Financial Risks Identification Model based on Reinforcement Learning

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Abstract. At present, financial risks have become an important problem for companies due to the large amount of transcation data and the uncontrolled transcation behaviours. Therefore, identifying the risks is essential for companies to know the possible crisis and provide corrsponding measures, which also plays an irreplaceable component for marketing and economic development. However, existing identification methods are concentrated on using mathematical models and analyzing the correlations among risk factors, which can not satisfy large amount of financial data and complex risks relationships. In this work, we initally attempt to establish a learning model to extract the features of financial risks. Subsequently, a reinforcement learning model is trained to classify risks and non-risks data with enough training iterations. Finally, we evaluate the proposed model with real-life data-set and compare with existing risk identification models to measure the performance of proposed model with multi-levels metrics. From our experimental results, we can observe that our model can achieve the identification of risks data with acceptable accuracy and reasonable computation costs.

Keywords: Financial risks identification, Risk feature extraction, Reinforcament learning, Classification accuracy.

1 Introduction

Financial risks identification is a crucial component in economic planning and management for individuals, companies, and governments. It encompasses the process of understanding and analyzing the potential crisis that can adversely influence the financial objectives and performance [1]. These risks may arise from various sources including changes in market conditions, interest rates, exchange rates, credit risks, liquidity constraints, operational failures, and more. The importance of identifying financial risks can not be overstated, as it enables stakeholders to implement timely and effective measures to mitigate potential losses. Specifically, economic environments are constantly changing, which is fueled by technological advancements, globalization, and shifting regulatory landscapes, financial risks can be both complex and unpredictable [2].

For businesses aspect, this process can be an integral part of strategic planning, where it aligns with the organization's risk appetite and tolerance levels. The procedure can also assist in developing risk management strategies, prioritizing resources, and ensuring that risks are managed in accordance with the organization's overall objectives [3]. In personal finance environment, identifying risks assists in creating a robust financial plan that can withstand unexpected shocks, ensuring long-term financial stability and security. Whether through

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quantitative modeling, qualitative assessments, or a combination of both, financial risks identification demands a systematic approach and deep understanding of the financial landscape [4]. It's a continuous process that requires regular monitoring and updating as market conditions evolve. Engaging in this practice helps secure the financial future, minimize unexpected losses, and foster sustainable growth, making it indispensable in today's fast-paced financial world.

Reinforcement learning represents a paradigm of learning that is inspired by behavioral psychology and concerns the way in which intelligent agents take actions in an environment to achieve specific targets. Unlike other supervised learning, where the correct answers are provided, or unsupervised learning, where only the input data is given, reinforcement learning operates in a manner where a module learns by interacting with its all samples and receiving feedback in the form of rewards or penalties [5]. The target can be generated from a simple software algorithm to a complex robotic system, takes actions according to its current understanding or policy. In response to each action, the environment provides a new state and a numerical reward, reflecting how beneficial or detrimental the action was. Over time, the agent seeks to optimize its policy to accumulate the maximum possible reward, learning the best actions to take in various situations [6].

Reinforcement learning is often associated with a trial-and-error learning process, where the agent explores different strategies and gradually hones in on the optimal way to act. The core components of reinforcement learning process include defining what the states of the environment are, what actions the agent can take, and how the rewards are structured. The balance between exploration and exploitation is a central challenge in reinforcement learning [7]. Applications of RL are broad and expanding, including areas including gaming, robotics, financial trading, healthcare, energy management, and real-life applications.

The reminder of this paper is allocated as an introduction about existing indentification methods and used parameters in proposed model in Section 2. Subsequently, we illustrate the general framework and specifical components in the proposed reinforcement model in Section 3. Experimental results and comparison analysis with existing identification methods are provided in Section 4. Finally, we conclude the proposed model and offer several improvement mechanisms for the future investigations.

2 Preliminaries

In this section, we initially introduce the related contributions towards finicial risks identification. Indeed, the primary parameter symbols and corresponding explanations are provided.

