Researches Advanced in Finance based on Generative Adversarial Networks

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Abstract. Topics about how to apply Generative Adversarial Networks (GANs) to finance industry and research to promote financial market prosperity and progress with deep learning technology never fail to arouse public attention. For instance, financial academic realm such as portfolio optimization, trade execution strategies and financial information progressing have made use of machine learning. After a large number of literature retrieval and attempts to classify from different aspects, we ultimately find out that GAN is one of the most famous and appropriate technologies widely adopted in academic research and commercial applications. Aiming at assisting reader with having insight into how GAN improved financial work's efficiency, in this paper, we propose three research perspectives of GAN in financial work: Stock Market Prediction, Fault Detection, and Time Series. By organizing from an innovative and macro perspective, we present and classify the application methods of GAN and the improvement of the basic model of GAN in order to adapt to the corresponding fields under the corresponding research directions. In general, the following improved models based on the basic GAN model for the corresponding financial perspective are involved: GAN of three-layer dense network, GAN with the MLP and LSTM separately as the discriminator and the generator, GAN-FD stock projection model, BERT and GAN in Stock Prediction; SSGANs, DAEGAN in Fault Detection; SeqGAN, Quant GAN, RNN-GAN, PSA-GAN in Time Series.

Keywords: Generative Adversarial Networks; Stock Market Prediction; GAN of Three-layer Dense Network.

1. Introduction

With the growth in computer power and the increase in data volume in many industries, artificial intelligence has made tremendous progress, resulting in unprecedented attention from researchers and public anticipation of artificial intelligence. In general, machine learning algorithms may be loosely separated into supervised learning and unsupervised learning based on whether the dataset is labelled. Supervised learning must rely on data with established labels. Although good results have been obtained, the price is significant, hence unsupervised learning is gaining increasing interest. As the most representative technique in unsupervised learning, generative models have garnered significant interest from researchers. Early models include the limited Boltzmann machine, the deep belief network, and the variational automated encoder, among others. However, their performance and outcomes are impacted by insufficient generalization. In 2014, Goodfellow et al. introduced the Generative Adversarial Network (GAN) [1], a next generation model of unsupervised learning that has garnered significant interest. GAN is a training network similar to an adversarial game, which originates from the two-person zero sum game idea in game theory and learns by making two neural networks play each other. After continuous optimization and iteration, it makes the model reach the optimal state, that is, Nash equilibrium state. GAN has been studied and applied in image generation, speech synthesis, object detection, style migration, privacy protection, etc. As one of the industry's most significantly affected by the development of AI, the financial industry has created a large amount of data, creating new opportunities for the application and use of models. To this end, relevant algorithms of artificial intelligence have also been widely used, mainly including stock forecasting, risk management, image synthesis, data generation and anomaly detection. In this study, in order to further discuss the application of GAN in the financial field, we introduced the latest research progress of GAN in the financial field from three perspectives of stock market prediction, time series and fraud detection according to the differences of research objects.

(1) Stock market prediction based on GAN. As an investment target with convenient operation, high risk and high return, stocks are deeply concerned by investors. There are many factors that affect the stock price trend, such as large data volume and difficult to quantify. The traditional stock forecasting methods are mainly econometrics. In the 1980s, with the emergence of Boltzmann machine and back-propagation algorithm to solve the training problem of multi-layer networks, neural networks gradually entered the vision of researchers. The technical analysis theory of stock market has three assumptions, one of which is that the historical trend of stocks will repeat. This means that the stock trend is not completely random, and there is a certain probability that the past trend will reappear. In the prediction task, the historical data distribution of stock trend is particularly important, and the deep learning model is to learn the distribution of historical trend. The GAN model can continuously resist and learn the data distribution of the stock historical trend through the generator and discriminator, generate prediction data similar to the historical distribution, and improve the prediction accuracy.

(2) Time series finance data analysis based on GAN. As for Time series, they are formed sequentially and constantly by data from a wide variety of industries collected at varying time intervals. They often include detailed and intricate information. As a result of the necessity to collect useful information from the time sequence, Time Series analysis technology is developed. Forecasting is essential to the subject of Time Series analysis. The objective of time series prediction is to provide a fair forecast of the future development of data based on the historical law and pattern of data change. Financial Time Series is a specialized type of Time Series that has significant significance for the government, investment machines, and investors, and has been a long-standing research hotspot in the fields of finance and computer science. Due to the features of nonlinear and non-stationary financial time series forecasting issues, prediction accuracy is not great. Thus, a large number of academics both at home and abroad have proposed supervised learning models for Financial Time Series, such as LSTM, RF, ARMA, and others. With its distinctive adversarial concept and unsupervised learning technique, Generative adversarial networks (GANs) have become an important subfield in the field of deep learning in recent years. Yu et al. originally suggested a framework for sequence generation [2] to effectively improve the limitations of traditional GAN in modelling discrete sequence. Combining recurrent neural networks with GANs (C-RNN-GAN), a novel generative adversarial model capable of producing continuous sequential data was proposed [3]. Other researchers have proposed a framework [4] that captures the heterogeneity of data which influence the decision-making and reach a new level of efficacy in helping users' decision processes. Recent studies, such as PSA-GANs [5], propose a network that employs progressively increasing self-attention in GANs to produce prediction inaccuracies compared to a baseline that utilizes only actual data.

