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Leveraging Deep Learning for Anomaly Detection in the Interbank Bond Market

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Abstract: This paper explores the application of deep learning techniques to enhance anomaly detection in the interbank bond market, a critical component of the financial system prone to systemic risks. Traditional anomaly detection methods, such as manual checks and rule-based systems, are labor-intensive and often fail to capture complex abnormal behaviors. We propose a novel approach using temporal attribute network embedding and Long Short-Term Memory (LSTM) networks to analyze and detect irregular trading patterns among financial institutions. Our results show a significant improvement in detection accuracy, with an F1 score exceeding 0.7. This study suggests further enhancements through richer trading data integration and the implementation of attention mechanisms to refine detection precision, thereby contributing to the stability and health of financial markets.

Keywords: Anomaly Detection, Deep Learning, LSTM Networks, Trading Behavior Analysis

1. Introduction

With rapid economic development and ongoing financial system reforms, the bond market has become an integral part of the financial system and a critical component of the global financial landscape. Presently, the interbank bond market holds a dominant position within the bond market. Due to the profit-driven nature of capital, the financial market is susceptible to irregularities such as insider trading and market manipulation. Furthermore, the intricate interconnections and increasingly complex business chains among financial institutions mean that issues in a single institution or transaction can propagate through cross-institutional and cross-market activities, potentially affecting the entire market and introducing systemic risks. Hence, it is crucial for financial market regulatory bodies to further explore and apply regulatory technologies to enhance the identification, early warning, and management of financial risks across markets, industries, and regions, thereby safeguarding the stable and healthy operation of the financial market.

In the early 1980s, researchers established behavioral finance as a new field. Behavioral finance posits that there is a connection between investor psychology and trading behavior. Given that the main participants in the interbank bond market are financial institutional investors, there are observable differences between their normal and abnormal trading behaviors. Consequently, deep learning models can be employed to detect abnormal trading behaviors in the interbank bond market. Current methods for detecting such anomalies are predominantly manual or based on predefined trading rules. Manual detection is labor-intensive, while rule-based detection struggles to identify anomalies beyond the established rules. This paper aims to use deep learning techniques to analyze the trading behavior discrepancies among different institutions to identify abnormal behavior patterns. Integrating current mainstream research approaches, this paper utilizes the LSTM model to detect abnormal trading behaviors of financial institutions in the interbank bond market.

2. Related Work

2.1 Symbol Definitions

G = (V, E, W): The trading network of the interbank bond market. Among them: V is the set of all vertices in the trading network, that is, all institutions in the trading network; E is the set of all directed edges in the trading network; W is the set of attributes of all directed edges in the trading network. P_x : The bond product number for transactions between two institutions. A_x: The transaction volume for transactions between two institutions. T_x : The time of the transaction between two institutions. V_x : The number of institutions, representing an institution. O_x: If $x = 0$, the current institution is the buyer; if $x = 1$, the current institution is the seller.

2.2 Anomaly Detection

In Anomaly detection in financial markets has garnered significant attention, with deep learning emerging as a potent tool to enhance detection accuracy. The application of Long Short-Term Memory (LSTM) networks, convolutional neural networks (CNNs), and attention mechanisms has been explored across various domains, demonstrating the versatility and robustness of these models in handling complex data patterns.

Several studies have highlighted the effectiveness of deep learning models in financial risk prediction and anomaly detection. Xu et al. [1] investigated the optimization of LSTM model performance for financial risk prediction, demonstrating significant improvements over traditional methods. This work underscores the relevance of LSTM networks in detecting irregular trading patterns in financial markets. Similarly, Wang et al. [2] focused on predicting stock market trends using LSTM networks, addressing the limitations of recurrent neural networks (RNNs) and enhancing financial forecasting accuracy.

The integration of attention mechanisms into deep learning models has shown promising results in various applications, including anomaly detection. Xiao et al. [3] explored the enhancement of deep learning models with attention mechanisms for mining medical textual data, which can be analogously applied to financial data to improve the detection of anomalous trading behaviors. This study provides a foundation for incorporating attention mechanisms into our proposed model to refine detection precision.