2.1 Related works

Initially, Amirhossein Sadoghi introduces a robust metric to identify Systemically Important Financial Institutions (SIFI) in a financial network, developing an efficient algorithm to rank institutions, studying the underlying distribution of the proposed metric, and analyzing the possible indicators by showing the credit risks including credit default risk, market risk, purchasing power risk, etc [8]. Indeed, researchers Maha Bakoben, Tony Bellotti, and Niall Adams utilize cluster analysis (CA) of credit card account behaviors to assess credit risk levels, modeling account behavior parametrically, and implementing behavioral cluster analysis using a recently proposed dissimilarity measure of statistical model parameters, leading to interesting clusters of real credit card behaviors and superior prediction of account default [9].

With the development of interdisciplinary and machine learning methods, Researcher Antoaneta Sergueiva outlines an integrated approach for systemic risk evaluation based on multiple types of interbank exposures (MIE) through innovative modeling approaches as tensorial multilayer networks, reasoning about data requirements and time scale effects, and suggesting a multi-model hypernetwork of systemic risk knowledge as a scenario analysis and policy support tool [10]. Furthermore, Jie Dong constructs a system to identify financial risk paths in the context of digital transformation, exploring the intrinsic association among the influencing factors of corporate financial risks, identifying key factors, and analyzing the dependency and driving relationships among them using DEMATEL-ISM-MICMAC (DIM) [11].

2.2 Parameters description

After knowing the existing identification methods, we will illustrate our used parameters and corresponding explanations in the reinforcement model. Following Table 1 shows the deatil information.

Table 1. Parameters Description.

Parameter Symbols	Explanations
I	Input data
Acc	Identification accuracy
y	Prediction labels
r	Reward values
Q	States of prediction

3 Methodologies

After knowing backgound knowledge, we will introduce our proposed model with detail component and training process in this section. Initially, we provide the primary procedures of proposed model. Subsequently, the model components and training principle is given to explain the reinforcement mechanism.

3.1 Primary procedures description

We summarize the main components of our model in following items and illustrate the functions of these modules.

- Collection: Collect historical financial data including the market trends, asset prices, interest rates, and other relevant information. These data will be utilized to train and test the proposed model.
- Preprocessing: Update and preprocess the data to remove any inconsistencies or missing values. Normalize or scale the features to make them suitable for training the reinforcement model.

- Environment Design: Create a simulated environment that represents the financial market or system. This environment will allow the learning agent to interact and learn from its actions and the corresponding rewards or penalties.
- Model Architecture: Deploy the learning model architecture, including the selection of appropriate algorithms including the Q-learning and Deep Q-Networks. Define the state space, action space, reward function, and other hyperparameters.
- Training: Train the proposed agent by allowing it to interact with the simulated environment. The agent will explore different actions and learn from the rewards to develop a policy that maximizes the expected cumulative reward.

3.2 Framework illustration

Subsequently, we show the general framework of proposed reinforcement module in following Figure 1.