(3) Fraud detection based on GAN. The Internet has brought convenience to people and improved their living standards. The development of Internet finance and e-commerce enables people to conduct transactions and sales without leaving their homes. Online trading and online shopping have become a lifestyle. Logistics, e-commerce, and online trading have been integrated into every part of people's lives and connected to every product. However, with the continuous surge in the number and scale of online trading, different forms of online trading fraud also emerge in an endless stream. Fraud detection refers to a set of activities or techniques implemented by a business to protect assets, identities, customer and business information, accounts, and transactions from fraudsters. It has many applications, mainly including online gambling fraud, gambling fraud, credit card fraud, and insurance fraud. If not detected, fraud will encourage a series of illegal and criminal activities, which will cause huge losses to fit and users. Therefore, how to detect online transaction fraud in advance

and give early warning has been very important, which is of great significance to protecting the interests of consumers and merchants.

2. Generative Adversarial Networks in Stock Market Prediction

2.1 GAN for Three-layer Dense Network

The first application of GAN to stock market forecasting we will discuss is a kind of GAN architecture with three-layer dense network used as generator and a three-layer CNN used as the discriminator [6].

In this paper, the researchers used GAN to conduct experiments under different epochs and Adam optimizer, and finally found the best matching results of 50K epochs and the Adam optimizer with the best value in 1e-4. As the confusion matrix below, the predicted up-price was 72.68%, which was better than the prediction of the decrease of a price.

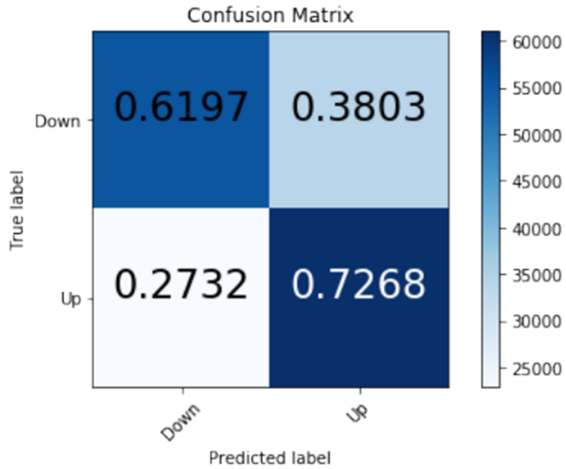

Figure 1. Confusion Matrix of the result

2.2 GAN with the MLP as Discriminator and LSTM as the Generator

Based on a hypothesis called "mean regression" and a deeper improvement called "moving average regression", this paper proposed a nascent model to predict the stock price everyday [7].

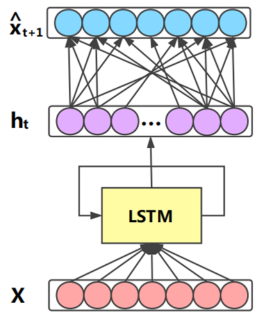

Figure 2. Generator using LSTM

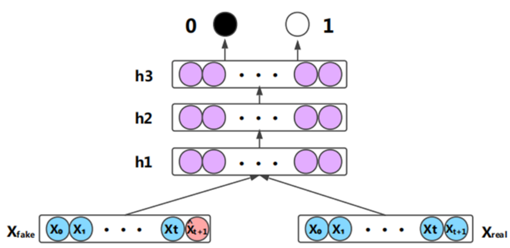

Figure 3. Use MLP's discriminator with Xfake and Xreal as inputs.

2.3 A General Framework for Adversarial Training Using LSTM and CNN

The model used publicly available indices as input, avoiding complex financial theory studies [8]. It simulated the trading patterns of actual traders and analysed the impact of model update period on the prediction performance by using a rolling split training and test set. This experiment used Chinese stock market data as the dataset. They set the learning rate as follows.

(1) Try to decide the learning rates ρ_D and ρ_G, and determine parameters λ_{adv}, λ_p, λ_{dpl};

(2) Initialize the weights W_D and W_G.

(3) If there is no convergence, then turn to (4)

(4) Then reset the generator G:

(5) Obtain K new data samples $(X^{(1)}, Y^{(1)}), (X^{(2)}, Y^{(2)}), \cdots, (X^{(K)}, Y^{(K)})$

(6) $W_G = W_G - \rho_G \sum_i^K \frac{\partial L_G(X^{(i)}, Y^{(i)})}{\partial W_G}$

(7) Renew the discriminator called D:

(8) Obtain K new data samples $(X^{(1)}, Y^{(1)}), (X^{(2)}, Y^{(2)}), \cdots, (X^{(K)}, Y^{(K)})$

(9) $W_D = W_D - \rho_D \sum_i^K \frac{\partial L_D(X^{(i)}, Y^{(i)})}{\partial W_D}$

(10) end the programming in “while”

This method could greatly develop the precision of stock direction prediction and make the prediction error less. The results in Figure 4 showed that if N is 20, the RMSRE increased sharply and fluctuated sharply, varying between 1.21% and 4.96%. Therefore, the model updated period N should be reduced, and the model parameters should be modified periodically to accommodate changes in market styles.