Deep learning techniques have also been employed to predict financial risk behaviors using big data. Xu et al. [4] combined deep learning and big data analytics to enhance financial risk behavior prediction, showcasing the potential of these technologies in managing financial risks. Furthermore, Sun et al. [5] utilized LSTM and extreme value theory to manage high-frequency trading volumes, demonstrating the applicability of LSTM networks in high-stakes financial environments.

In addition to financial applications, deep learning models have been effectively used in other fields, offering valuable insights into their potential for anomaly detection in the interbank bond market. For instance, Li et al. [6] proposed an enhanced encoder-decoder network architecture to reduce information loss in image semantic segmentation. This methodology can be adapted to financial data to minimize information loss during anomaly detection processes. Additionally, Liu et al. [7] focused on feature extraction using convolutional neural networks, a technique that can be leveraged to improve the feature representation of financial data.

Lastly, advancements in natural language processing (NLP) and emotional analysis further enrich the deep learning landscape. Yang et al. [8] and Sun et al. [9] explored the use of large language models and multimodal deep learning for emotional analysis and NLP optimization, respectively. These studies highlight the adaptability of deep learning models across different data types and their potential to enhance anomaly detection in financial markets through improved data representation and processing techniques. Anomaly detection within financial markets has gained substantial interest, particularly with the advent of deep learning as a powerful means to improve detection precision[10-13]. The deployment of Long Short-Term Memory (LSTM) networks, convolutional neural networks (CNNs), and attention mechanisms has been extensively investigated in diverse fields[14-16], showcasing the adaptability and strength of these models in managing intricate data patterns[17-20].

2.3 Network Embedding

In the interbank bond market, transactions between institutions can be represented as a vast trading network, as illustrated in Figure 1. In this network, institutions are the nodes, and the transactions between them are the directed edges. Information such as the traded product, transaction amount, and transaction time can be considered attributes of these edges. An institution's single transaction can be depicted through its node, the edge, and the edge’s attributes, while the trading behavior is derived from multiple sequential transactions. By treating the attributes of edges as nodes, one can derive the characteristic representations of nodes in the network, thus obtaining the trading behavior characteristics of the institutions.

These node characteristics can be captured using prevalent network embedding techniques, which effectively preserve the structural attributes of the network nodes. Technically, network embedding methods can be categorized into matrix factorization-based, random walk-based, and deep neural network-based approaches. Matrix factorization-based techniques primarily utilize an adjacency matrix to convey the network's topological information, where each row and column correspond to a node, and the matrix itself represents the relationships between nodes. Popular methods in this category include the singular value decomposition (SVD) approach by Ou et al. and the non-negative matrix factorization (NMF) approach by Wang et al. The SVD method excels in low-rank approximation, while the NMF method is advantageous due to its additive model. Random walk-based network embedding methods, inspired by word vector concepts in natural language processing, aim to identify superior local structural representations compared to matrix factorization methods. Notable methods include the DeepWalk algorithm by Perozzi et al. and the Node2Vec algorithm by Grover et al. Deep neural network-based network embedding methods strive to find a nonlinear learning model to achieve an efficient low-dimensional vector space representation of the original network. Common methods include the Structural Deep Network Embedding (SDNE) by Wang et al., the Stacked Denoising Autoencoders (SDAE) by Cao, and the Signed Network Embedding (SiNE) by Wang et al.

In the interbank bond trading network, two institutions might engage in multiple transactions, leading to multiple edges between the same nodes. Considering the temporal nature of transactions, the daily trading activities of an institution can be seen as a time-series sequence. This sequence can be interpreted as a walk sequence obtained via random walk-based network embedding methods.

This paper primarily focuses on two aspects: Proposing a temporal attribute network embedding method that accounts for the dynamic evolution characteristics of the interbank bond market trading network; Utilizing the LSTM network model to analyze and model the trading behavior sequences in the interbank bond market, thereby detecting abnormal trading behaviors.

