems in Decision Tree Models

3.1. Fairness Issues in Decision Tree Modeling

Decision tree models perform well in credit scoring, with precise predictions, simple and intuitive logic, and the ability to handle complex data. But it also has an obvious problem - fairness [6]. The model’s training requires a lot of historical data, but these data are often not fair enough and even come with some bias. For example, different economic conditions in other regions may lead to poorer loan records for certain areas; because of historical and cultural reasons, people of other genders or races have other performances in financial data [14]. However, these differences do not indicate how good or bad an individual's credit is. The model often fails to distinguish the social factors behind these, so the question arises. If the model sees that people in a particular area have had low loan success in the past, it may simply default to “people in this area are risky.” Even if the applicant's financial situation is good, the model may determine that the applicant is “unreliable.” This bias directly affects key decisions such as loan approvals and interest rate settings, and people who would otherwise be able to repay a loan may be denied a loan or receive a high interest rate due to these historical biases. This is unfair to the individual and not suitable for the bank, as they may miss out on a quality customer.

Unfairness in decision tree modeling has also caused a lot of trouble in the financial industry. First, it can lead to discriminatory decisions. This is because the model assigns lower credit scores to specific groups of people, directly affecting their success in applying for a loan and the interest rate they ultimately receive. For example, some people with low income or low credit history may be regarded as high risk by the model because of these “labels,” even if their repayment ability is very strong [15]. This phenomenon not only limits these groups’ access to financial services but also may further widen the gap between the rich and the poor and increase social inequality. Second, the bias in the modeling poses legal and ethical risks. Some countries and regions explicitly state that financial institutions cannot discriminate against borrowers based on race and gender. If the model’s results show such bias to some extent, it may be difficult for financial institutions to prove that their decisions are fair [6]. In the event of customer complaints or even legal actions, financial institutions may find it challenging to defend themselves and get into trouble. Not only that, but customers' trust in financial institutions may also be affected as a result. Once this trust crisis spreads, it not only affects the brand reputation but also causes the organization to lose competitiveness in the market. Therefore, the fairness of decision tree modeling is not only a technical issue but also an important topic in financial ethics [16]. With the rapid development of data science and artificial intelligence, financial institutions must abandon the practice of focusing only on the predictive effect of the model and cannot limit themselves to solving technical problems in relevant aspects by testing data after model design, but need to prejudge in advance whether the model is fair or not, and realize the vision of making the model fairer at the beginning of model design. This is not only a respect for the rights and interests of borrowers but also a wise choice in line with long-term development. From a current perspective, addressing data bias and model unfairness will help institutions improve the practical application of their models and avoid potential legal and social risks. Such efforts will ultimately create more value for the financial industry and give everyone fair access to financial services.

3.2. Introduction to Data Preprocessing, Model Training Phase Method and Model Post-Processing Method

3.2.1. Data Preprocessing Method

Preprocessing the data, mainly by changing the training data to reduce the bias in the model, Kamiran and Calders proposed a method called “re-sampling” [5], which reduces the unfairness of the data by balancing the sample size of different groups in two ways, namely, over-sampling and under-sampling. Oversampling is to replicate a smaller number of group samples so that these sample sizes are close to the larger group while under-sampling is to reduce a more significant number of group samples so that the sample sizes of the groups are closer to each other. This method is straightforward and efficient and can reduce inequities in the data before the model is trained. Another method is “unbiased feature selection,” which removes highly correlated variables, such as gender and race, to reduce the bias that the model may have learned from that information. For example, if variables that are highly correlated with income or occupational category but may be biased are removed, the model may score different groups more fairly.

3.2.2. Model Training Phase Method

Adding fairness constraints to model training is also a practical approach, and Chouldechova proposes a new approach by designing a “weighted loss function” [6]. This function looks at both the overall error and the difference in error between different groups when calculating the model error and sets different weights for each group. When a group has a higher error, the model is penalized more highly, forcing the model to reduce its bias against that group. For example, if men have a small mistake in predicting loan approval rates and women have a significant error, the model will put a higher weight on women's errors. In this way, the model pays more attention to the female group when optimizing, thus making the gap between the two narrower.