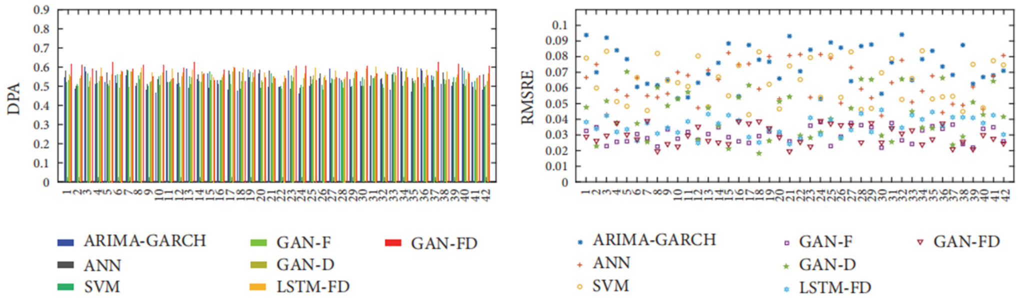

Figure 4. DPA and RMSRE for each stock when (M, N) is (60,20) and the X-axis represents the stock ID.

2.4 Stock Price Prediction Model Combined BERT and GAN

To begin with, the sentiment analysis of news and headlines of Apple was researched using the transformer model pre-trained by Google for NMP, called BERT [9]. technical indicators and stock indices of a number of countries, some commodities, and historical price and sentiment scores were then predicted by GAN. Figure 5 shows the dataset they used, while Figure 6 shows the proposed model.

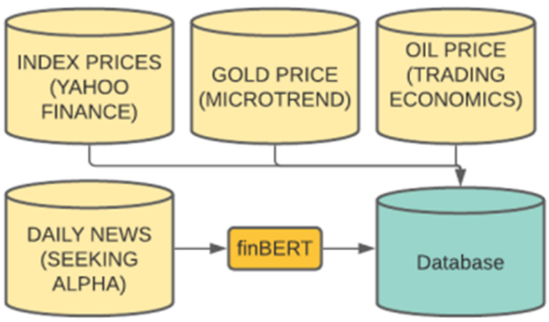

Figure 5. Data Preparation

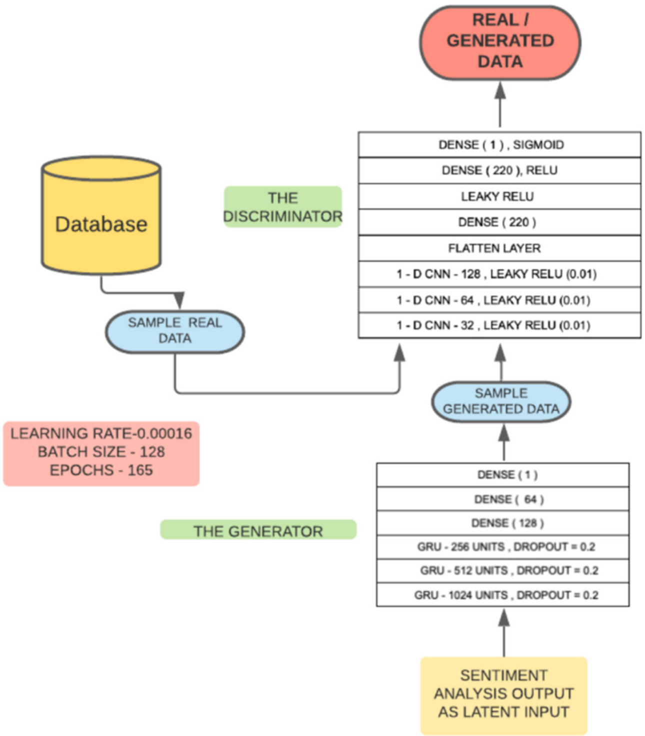

Figure 6. Proposed Model

This paper also evaluated and compared with the mentioned models ARIMA, LSTM, GRU and the general canilla GAN with noise. The predictions of these models were also compared for 5, 15 and 30 days. The consequence of this experiment is shown in Table 1.

Table 1. S-GAN comparing with other traditional models in the range of 5, 15 and 30 days.

Models	5Days	15Days	30Days
ARMIA	12.10%	36.58%	73.17%
LSTM	1.96%	5.85%	11.70%
GRU	1.975%	5.925%	11.85%
GAN	1.58%	4.74%	9.48%
Proposed Model (S-GAN)	1.22%	3.66%	7.32%

3. Generative Adversarial Networks in Stock Market Prediction

In the previous work done by other researchers, Time series-based GANs can be divided into discrete time series-based GANs and continuous time series-based GANs [10]. Discrete time series are data points partitioned with respect to the time intervals, these data include infrequent or irregular data reporting intervals, such as 1 point per second. Continuous time series are composed of data values corresponding to each single time point and mainly focus on creating a time-dependent, real-valued signal x, where $x \in R$.

