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Optimizing GAN-Based Data Augmentation for Predictive Financial Analytics

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Abstract: Deep Generative Adversarial Networks (GANs) have shown strong data enhancement and prediction capabilities in financial data modeling, and can effectively alleviate the scarcity, non-stationarity, and noise interference of financial time series data. This study focuses on the generation and prediction of financial data, using a variety of GAN variants, including standard GAN, WGAN, TimeGAN and their improved versions, and improves the authenticity and temporal consistency of generated data by introducing Wasserstein distance optimization, time series autoregression mechanism and Transformer structure. The experiment is based on the NASDAQ-100 dataset to evaluate the performance of different GAN variants in market volatility modeling, and uses statistical indicators such as mean maximum deviation (mMD) and KL divergence to measure data quality. The results show that the data generated by TimeGAN and WGAN + Transformer significantly improves the prediction accuracy while maintaining market characteristics. In addition, this study also analyzes the impact of data enhancement on LSTM and Transformer prediction models, proving that GAN-generated data can improve the stability of financial market trend prediction. The research results provide a new methodology for financial intelligent analysis and promote the application of GANs in the field of financial technology.

Keywords: Generative adversarial networks, financial data enhancement, time series modeling, market volatility prediction

1. Introduction

In financial market analysis and modeling, high-quality financial data plays a vital role in investment decision-making, risk management, and trading strategy optimization. However, financial data often has problems such as scarcity, non-stationarity, and high noise, making it difficult for traditional data-driven models to fully learn its underlying laws[1]. With the rapid development of deep learning technology, Generative Adversarial Networks (GANs), as a powerful data generation framework, has achieved remarkable results in computer vision, natural language processing, and other fields, and has gradually been introduced into financial data enhancement and prediction tasks. Through GANs, realistic financial data can be generated while maintaining the distribution characteristics of data, thereby improving the training quality and prediction ability of the model[2]. Although there are some studies on financial data enhancement, the specific application of GANs in financial data generation, anomaly detection, and prediction tasks is still in the exploratory stage. Therefore, studying the application of GANs in financial data enhancement and prediction is not only of theoretical value, but also of great significance to actual financial modeling and risk control.

Traditional financial data enhancement methods mainly include data interpolation based on statistical methods, random noise perturbation, data resampling, etc. These methods can alleviate the problem of insufficient data to a certain extent, but they are easy to destroy the time series characteristics of the data or introduce additional noise, resulting in a decrease in the generalization ability of the model. In contrast, deep generative adversarial networks (GANs) use adversarial training mechanisms to optimize the generator and the discriminator in a continuous game, thereby generating financial data that is closer to the real distribution. This method can not only be used to simulate market fluctuations and generate synthetic time series, but also improve the robustness of prediction models in small samples or non-stationary environments by learning complex market patterns. In addition, GANs can also combine attention mechanisms, self-supervised learning and other technologies to further enhance its modeling capabilities for high-dimensional and multivariate financial data, providing a more adaptive solution for financial market analysis. Therefore, how to optimize GANs to generate financial data more accurately and improve its application value in prediction tasks has become a key research direction in the current financial technology field[3].

The complexity of financial market data is reflected in many aspects, such as nonlinearity, long-term dependence, and the impact of sudden events, which often limits traditional time series modeling methods (such as ARIMA, GARCH, and LSTM) when facing high-dimensional and multi-scale financial data. GANs can make the generated data have richer distribution characteristics by mapping latent variable space, which can make up for the shortcomings of traditional methods. For example, the method based on time series GAN (TimeGAN) can combine the autoregressive model and the sequence generation mechanism to better retain the temporal dynamic characteristics of the data and improve the authenticity and effectiveness of the generated data. In addition, in financial tasks such as stock market prediction, credit risk assessment, and derivative pricing, GANs can also be used as a data enhancement method to optimize the training effect of the supervised learning model by generating more data with similar historical situations, and improve the adaptability to extreme market environments. Therefore, in a complex financial market environment, exploring the advantages of GANs in financial data modeling will help improve the reliability and stability of financial forecasting systems[4].