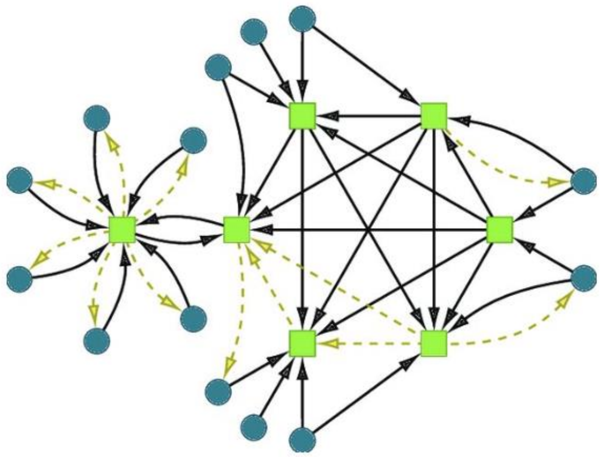

Figure 1 Schematic Diagram of the Interbank Bond Trading Network

3.Methodology

3.1.Framework for Abnormal Trading Behavior Detection

Previous studies have demonstrated the feasibility of using deep learning for anomaly detection. In the context of the interbank bond market, it is essential to apply network embedding methods to derive characteristic representations of the nodes within the trading network, which in turn provides insights into the trading behavior of institutions. Furthermore, considering that trading behaviors in the interbank bond market can be viewed as time-sequential trading series, recurrent neural networks (RNNs) are well-suited for processing such time-series data. Nevertheless, RNNs encounter long-term dependency challenges, which this study addresses by employing the long short-term memory (LSTM) network model to detect abnormal trading behaviors effectively.

Integrating network embedding with the LSTM network model, this paper proposes a framework for detecting abnormal trading behaviors in the interbank bond market, illustrated in Figure 2. The left side of Figure 2 depicts three spaces, namely the original feature space, the behavior embedding space, and the LSTM training space, arranged from top to bottom.

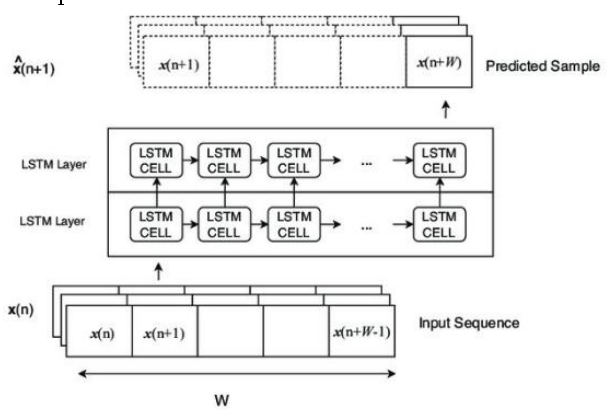

Figure 2: Framework for Abnormal Trading Behavior Detection

Original Feature Space. This space holds the original trading behavior sequences. The existing transaction data is preprocessed to extract the necessary features for the model, and then these features are organized into the original trading behavior sequences following a specific format and chronological order. This step is shown as step 1 (feature preprocessing) in Figure 2. Each original trading behavior sequence comprises all transactions conducted by an institution within a day, with each transaction consisting of four elements: trading institution, trading product, trading volume, and trading direction. Different institutions' trading sequences are denoted by different alphabetic codes. Each column with an alphabetic code represents a single transaction, and columns separated by horizontal lines represent a series of transactions, which is the trading sequence of a particular institution on a given day.

Behavior Embedding Space. This space contains the embedded representations of institutional trading behaviors. These representations are derived by transforming the original trading behavior sequences, integrating the dynamic evolution characteristics of the trading network in the interbank bond market. The transformed representations maintain both the temporal characteristics and attributes of the trading network. The temporal characteristics reflect the chronological order of financial institutions' transactions, while the attributes represent the elements of these transactions. This transformation and embedding of the original trading behavior sequences correspond to step 2 (behavior embedding) in Figure 2.

LSTM Training Layer. This layer is dedicated to training deep learning models for detecting abnormal trading behaviors in the interbank bond market, which is a crucial component of the anomaly detection framework. The input for the model is sourced from the behavior embedding space. Given that the daily transaction count varies for each institution, the lengths of the trading behavior sequences differ accordingly. However, the LSTM model requires input sequences of consistent length. Thus, a forward sequence padding method is employed, using the maximum number of daily transactions among all banks as the standard sequence length. If an institution's trading behavior sequence is shorter than this maximum, zeros are padded at the start to achieve the required length. These padding "zeros" are depicted as white columns in Figure 2.