3.1 Discrete Time Series based GANs

3.1.1 Sequence GAN (SeqGAN).

The researchers created a continuous data production method that circumvents the difficulties associated with producing discrete data without causing the gradient vanishing problem that found in traditional RNNs. This approach outperforms many previous generative model approaches like PG-BLEU and LSTM in practical applications. As shown in Figure 7, the generative model of SeqGAN consists of an RNN with LSTM units, while the discriminator of the model is designed to be a CNN.

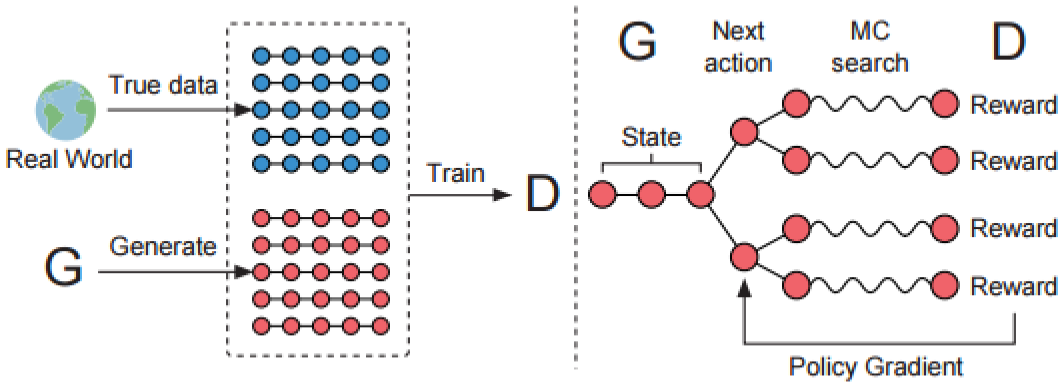

Figure 7. Architecture of SeqGAN

This model gives great performance in real-world applications of music, poems and speech generation. Although the goal of SeqGAN is to generate discrete sequential data, it shows great potential of its framework in generating continuous data of time series.

3.1.2 Quant GAN. Quant GAN [11]

which aimed at finding long-term correlations in financial time series data, has both its generator and discriminator being a temporal convolutional network (TCN) with skip connections. As for the generator in Quant GAN, it is a novel stochastic volatility network (SVNN) consisting of drift and volatility TCNs. As for the time block, it is a TCN module with crucial components consisting of expanded causal convolutional layers (which can be seen in Figure 8) and parametric rectangular linear units (PReLU) as activation functions.

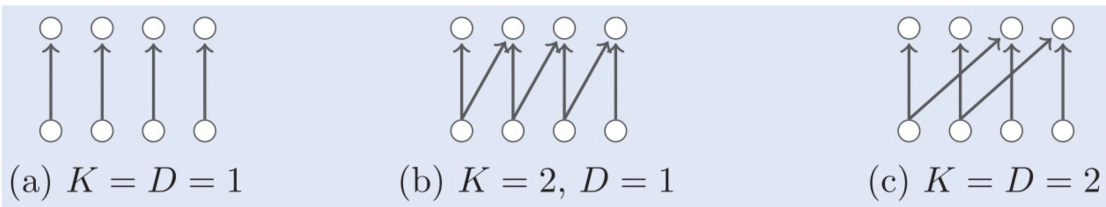

Figure 8. Dilated causal convolutional operator for different dilations D and kernel sizes K: (a) K = D = 1, (b) K = 2, D = 1 and (c) K = D = 2.

The writers tended to find the interconnectedness of financial time series over the long period, however, modelling the continuous time series over this architecture will raise a big problem in the computational complexity. Thus, this approach classified the time series as discrete-time model. Even though the authors claim this approach is superior to more traditional mathematical financial models (GARCH), this problem needs to be proved reliable before this approach can be widely used.

3.2 Continuous Time Series based GANs

3.2.1 Continuous RNN-GAN (C-RNN-GAN)

RNNs have been used to model music in years. Based on RNNs, the C-RNN-GAN (shown in Figure 9), offered one of the earliest examples of using GANs to generate continuous data in sequential form. The generator is defined to be an RNN, whereas the discriminator being capable of receiving the sequences in both directions is defined to be a bidirectional RNN.