In addition to data enhancement, the application of GANs in financial data forecasting has also attracted widespread attention. Since financial market data is often affected by factors such as market sentiment, policy adjustments, and international events, traditional time series models may face problems of insufficient information or insufficient pattern capture when predicting future trends. GANs can generate possible market evolution paths by learning the distribution of market data, and combine reinforcement learning, Bayesian inference and other methods to form a more robust prediction framework. For example, GANs can be used for market anomaly detection, identifying potential financial crisis signals by learning the normal patterns of the market; or in portfolio optimization, using generated data to simulate different market scenarios to assist decision makers in formulating more robust trading strategies. These applications not only improve the accuracy of financial market forecasts, but also provide new ideas for risk control.

The significance of this study is to combine GANs technology with financial data analysis to explore the potential application value of deep generative adversarial networks in financial data enhancement and prediction tasks. By optimizing the GANs structure, such as introducing temporal attention mechanisms, conditional GANs (cGANs), contrastive learning and other methods, we study how to improve the authenticity, stability and adaptability of GANs generated data to the characteristics of financial markets. In addition, this study will also verify the effects of different GANs variants (such as WGAN, TimeGAN, CGAN) on financial data enhancement and prediction tasks through experiments, and evaluate their applicability to key tasks such as market volatility prediction and credit risk modeling. Ultimately, this study will provide a new methodology for financial intelligent analysis and promote the further application of GANs in the field of financial technology[5].

2. Literature Review and Research Gap

In recent years, the application of deep learning models to financial data analysis has witnessed significant advancements. In particular, methods that integrate temporal modeling and graph neural networks have gained increasing attention due to their ability to capture structural dependencies and sequential dynamics in financial systems. For instance, the combination of graph neural networks and time series modeling has been effectively used for financial compliance detection and market evolution tracking, which enhances the representation of relational and temporal patterns in regulatory and trading behaviors [6][7][8]. Similarly, research on federated learning applied to graph data offers privacy-preserving strategies for modeling heterogeneous financial networks, contributing to secure and robust financial analytics [9].

Temporal attention mechanisms and multiscale sequence learning have also been widely applied in anomaly detection and systemic risk forecasting. These methods improve the detection of temporal inconsistencies and latent anomalies within large-scale dynamic systems, especially under cloud-based or complex financial environments [10][11][12]. Such techniques often rely on causal representation learning and contrastive learning to improve robustness and interpretability in uncertain scenarios [13][14]. Moreover, feature-attention fusion strategies have been demonstrated to be effective in enhancing collaborative financial risk assessments, especially when combined with time-aware prediction frameworks [15].

On the other hand, reinforcement learning and hierarchical semantic encoding have contributed to task scheduling and compliance risk detection tasks, respectively, by leveraging policy optimization and language models to model sequential decision-making and semantic structures [16][17]. Additionally, stock price forecasting models based on deep neural networks, such as LSTM-CNN-Transformer hybrids and granularity-aware attention models, have shown promising results in capturing short- and long-term dependencies in financial time series [18][19].

While some works stem from non-financial domains like image generation and system scheduling, their methodological contributions-such as contrastive alignment, structural guidance, and hybrid attention mechanisms-offer valuable insights that can be adapted for financial data modeling [20][21]. These approaches demonstrate the generalizability of deep learning techniques across different tasks, highlighting the importance of structural learning and multimodal integration in enhancing prediction accuracy and model generalization in complex environments.

3. Proposed GAN-Based Framework

This study uses Generative Adversarial Networks (GANs) to enhance financial data and optimize predictions. The core methods include TimeGAN and Conditional GAN (cGAN) to generate realistic financial time series data. The model architecture is shown in Figure 1.