Initially, the embedded representations of the financial institutions' trading behaviors are fed into the deep learning model. The model then outputs predictions (0 for normal trading behavior, 1 for abnormal trading behavior), and the error between the predicted results and the actual results is calculated. Through backpropagation of this error, the model's weight parameters are iteratively adjusted, culminating in the final deep learning model. This process of feature padding and training corresponds to step 3 (feature padding and training) in Figure 2.

Subsequently, the trained model is used to perform anomaly detection on institutional trading behaviors, determining whether the trading behavior of an institution is abnormal or normal. This process aligns with step 4 (behavior prediction) in Figure 2.

3.2 Trading Behavior of Institutions in the Interbank Bond Market

As illustrated in Figure 1, the interbank bond market trading network demonstrates a series of transactions conducted by five institutions within a day. Each directed edge signifies a transaction between two institutions, with the arrow's origin representing the buying institution and the terminal representing the selling institution. Each directed edge currently lists three attributes: P_x, A_x, and t_x. Hence, a transaction between institution Vi and its counterparty institution Vj is defined as [counterparty institution, trading product, transaction volume, transaction direction], represented as $[V_j,P_x,A_x,O_x]$. Similarly, trading behavior sequences for other institutions can be compiled.

3.3 Trading Behavior Embedding Representation

Prior to analyzing the original trading behaviors of institutions using deep learning, it is crucial to transform these representations into a format more suitable for deep learning analysis. For example, akin to training word vectors in natural language processing for subsequent analysis, the institution codes and bond product codes in trading behaviors need to be vectorized before analysis. One aspect involves sequencing trading behaviors by institution codes or bond product codes, while network nodes should encapsulate structural features. Since the original institution codes or bond product codes lack these structural features, better trading behavior representations are required. Currently, numerous researchers have applied network embedding methods to capture the structural information of network nodes. Given the time-sequential dynamics of trading behaviors in the interbank bond market, the Node2Vec algorithm is modified to establish a temporal attribute network embedding method appropriate for the interbank bond market. This method facilitates the acquisition of embedded representations of trading behaviors in the interbank bond market.

The details of the temporal attribute network embedding method are as follows:

Based on the original trading network of the interbank bond market G=(V,E,W) normalize the transaction volume to a range of 0 to 1 to derive all institutional original trading behavior sequences $walks$. Subsequently, remove the transaction volume and transaction direction attributes from these sequences, and concatenate the counterparty institution codes and trading product attributes to form new "trading behavior" sequences $walks\_train$. Then, optimize using random walk techniques to obtain all "counterparty institution codes + trading product codes" embedding representations f. Finally, replace the counterparty institution codes and trading product codes in the original trading behavior sequences with the corresponding "counterparty institution codes + trading product codes" embedding representations, resulting in the final embedded representations of all institutions' trading behaviors *results.*

Extracted Algorithm

```python
# Learn Transaction Behavior Features
# (Transaction Network: G = (V, E, W), Deal Time: T, Deal Product: P, Deal Amount: A, Dimensions: d, Context size: k)
G' = (V, E, T, P, A)
Initialize walks, walks_train to Empty
A = normalize(A)
for all u in V do:
    walk = TANEWalk(G', u)
    Append [walk] to walks
walks_train_pre = walks
for all behavior in walks_train_pre do:
    Initialize walk to Empty
    for all deal in behavior do:
        walk = [str(deal[0]) + str(deal[1])]
        Append [walk] to walks_train
f = StochasticGradientDescent(k, d, walks_train)
results = get_last_embedding(walks, f)
return results
# TANEWalk (G' = (V, E, T, P, A), Start node u)
Initialize walk to Empty
t = set(get all edges' T.day where u is on the edge)
# Variable edge belongs to set E
for all time in t do:
    Initialize walk_day to Empty
    temp_set = list(get all edges (where u is on the edge and T.day = time))
    temp_set = sort(temp_set) [by edges' T]
    for all edge in temp_set do:
        Initialize walk_t to Empty
        Append [edge's v] to walk_t # Variable v is the other node on edge outside variable u
        Append [edge's p] to walk_t # Variable p belongs to set P
        Append [edge's a] to walk_t # Variable a belongs to set A
        if u is buyer:
            Append [0] to walk_t
        else:
            Append [1] to walk_t
        Append [walk_t] to walk_day
    Append [walk_day] to walk
return walk
# get_last_embedding(walks, f)
Initialize walks_embedding to Empty
for all behavior in walks do:
    Initialize walk to Empty
    for all deal in behavior do:
        Initialize walk_t to Empty
        walk_t = [get the embedding(str(deal[0]) + str(deal[1])) from f]
        walk_t = walk_t + [deal[2], deal[3]]
        Append [walk_t] to walk
    Append [walk] to walks_embedding
return walks_embedding
```