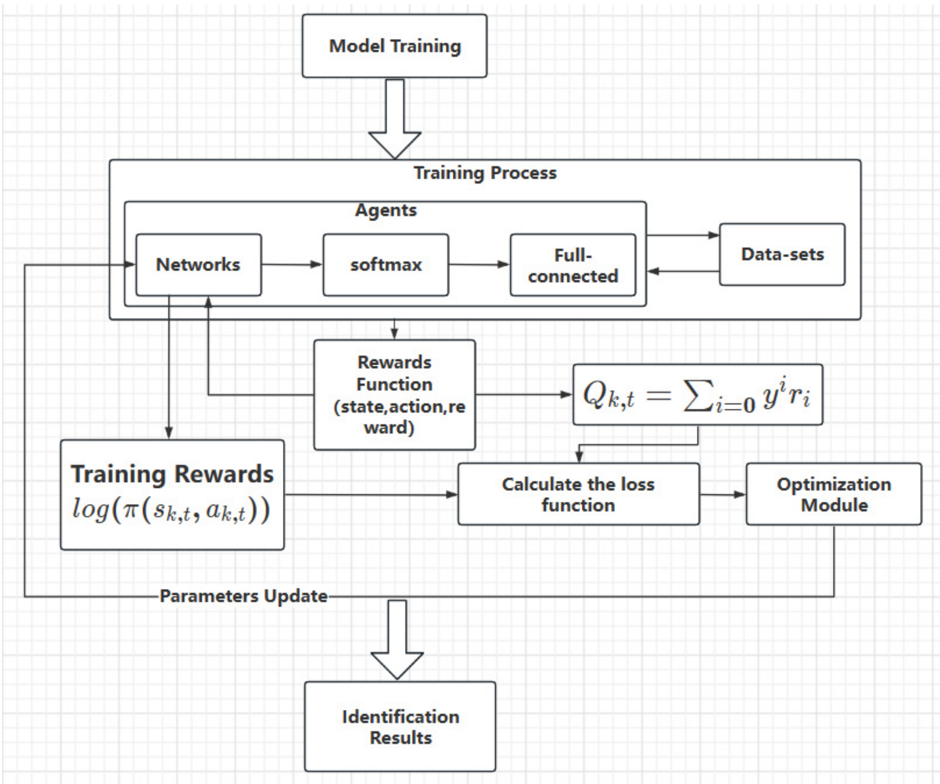

Fig. 1. Architecture of proposed reinforcement model.

4 Experimental Analysis

In this section, we demonstrate the risk identification accuracy comparison results through simulating the proposed method and related mechanism in the identical envoronment by using the Public Financial Datasets for NLP Researches. Following Figure 2 shows the comparison results.

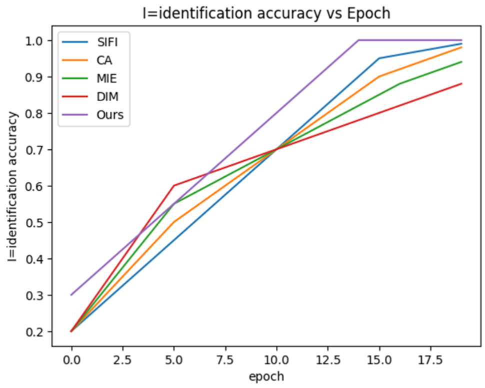

Fig. 2. Identification accuracy comparison results.

The model achieved an accuracy more than 90% in identifying financial risks on the testing data. This indicates a strong ability to recognize patterns and correlations that signify potential risks. The model demonstrated adaptability by adjusting its strategies in response to changing market conditions. This was evident in its performance during simulated market crashes and booms.

Additionally, the computation costs in another essential metric for the idnetification model and following Figure 3 shows the computation costs comparison results in the same 100 samples inputs.

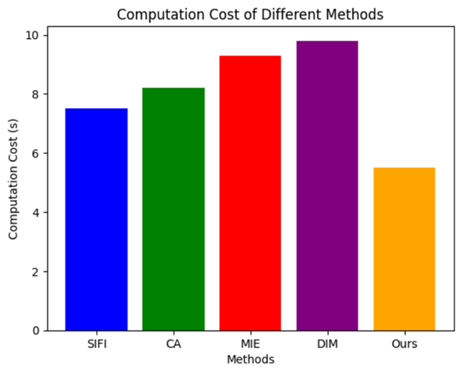

Fig. 3. Computation costs comparison results.

The proposed model significantly reduced the time required for risk identification compared to traditional methods. The automation of the process allowed for real-time risk assessments. One of the challenges faced was the interpretability of the model. While it performed well, understanding the reasoning behind its decisions was complex. Further work is needed to make the model more transparent.

5 Conclusion

In conclusion, the proposed model provides a promising avenue for enhancing risk management in the financial platforms. Its adaptability, efficiency, and ability to handle complex relationships is apart from traditional methods through evaluating our model in the experimental analysis. As for the future improvements, collaboration between finance and technology experts, and adherence to ethical guidelines can pave the way for learning to revolutionize financial risk identification and management. The integration of reinforcement into financial risk systems signifies a step towards a more robust and intelligent financial ecosystem, capable of navigating the intricate and ever-changing global financial landscape.

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