3.2.3. Model Post-Processing Method

The model post-processing method mainly adjusts the model results appropriately after the prediction results are available. Lipton et al. proposed a technique called “Threshold adjustment” [7]. They set different decision thresholds for different groups after model training. For example, a standard score is usually set in loan approval, and those who exceed this score can get a loan. The “threshold adjustment method” will set different standard scores for different groups according to their situations, which can make the scores of each group more fair. For example, if women's scores are generally lower than men's, the scoring criteria should be adjusted downward so that women are not disadvantaged. Essentially, this approach makes the model's predictions more balanced by changing decision-making boundaries.

3.3. Comparative Analysis of Different Methods

When optimizing model fairness, data preprocessing, model training phase method, and model post-processing method all have their characteristics and obvious advantages and disadvantages in different scenarios. In the following, we analyze them from three aspects: application stage, technical implementation, and stability of effect. The data preprocessing method adjusts the data before model training, and researchers improve the model's fairness by cleaning out the bias in the data. Because this method is not directly related to the model, it can be applied in a broader range. It has the advantage of being simple and efficient to implement, and it saves computational resources and training time because it deals directly with the raw data and does not require modification of the model structure. It also reduces the bias effect in the data and provides a fairer training environment for the model. However, it also has significant drawbacks; if the data is cleaned too thoroughly, there is a risk that important information will be cleaned out, indirectly affecting the model's predictive ability. In addition, in practice, biases are often profoundly hidden, and tough to detect and clean them up. The model training phase method adds fairness constraints in the model construction process, and the purpose of doing so is to try to find a balance between model prediction accuracy and model fairness by modifying the objective function in the model training process. Its advantage lies in its ability to dynamically optimize according to the errors of different groups because it directly affects the model during the model training process, so it can effectively reduce the unfair performance of the model for specific groups. However, the disadvantages of this method are also apparent. First, it is relatively complex to implement and requires significant modifications to the model algorithm and objective function; second, adding the fairness constraints may reduce the model accuracy, resulting in worse overall prediction; finally, the time for training will also increase significantly, which is not suitable for scenarios with short deployment cycles. The model post-processing method adjusts the output results after the model training is completed. The method does not change the structure of the model but only processes the prediction results. It has the advantage of being flexible and efficient, and since there is no need to retrain the model, this method can quickly adapt to various types of models. At the same time, it shows significant advantages in terms of time and cost and is suitable for optimizing existing systems. However, it may also over-adjust the final results, making the model's decisions ambiguous or questionable, and extreme over-correction strategies may also reduce the stability of the model's prediction results. The analysis shows that a single method often cannot solve all problems, and different scenarios may require a combination of methods to achieve fairness in optimization. By combining these methods, the model's prediction accuracy and practical application value of the model can be maximized while reducing bias.

3.4. Solutions and Innovative Proposals

When implementing fairness optimization for decision tree models, a single method often finds it challenging to meet practical needs. Therefore, it is an effective strategy to combine data preprocessing, model training, and post-processing techniques. First, data preprocessing methods can be used to remove obvious bias factors and ensure that the model's training data is fair. For example, resampling techniques are used to adjust the sample distribution and reduce the difference in data proportions between different groups; subsequently, moderate fairness constraints, such as the introduction of a fairness regularity term, are added in the model training stage to help the model handle data from different populations in a more balanced way. This two-stage approach can both reduce data bias and improve model performance. In addition, model post-processing can be used as an effective aid to optimization. It can appropriately correct the scoring results of special groups without changing the model structure. For example, adjusting the threshold strategy can allow the population close to the scoring boundary to obtain more reasonable decision results. This approach is

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flexible and efficient and can quickly respond to new problems after deployment. However, there are several other points of concern in the specific implementation process. The first is the screening of sensitive features, such as gender, age, and other variables. These factors are often prone to trigger model bias, and their reasonable treatment can effectively reduce the risk. The second is to set the fairness weights in the model training and balance the performance and fairness of the model by dynamically adjusting the fairness constraints. Finally, dynamic result monitoring is also needed after model deployment. Once a new bias phenomenon appears, post-processing methods can be used to make timely corrections. Some innovative solutions can further improve fairness optimization. For example, establishing dynamic fairness constraints so that the model automatically adjusts the degree of fairness optimization according to the different characteristics of each group and then using multi-objective optimization to balance the optimization space of the model on the fairness objective. In addition, a real-time feedback system can be constructed to record the unfair feedback of the model output results so that the model can automatically improve the decision. Through the above comprehensive strategies, the decision tree model can not only achieve higher fairness in personal credit scoring but also maintain better prediction accuracy, effectively reduce the ethical and legal risks caused by bias, and provide a more reliable and scientific credit assessment tool for the financial industry (All of the above can be seen in Figure 2).