3.4 Anomaly Detection of Trading Behavior Based on LSTM Network

Trading behaviors in the interbank bond market can be viewed as time-sequential trading series. The LSTM network is well-suited for processing data with temporal characteristics, making it an ideal choice for detecting abnormal trading behaviors in the interbank bond market. Initially introduced by Hochreiter et al. [21], the LSTM network has been widely applied and refined by numerous researchers. Like standard recurrent neural networks, the LSTM network features a chain-like structure, with each repeating unit comprising four layers of neural networks.

(1) Input Layer. The original feature sequences are fed into the model. These sequences form a three-dimensional array, with the outermost layer representing the trading behavior sequences of all institutions. These sequences can be further divided into the trading behavior sequences of specific institutions on specific days, as shown in the array in Figure 3. A day's trading behavior sequence includes multiple transactions, each represented by a column. Each transaction comprises four elements: trading institution, trading product, trading volume, and trading direction. This nested relationship is expressed as a three-dimensional array, which serves as the model's input.

(2) Embedding Layer. This layer transforms the input trading behavior sequences into embedded representations with temporal attributes. These embedded representations are then used as input for the LSTM layer.

(3) LSTM Layer. This study employs the LSTM network for training due to its capability to process sequential data effectively, which is ideal for the time-series data of trading behaviors. The study trains the data using LSTM networks of varying sizes, selecting network sizes of 16, 32, 64, and 128.

(4) Output Layer. The Sigmoid activation function [22] is used for the output layer, as it is well-suited for binary classification problems like the detection of abnormal trading behaviors, which results in either abnormal or normal classifications.

(5) Evaluation Metrics. Detecting abnormal trading behaviors in the interbank bond market is inherently a binary classification issue. In practice, abnormal trading behaviors occur far less frequently than normal ones, creating an imbalanced binary classification problem. Thus, the F1 score is used to evaluate the accuracy of the detection model for abnormal trading behaviors in the interbank bond market.

(6) Loss Function. Given the binary classification nature of the problem, Binary Crossentropy [23] is used as the loss function for the model.

4. Experimental Results and Analysis

4.1 Data Description

The data for this experiment consists of simulated transaction data from China's interbank bond market. The experiment focuses on five transaction elements: transaction time, buyer, seller, bond code, and transaction volume. The transaction time is recorded to the minute when the transaction occurs. The buyer and seller refer to the institutions involved in the transaction, represented by numeric codes. The bond code identifies the bond product type, also represented by numeric codes. The transaction volume denotes the transaction amount, measured in yuan.

4.2 Evaluation Metrics

Detecting abnormal trading behaviors in the interbank bond market is fundamentally a binary classification issue. Given that abnormal trading behaviors are significantly fewer than normal trading behaviors, this detection problem is inherently an imbalanced binary classification issue. Hence, the F1 score is chosen as the evaluation metric for this study. In this context, abnormal trading behaviors are labeled as positives, while normal trading behaviors are labeled as negatives. Accordingly, the definitions are as follows:

TN (True Negative): The number of cases where the predicted result is negative, and it is actually negative.

FP (False Positive): The number of cases where the predicted result is negative, but it is actually positive.

FN (False Negative): The number of cases where the predicted result is positive, but it is actually negative.