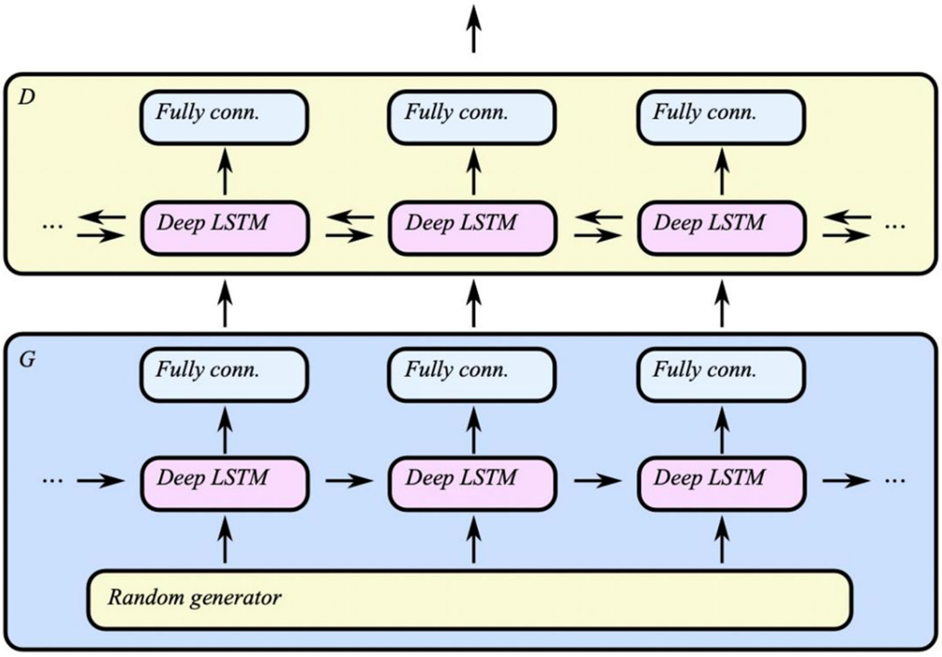

Figure 9. Architecture of C-RNN-GAN

Two stacked LSTMs layers were employed in RNNs of this study, with 350 hidden units in each cell. In the paper, the loss function is given by:

$$L_D = \frac{1}{m}\sum_{i=1}^{m} \log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right) \quad (1)$$

$$L_D = \frac{1}{m}\sum_{i=1}^{m} \left[-\log D\left(x^{(i)}\right) - \log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right)\right] \quad (2)$$

Where $z^{(i)}$ is a sequence of uniform random vectors in $[0,1]^k$, and $x^{(i)}$ is a sequence from the training data. k is the dimensionality of the data in the random sequence.

The C-RNN-GAN is trained by backpropagation through time (BPTT) and mini-batch stochastic gradient descent with L2-regularization on both Generator and Discriminator. When one network gets excessively powerful in comparison to the other, both G and D are frozen. 3697 midi files from 160 distinct classical music composers were employed in a batch size of 20. Gradient Descent Optimizers were applied during training along with Adam Optimizers. To avoid too powerful comparison between Generator and Discriminator, both were frozen in the study at the time when it happened.

To conclude, this model was able to capture the characteristics of input data and produce music. In addition, the author stressed that their approach requires more efforts, particularly when it comes to a comprehensive analysis of the quality of the generated data.

3.2.2 PSA-GAN.

PSA-GAN is an incremental convolutional self-attention-based time series GAN model, which scales to long time series due to its progressive architecture [12]. The self-attention approach will identify long-term dependencies in the data [13]. As shown in Figure 10, the architecture of the proposed model is depicted on the left side. Specifically, through the process of Linear Interpolation, n blocks in the generator of PSA-GAN doubles its size in the output. On the right side depict the main generator and discriminator blocks.

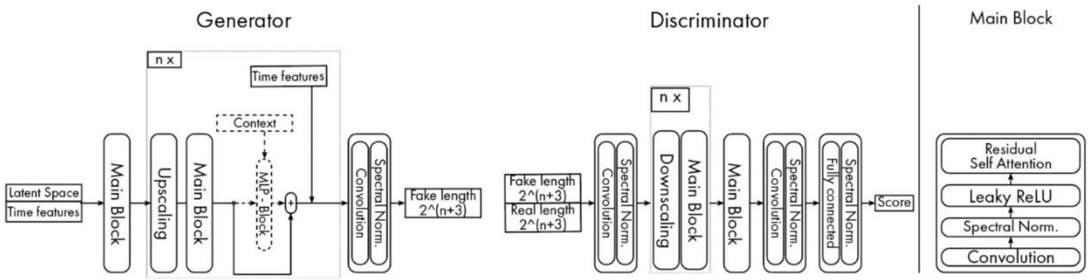

Figure 10. Architecture of PSA-GAN

The LSGAN loss, whose ability of dealing with mode collapse has already been proved, was employed in the training of PSA-GAN. Besides, the embedding space losses of least squares have been successfully applied to the field of time series. But in order to match the first and second order moments between the synthetic and real samples, another loss (auxiliary moment loss) is adopted in the paper:

$$ML(\widehat{Z_\tau}, Z_\tau) = \left|\mu(\widehat{Z_\tau}) - \mu(Z_\tau)\right| + \left|\sigma(\widehat{Z_\tau}) - \sigma(Z_\tau)\right| \quad (3)$$

As indicated by the researchers, due to the complexity of evaluating data synthesized by Time Series GAN models, there does not exist widely acknowledged evaluation system in the time series community. In order to determine whether GAN models can recover the statistics in training set, the Context-FID score was proposed to be the evaluation metric. Due to its ability in computing the difference between real and synthetic data, the FID score is also commonly employed in computer vision [14]. As shown in the Figure 11, the Context-FID score was given in order to evaluate the performance of the ablation models.