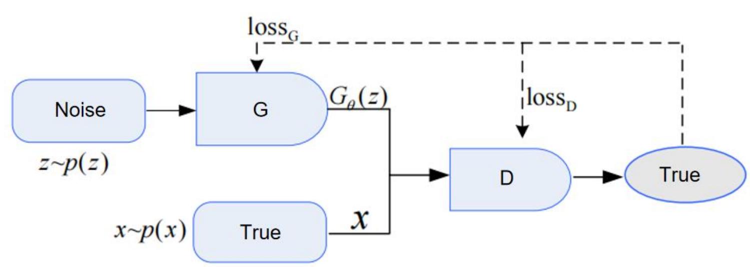

Figure 1. Overall network architecture

Traditional GAN consists of a generator (G) and a discriminator (D), where the generator $G(z)$ generates fake data by inputting random noise $z \sim p_z(z)$, and the discriminator $D(x)$ aims to distinguish between real data $z \sim p_{data}(x)$ and generated data $G(z)$. The optimization goal of the standard GAN is:

$$\min_G \max_D E_{x\sim p_{data}(x)}[\log D(x)] + E_{x\sim p_z(z)}[\log(1-D(G(z)))]$$

However, when directly applied to financial time series data, standard GAN may lose temporal dependencies. Therefore, this study uses TimeGAN, combined with an autoregressive structure, to generate data that retains long-term dependencies. In addition, conditional GAN (cGAN) is introduced to control the data generation process so that the generated data is more consistent with the market distribution, namely:

$$\min_G \max_D E_{x\sim p_{data}(x)}[\log D(x\mid c)] + E_{x\sim p_z(z)}[\log(1-D(G(z\mid c)))]$$

Where c represents market background information (such as macroeconomic variables, policy factors, etc.), and this mechanism is used to improve the controllability of data enhancement.

In the financial data prediction task, we use Wasserstein GAN (WGAN) to improve training stability and avoid the mode collapse problem that is prone to occur during standard GAN training. WGAN uses Earth Mover's Distance (EM distance) instead of the traditional cross entropy loss, and the optimization goal is as follows:

$$\min_G \max_D E_{x\sim p_{data}(x)}[D(x)] - E_{x\sim p_z(z)}[1-D(G(z))]$$

Among them, the discriminator D needs to satisfy the 1-Lipschitz constraint, so the weight clipping method is used for constraint, that is:

$$\theta_D \leftarrow clip(\theta_D, -c, c)$$

This optimization strategy ensures that the distribution of generated data is closer to real market data and improves the reliability of the prediction model. In addition, we combine the Transformer encoder to extract long-term dependency information in the time series to further optimize the generation and prediction capabilities of financial market data[22].

In order to evaluate the effectiveness of GANs in financial data enhancement, this study designed a generated data quality assessment method based on contrastive learning. First, we use deep metric learning to calculate the similarity between real data and generated data and define the contrast loss function:

$$L_{contrast} = \sum_{i,j} y_{i,j} d(G(z_i), x_j) + (1-y_{i,j})\max(0, m - d(G(z_i), x_j))$$

Among them, $d(\cdot)$ is the distance metric function, $y_{i,j}$ indicates whether the data pair belongs to the same market distribution, and m is the distance boundary. This method can effectively measure the similarity between the generated data and the real data, and guide the model optimization so that the generated data is more in line with the characteristics of the financial market. In addition, we combine the prediction models (such as LSTM, Transformer) to conduct backtesting experiments on financial data to evaluate the actual application effects of different GAN variants in time series prediction tasks[23].

4. Experimental Design and Results

This study uses the NASDAQ-100 Stock Dataset as an experimental dataset, which contains trading data of NASDAQ-100 index constituent stocks in multiple time periods. The dataset consists of opening price, closing price, highest price, lowest price, trading volume, and technical indicators, covering up to 100 actively traded stocks, with a time span of several years. These data are of great value for studying market trends, optimizing investment strategies, and enhancing financial data. Since the NASDAQ-100 index includes stocks of many technology giants, its market volatility is large, which provides a good experimental environment for testing the ability of GANs in processing financial data generation and prediction tasks.