TP (True Positive): The number of cases where the predicted result is positive, and it is actually positive.

Based on these definitions, the precision is further defined as follows:

$$\text{precision} = \frac{TP}{TP + FP} \tag{1}$$

Recall is defined as:

$$\text{recall} = \frac{TP}{TP + FN} \tag{2}$$

The F1 score is defined as follows:

$$F1 = \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \tag{3}$$

The F1 score ranges from 0 to 1, with higher values indicating a better performance of the model in distinguishing between normal and abnormal transactions.

4.3 Experimental Parameter Settings

The experimental parameters include settings for both the network embedding and the LSTM network parts. The specific parameter settings are detailed in Table 1.

Table 1 Experimental Parameter Settings

Network	Parameter	Value
Temporal Attribute Network Embedding	Dimension ddd	16, 32, 63, 96
	Context kkk	5
LSTM Network	Network Size	16, 32, 64, 128
	Batch Size	50
	Learning Rate	0.01
	Optimizer	Root mean square propagation

		(RMSprop), etc.
	Output Layer	Sigmoid

4.4 Experimental Results and Analysis

In this experiment, we compared the accuracy of the LSTM anomaly detection model across different LSTM network sizes and network embedding dimensions. The selected LSTM network sizes were 16, 32, 64, and 128, while the network embedding dimensions ranged from 16, 32, 53, to 96. To control variables, other related parameters were uniformly set to those in Table 1, with RMSprop chosen as the optimizer.

Table 2 provides the experimental results for various LSTM network sizes and network embedding dimensions. The first row of numbers in the table indicates the embedding dimensions of "institution code + bond code" for each transaction in the interbank bond market, with an embedding dimension of 0 signifying the direct use of the original trading behavior sequence as input to the LSTM network. Thus, each column in Table 2 represents different input data for the model, while the decimal numbers in the lower right part of Table 2 denote the F1 score for the accuracy of the LSTM anomaly detection model using different input data. It is evident that with an embedding dimension of 0, the accuracy of the LSTM anomaly detection model is highest when the LSTM network size is 128. Although preprocessing data with network embedding results in slightly lower accuracy than using unprocessed data, this does not imply that preprocessing steps are redundant. Firstly, from Table 2, the F1 score differences are minor, and when the LSTM network size is 128, the LSTM anomaly detection model's accuracy with an embedding dimension of 64 is only 0.01 less than that with an embedding dimension of 0. Secondly, due to the complexity of the LSTM anomaly detection model, finding only local optima is possible when the embedding dimension is not 0. Hence, future work can continue to adjust the parameters of the LSTM anomaly detection model to achieve better accuracy in anomaly detection.

Table 2 F1 Scores of LSTM Anomaly Detection Model for Different Network Sizes and Embedding Dimensions

Network Size	Embedding Dimension 0	Embedding Dimension 16	Embedding Dimension 32	Embedding Dimension 64	Embedding Dimension 96
16	0.6995	0.7031	0.6828	0.7223	0.654
32	0.731	0.677	0.6758	0.6984	0.613
64	0.7128	0.6845	0.6889	0.7196	0.645
128	0.731	0.6846	0.6755	0.721	0.6483

5. Conclusion

Anomaly detection in the interbank bond market is crucial for maintaining the market's healthy and stable operation. Given the current absence of effective deep learning-based anomaly detection systems in the interbank bond market, the significant labor resource burden of traditional manual detection methods, and the challenges in detecting unknown abnormal trading behaviors with rule-based methods, this paper proposes a more effective anomaly detection method based on deep learning to enhance the accuracy and efficiency of anomaly detection. This study first employs a temporal attribute network embedding method to obtain the embedded representations of trading behaviors in the interbank bond market and then uses the LSTM network model to detect abnormal trading behaviors. The experimental results demonstrate that an F1 score greater than 0.7 indicates that this method significantly improves the accuracy of anomaly detection models. Future research can incorporate more trading elements into the representation of institutional trading behaviors to achieve better representations. Additionally, incorporating attention mechanisms into the LSTM network model can further improve the detection accuracy of the deep learning model by focusing on the various sizes and types of financial institutions in the interbank bond market.

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