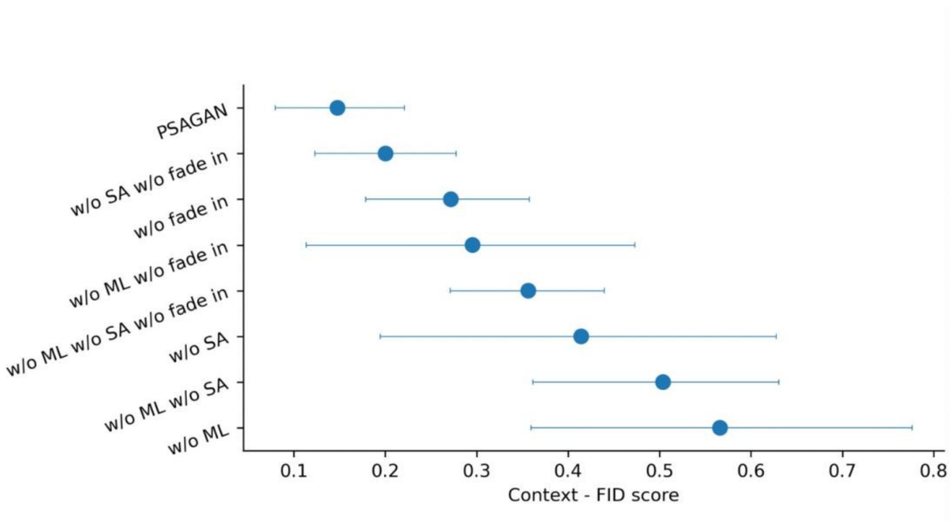

Figure 11. Context-FID score of the ablation models

As it was proposed by the authors, the model that performed best in forecasting turned out to be the one that with the lowest Context-FID score. It was also pointed out that time-series GANs can be made widely available for time-series modelling if they are extended to lagged values and accompanied by proper metrics to evaluate their performance.

4. Generative Adversarial Networks in Fraud Detection

4.1 SSGANs

Anastasiia Izotova and Adel Valiullin proposed to use a GANs model based on semi-supervised learning of sparse auto-encoders for online gambling fraud detection [15][16]. They suggested that semi-supervised networks could provide a powerful and multi-purpose framework to approach supervised learning from unbalanced and fragmented structured data. The structure of semi-supervised GANs (SSGANs) was proposed in Figure 12. The SSGANs framework comprised two parts, a sparse auto-encoder, and the generative antagonist array. The sparse automatic encoder had two coding layers and two decoding layers. The input data in the encoding phase will be projected to the decoding layer of a higher dimension, and then the processed information will be put into the adversarial generation network. After training, the GANs discriminator could determine whether the information was normal or fraudulent.

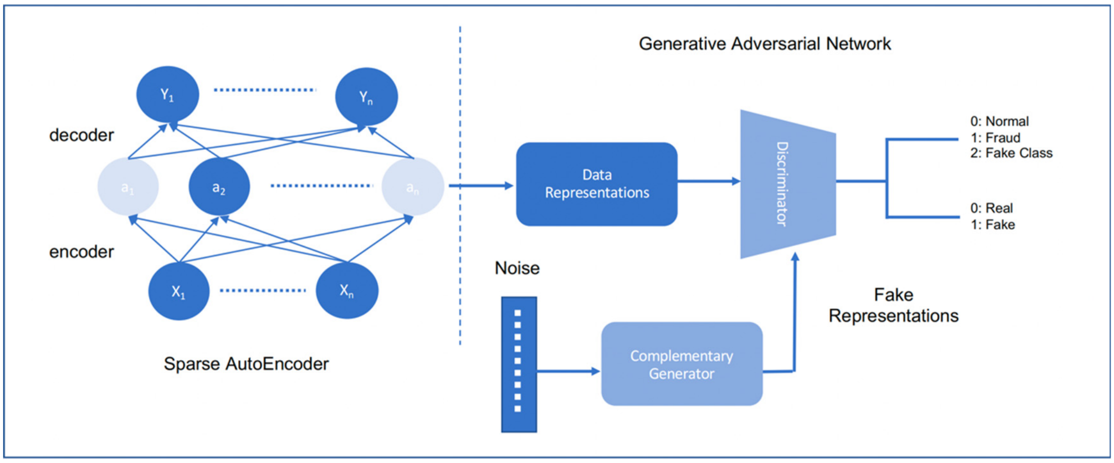

Figure 12. The structure of Semi-supervised Generative Adversarial Network

Table 2. Results of detecting gambling fraud on SSGANs

Method	Accuracy	Recall	Precision	F1
LR	87.3±0.9%	61.0±3.0%	87.5±2.2%	71.9±2.3%
LR+SMOTE	90.9±1.0%	84.8±2.1%	81.6±2.3%	83.2±1.9%
LR+ADASYN	90.0±0.7%	89.6±1.5%	76.7±1.7%	82.6±1.0%
RF	94.2±0.6%	91.0±2.1%	87.8±1.2%	89.3±1.2%
RF+SMOTE	93.6±0.7%	94.6±0.6%	83.6±1.5%	88.7±1.1%
RF+ADASYN	93.5±0.6%	95.7±1.4%	82.6±1.7%	88.6±0.9%
MLP	91.9±1.0%	84.2±2.9%	85.3±2.5%	84.7±2.0%
MLP+SMOTE	92.0±0.6%	93.7±2.5%	79.8±1.7%	86.2±1.0%
MLP+ADASYN	92.2±0.4%	95.3±1.3%	79.5±1.2%	86.6±0.6%
SSGAN-c+SAE	94.4±0.5%	93.1±1.6%	86.7±1.7%	89.9±0.9%