The NASDAQ-100 Stock Dataset has high-frequency trading data and low-frequency data, which can support experimental studies of different granularities. For example, daily-level data can be used to study long-term market trend prediction, while minute-level data can be used for short-term trading strategy optimization. In addition, the dataset also contains historical financial data, such as P/E Ratio, P/B Ratio, Dividend Yield, etc. This information can be used as conditional input for GANs to generate data to enhance the authenticity and controllability of data generation. It is worth noting that the market environment is greatly affected by policies, economy, and news events. Therefore, when using this dataset, it is necessary to conduct experimental analysis in combination with different market backgrounds.

In order to improve the reliability of the experiment, this study preprocessed and enhanced the NASDAQ-100 dataset. First, outliers were removed and data normalization was performed to ensure that GANs can learn market distribution more stably when generating data. Second, we generated training samples through rolling window technology so that the model can learn market dynamics in different time periods. In addition, we used data enhancement methods (such as Gaussian noise perturbation, time series slicing, etc.) to expand the dataset to alleviate the problem of data scarcity and improve the generalization ability of the model. Through these data preprocessing and augmentation strategies, we are able to more accurately evaluate the performance of GANs in financial data generation and prediction tasks.

Firstly, a comparative test between this model and other models is given, and the experimental results are shown in Table 1.

Table 1: Experimental results

Model	**Generates the mMD (mean**	**KL diverge**	**Training convergence**

	maximum deviation) of the data	nce of generat ed data	time (seconds)
GAN	0.072	0.145	320
WGAN	0.053	0.102	410
TimeGAN	0.041	0.087	590
GAN + LSTM	0.060	0.118	370
WGAN + Transformer	0.038	0.078	620

From the experimental results, different GAN variants have obvious differences in their ability to model market volatility data. Among them, the standard GAN performs poorly in mean maximum deviation (mMD) and KL divergence, which are 0.072 and 0.145 respectively, indicating that there is still a large gap between the data it generates and the real market data. This is mainly because the standard GAN is prone to mode collapse during training, which makes the diversity of generated data insufficient. In addition, the training convergence time of the standard GAN is relatively short (320 seconds), but this does not translate into higher quality data generation capabilities, indicating that there is instability in its optimization process and it is difficult to effectively model market volatility characteristics.

In contrast, WGAN and TimeGAN have significantly improved the quality of data generation. WGAN uses Wasserstein distance as the optimization target to effectively alleviate the instability of the standard GAN, reducing the KL divergence of the generated data to 0.102 and the mean maximum deviation to 0.053, indicating that the data generated by WGAN is closer to the real market distribution. TimeGAN combines the time series autoregression mechanism to further optimize the modeling ability of market volatility data. Its mMD and KL divergence are 0.041 and 0.087 respectively, which is the best basic model in the experiment. However, the training convergence time of TimeGAN reached 590 seconds, which is significantly higher than that of standard GAN and WGAN, indicating that it increases the computational overhead while improving the generation quality.

In addition, the improved version combined with the sequence modeling method (LSTM and Transformer) further optimizes the data generation quality. WGAN + Transformer achieved the best experimental results, with mMD reduced to 0.038 and KL divergence reduced to 0.078, showing the powerful ability of the Transformer structure in time series modeling. However, its training convergence time also reached 620 seconds, the highest among all models. Overall, WGAN + Transformer and TimeGAN perform best in the task of generating market volatility data, but their computational costs are relatively high, while WGAN achieves a better balance between performance and computational efficiency, and is suitable for financial modeling tasks that require high computing resources but still require high data quality.