Figure 2: Comparative analysis of different methods.

4. Conclusion

Optimizing the fairness of the model based on ensuring its prediction accuracy is both an important research topic in current theoretical research and a realistic demand for high-quality development of the financial industry and maintenance of social fairness and justice. This paper systematically introduces the application of the decision tree model in personal credit scoring and its fairness optimization problem and thoroughly discusses the research in related fields. Firstly, it reviews the advantages of the decision tree model in the financial industry, especially in the application of personal credit scoring; secondly, it summarizes and analyzes the three types of fairness optimization methods, namely, data preprocessing to remove bias, adding constraints during model training to model post-processing, and elaborates the various techniques individually. Secondly, three types of fairness optimization methods, namely, data preprocessing to remove bias, adding constraints during model training, and model post-processing, are summarized and analyzed, and the characteristics of each method and the problems in practical promotion are elaborated one by one.

However, the current research on optimizing decision tree model fairness still has some limitations. First, most of the current methods for maximizing the fairness of decision tree models are solved on small datasets. When facing a large number of complex datasets in the financial field, the algorithms have a low training speed and high time complexity, and the computational efficiency of the models still needs to be improved. Second, there is a conflict between optimizing the fairness of the decision tree model and improving the model’s accuracy. The correlation model reduces the gap between individuals or groups through fairness constraints, and the accuracy of the model suffers a specific loss, how to improve the fairness of the decision tree model without loss of accuracy is a difficulty and research hotspot that still needs to be overcome. Third, many research studies have neglected the environmental dynamics in the financial field. Due to the dynamic changes in the financial market and customer behavior, the static data optimization strategy will lose its versatility, which requires the algorithm to be able to dynamically adapt to the dynamic adjustments of the environment, improve the practical use of the model in the financial field, and achieve the adaptation of the model to the environment. In addition, multi-objective optimization in the financial field is also worthy of attention, as well balancing fairness, prediction accuracy, customer satisfaction and risk control costs. To solve these problems, future research can start from the following aspects: first, develop dynamic fairness optimization models that can cope with the changes in the financial domain. Second, explore fairness strategies in federated learning to optimize fairness while protecting privacy. Third, multi-objective optimization methods should be tried to balance the needs of multiple objectives. Finally, the fairness measurement index can be improved and a more complex evaluation system can be designed to accurately assess the model's fairness performance. These innovations are expected to promote the fairness optimization of decision tree models in the financial field and support the healthy development of fintech.

This paper argues that with the popularization and development of data science and artificial intelligence, the optimization of model fairness in the future will have more critical research significance, that is, the achievability of model fairness optimization will no longer be a purely academic issue, but a realistic issue involving social fairness and financial services inclusion. With the development of AI models, the decision tree model will have more prominent breakthroughs in fairness optimization, especially after emerging algorithms, integrated algorithms, and other continuous optimization and upgrading of the model, AI will help financial institutions to build a fairer, more transparent and more trustworthy credit assessment system. The significance of fairness optimization is not only limited to the level of technology but also lies in how financial companies can make better use of AI technology and assume social responsibility, which is another direction for the future development of financial technology. In particular, how to treat the fairness between

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finance and technology is currently a very sensitive topic in applying fintech. With the extension of application scenarios, how to better utilize AI technology to protect the rights and interests of financial consumers and users and better serve customers is also a core point of the development of innovative finance. AI-driven balance between fairness and efficiency not only allows for an accurate assessment of risk, but also provides service recipients with the equal opportunities. Therefore, this paper combs and summarizes the existing optimization methods to offer financial institutions with AI-driven optimization model design ideas. At the same time, this is used as a reference to assist financial institutions and financial institution product design. The only way to promote the inclusive and fair development of the financial industry and contribute to the long-term sustainable development of society is to balance the fairness and efficiency of the AI model.

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