In this research, they used real-world data on gambling fraud, which consisted of 3,500 non-fraud players, and the remaining 1,200 players are potentially fraudulent players. They compared the experiment results with SSGANs with logistic regression (LR), random forest (RF), multi-layer perceptron (MLP), SMOTE (Synthetic Minority Over-sampling Technique), and ADASYN (Adaptive Synthetic Sampling Approach for Imbalanced Learning) and applied other data sets to train the SSGANS model [17][18]. Accuracy, recall, precision, and F1 scores were chosen to evaluate the quality of the above methods. The results are shown in Table 2. The accuracy and F1 score of the

SSGAN-C framework reached 94.37% and 89.85% respectively. The F1 score was 3.64% better than the company's existing monitoring system, and 0.52% higher than other methods.

4.2 DEAGAN

In the application for detecting credit card fraud on GANs, ENSEN WU proposed a new structure which was named Dual Autoencoders Generative Adversarial Network (DAEGAN). DAEGAN consisted of three phases, first training the WGAN model to generate fraudulent data, and then training two auto-encoders to learn the characteristics of normal data and fraudulent data, respectively [19]. The two sets of features, normal data, and fraudulent data were integrated into two autoencoding features. Finally, the model carried out the detection of credit card fraud in the training package generated under the WGAN model. The detailed phases for DAEGAN are shown in Figure 13 [20].

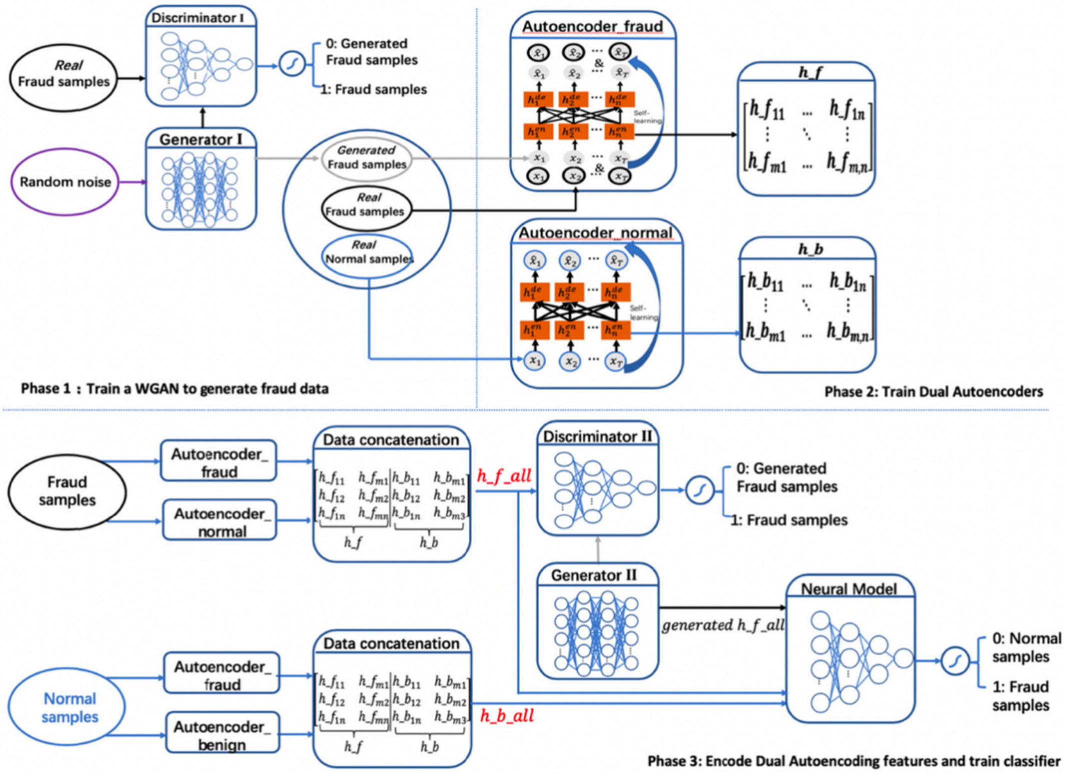

Figure 13. The structure of Dual Autoencoders Generative Adversarial Network

Table 3. Experiments results on DAEGAN

Method	Recall	Precision	F1	AUC	AUPRC
DAEGAN	81.5%	90.3%	85.7%	95.8%	80.5%
AEGAN	77.2%	91.0%	83.5%	91.0%	68.3%
Undersample_NN	85.9%	2.5%	4.8%	95.6%	16.3%
SMOTE_NN	75.0%	49.5%	59.6%	95.6%	70.0%
WGAN	78.2%	83.7%	80.8%	94.5%	67.5%
OCAN	80.8%	25.8%	39.0%	90.1%	40.5%