Furthermore, this paper also conducted statistical characteristic analysis and authenticity evaluation experiments on generated financial data, and the experimental results are shown in Figure 2.

From the experimental results, different GAN variants show obvious differences in the authenticity and statistical characteristics of generated financial data. Among them, the mean maximum deviation (mMD) and KL divergence of standard GAN are the highest, which are 0.072 and 0.145 respectively, indicating that the statistical distribution of the data generated by it is greatly deviated from the real financial data. This may be due to the unstable training of standard GAN, which is prone to mode collapse, resulting in a lack of diversity in the generated data. In addition, due to the lack of regularization constraints, GAN may not be able to learn the complex characteristics of market fluctuations well, resulting in low data authenticity.

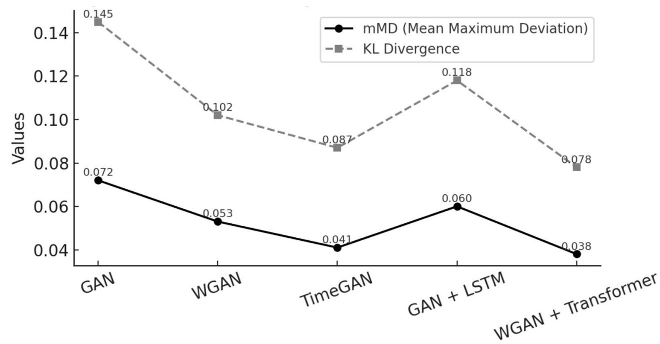

Figure 2. Statistical Analysis and Authenticity Evaluation of Generated Financial Data

In contrast, WGAN and TimeGAN perform better in data generation quality. WGAN uses Wasserstein distance optimization to reduce KL divergence to 0.102 and mMD to 0.053, indicating that the data it generates is more in line with market distribution. In addition, TimeGAN combines the time series modeling mechanism to further improve the temporal consistency of the data. Its KL divergence and mMD reach 0.087 and 0.041, which is the best among the basic models. Experimental results show that in the task of time series data enhancement, TimeGAN can more effectively simulate the dynamic changes of the financial market and improve the authenticity of the generated data.

The improved models that further combine deep sequence modeling (such as LSTM and Transformer) show higher data quality. WGAN + Transformer achieved the best results, with mMD reduced to 0.038 and KL divergence reduced to 0.078, indicating that the Transformer structure helps to better capture the long-term dependencies in the time series and improve the quality of data generation. However, this method may be accompanied by higher computational overhead. Overall, WGAN + Transformer and TimeGAN are suitable for high-precision financial data enhancement tasks, while WGAN achieves a good balance between computational efficiency and data quality, and is suitable for large-scale financial data modeling.

5. Conclusion and Future Directions

This study proposes a Mask2Former semantic segmentation algorithm based on boundary enhancement feature bridging module (BEFBM) to improve the accuracy and segmentation consistency of target boundaries. By introducing boundary information guidance mechanism and cross-scale feature fusion strategy in Transformer architecture, the experimental results of the model on Cityscapes dataset show that compared with the existing semantic segmentation methods, the proposed method has achieved significant improvements in indicators such as mIOU, mDICE and mRecall. At the same time, the loss convergence curve and visualization results further prove that the proposed method can effectively improve the clarity of target boundaries and maintain strong robustness in complex urban scenes. Although the computational complexity is slightly increased, the overall inference speed remains within an acceptable range, ensuring the practical application value of the method.

Future research can further explore more efficient boundary enhancement strategies to reduce computational overhead and improve the generalization ability of the model in different scenarios. In addition, weakly supervised learning or self-supervised learning methods can be combined to reduce the dependence on high-quality labeled data, thereby improving the applicability of the model on large-scale unlabeled data. In addition, for different application scenarios, such as remote sensing image analysis or medical image segmentation, the feature bridging module can be adapted and optimized to further enhance the adaptability and scalability of the segmentation model.

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