Researchers first used real transactions made by European cardholders where have 492 frauds out of 284,807 transactions and fraud data generated by WGAN as the data set. Then they divided the training set and test set by 80% and 20% respectively and evaluated the model with the indicators mentioned in the Table 3. The value of AUC is the area enclosed by ROC curve and X-axis, which is one of the main off-line evaluation indexes used in dichotomous classification model. The PRC curve is a dotted line of accuracy and recall. The value of AUPRC is the area enclosed by the PRC curve and X-axis. They compared the experimental results of the proposed GANs model with other traditional methods. AEGAN had the same structure with DAEGAN but missed AE_f part which had three hidden layers. Undersample_NN randomly removed some samples of the majority class to narrow the gap between classes [21]. OCAN is a one-class classification network which proposed by Panpan Zheng. The experimental results are shown as follows. The AUC and AUPRC values of DAEGAN were 0.958 and 0.805, respectively, which were higher than those of other methods. And F1 scores also performed the best.

5. Discussion

5.1 GANs in Stock Market Prediction

5.1.1 GAN for Three-layer Dense Network

From this paper, we can discover that GANs architecture can be used to make representations of time series of the distribution of the stock price of capital markets. Furthermore, in the deep learning models we used, GANs is almost same as models traditionally used as LSTM. To develop this topic, we may try different GAN architectures to simulate the time series and explore loss functions different from traditional GANs in future.

5.1.2 GAN with the MLP and LSTM Separately as the Discriminator and the Generator

In this paper, they tried to capture the distribution of truly stock data in market by GAN which they have created. Perhaps in the future, they could explore more important financial factors to optimize their model

5.1.3 A General Framework for Adversarial Training Using LSTM and CNN

Related to the GAN research, the model improved their prediction ability by means of adversarial training, forecast error loss, and minimizing direction prediction loss. Furthermore, the experimental results showed that the smaller model update cycle could obtain better prediction performance. They could try to integrate predictive models under multiscale conditions.

5.1.4 Stock Price Prediction Model Combined BERT and GAN

The models proposed from this paper demonstrated and validated traditional time series prediction models such as GAN, GRU, LSTM and ARIMA. Their next goal is to predict anything involving data and focus on reward-based learning and prediction.

5.2 GANs in Time Series

5.2.1 Discrete Time Series based GANs

The models of SeqGAN and Quant GANs, classified as discrete Time Series GANs, are both capable of generating discrete Time Series data. Even though Quant GANs, which made use of TCNs, was originally designed to extract characteristics of long-range Time Series, it is uncapable of modeling the continuous financial data due to its fast-increasing computational complexity. SeqGAN, on the other hand, which was originally designed for discrete sequential data generation, actually

5.2.2 Continuous Time Series based GANs

C-RNN-GAN and PSA-GAN are used as instances of continuous Time Series based GANs in this paper. Based on RNNs, C-RNN-GAN was proposed to generate continuous data of music and finally capable of composing(generating) music. It shows great potential not only in generating continuous data of music, but also in modeling other kinds of continuous Time Series. Different from C-RNN-GANs, PSA-GAN with self-attention creatively proposed Context-FID as the evaluation metrics, leading to its finding about the relationship between Context-FID and the downstream performance, which shows the great significance of finding a reliable metric.

5.3 GANs in Fraud Detection

5.3.1 SSGANs

This model had higher accuracy and F1 score, and the SSGANs structure model performed well in dealing with imbalanced data. The online gambling fraud detection system based on SSGANs was better than other systems mentioned in this article. However, the value of recall and precision was lower than other methods. In the future, sparse coding could be used to improve the system and compared the system with more deep learning models.

5.3.2 DAEGAN

Researchers solved the problem of classification imbalance well through DAEGAN model. And the WGAN model generates enough fraud data for training. The experimental results showed that the accuracy and sensitivity of the DAEGAN model were also better than those of other proposed models. However, there was a problem that the DAEGAN model was too complex, and the calculation took too long. Researchers may optimize the model from this aspect.

6. Conclusion

In this paper, we summarized and analysed the application of GANs in the field of finance, which was mainly divided into three parts: stock price prediction, financial time series prediction, and fraud detection. In stock price prediction applications, GAN with the MLP as discriminator and LSTM experiment results showed that the forecast of the closing price is close to the actual data. The general framework for adversarial training using LSTM and CNN could push the accuracy to a higher level. The model combined BERT and GAN worked best in the above methods. This model was more effective than other traditional models. It will be important if researchers further improve the model and apply it to other fields.

In addition, our research focused on the evolution of the architecture and the modification of the loss function in the creation of time series data. Even though there were some state-of-the-art efforts in time series-based GANs, the performance of model generalization and the stated principles still lag behind time series-based computer vision research. Significant efforts are needed to address the instability of training and to select integrated qualitative/quantitative data for evaluation.

In the field of fraud detection, we analyzed two optimized GAN models. SSGANs used real word online gambling fraud transactions as its dataset. The F1 value is better than the traditional models. DAEGAN also performed well in the credit card fraud data set, but the problem is that its structure is too complicated. In the future, researchers can improve the model by optimizing the structure and reducing the computation time.

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