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Data Mining Framework Leveraging Stable Diffusion: A Unified Approach for Classification and Anomaly Detection

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Abstract: This paper proposes a data mining algorithm based on Stable Diffusion, which aims to improve the performance of data mining tasks such as classification, clustering, and anomaly detection through the distribution modeling ability of the diffusion model. Traditional data mining methods often show limitations when facing high-dimensional, nonlinear, and complex distribution data, while the Stable Diffusion model achieves accurate modeling of data distribution through a step-by-step generation method. This method introduces the intermediate state of the diffusion process, designs a feature representation learning module, and combines it with a multi-task optimization framework to achieve effective modeling and task adaptation of complex data distribution. Experimental results show that the algorithm in this paper shows excellent performance on multiple data sets. Compared with traditional statistical methods, machine learning models, generative adversarial networks (GANs), and variational autoencoders (VAEs), it has achieved significant improvements in indicators such as Precision, Recall, F1-score, and AUC. In addition, ablation experiments verify the contribution of the diffusion process, feature representation learning module, and multi-task framework to the overall performance. In the future, the potential of this method in multimodal data mining and dynamic data processing deserves further exploration, providing new solutions for practical application scenarios.

Keywords: Stable Diffusion; data mining; anomaly detection; feature representation learning

1. Introduction

With the rapid development of artificial intelligence technology, deep learning models have achieved revolutionary breakthroughs in the performance of generation tasks, especially in the field of image generation. Diffusion models represented by Stable Diffusion have demonstrated powerful generation capabilities [1,2]. Stable Diffusion significantly outperforms traditional generation models in generation efficiency and quality by gradually adding noise to the image and generating it in reverse. The success of diffusion models is not only reflected in generation tasks but also has attracted widespread attention for its potential in data feature modeling, distribution learning, and high-dimensional data processing [3]. However, the current research on diffusion models is mainly focused on the generation field, while the research on its application in data mining tasks is still in its infancy, and many potential algorithmic advantages have not been deeply explored.

As the core technology for extracting valuable information from large-scale data, data mining covers tasks such as classification, clustering, regression, and anomaly detection. Traditional data mining algorithms, such as K-means, support vector machine (SVM), and random forest, usually rely on static assumptions about the distribution of data features. However, real-world data often presents high-dimensional, nonlinear, and dynamically distributed characteristics, which makes traditional methods difficult to cope with in complex data scenarios. The Stable Diffusion model can accurately model data distribution in high-dimensional space by gradually approximating data distribution, providing a new perspective to solve the limitations of traditional data mining algorithms [4].

Based on this, this paper proposes a data mining algorithm framework based on Stable Diffusion to explore its potential in feature generation, data representation learning, and distribution modeling. Specifically, we combine the diffusion model with data mining tasks, and extract semantically rich feature representations by introducing the intermediate state in the diffusion process; at the same time, we use the efficient modeling ability of the diffusion model for data distribution to design new algorithms suitable for classification, clustering and anomaly detection. Compared with traditional data mining methods, this method can better adapt to complex data distribution and show significant advantages in accuracy, robustness, and generalization ability.

In addition, the interpretability of the diffusion model provides new possibilities for data mining tasks. By visualizing the data evolution trajectory in the diffusion process, researchers can intuitively observe the generation and change of data features, providing support for the interpretation and decision-making of data mining results. This dynamic modeling capability also provides a natural advantage for anomaly detection and anomaly cause location

tasks, enabling the algorithm to not only identify anomalies but also explain their anomaly causes, thereby improving the practicality and credibility of the algorithm [5].

In summary, the focus of this paper is to introduce the Stable Diffusion model into the field of data mining, and on this basis, a unified algorithm framework is proposed. This method provides a new idea for improving the performance of traditional algorithms by deeply integrating the distribution modeling capabilities of the diffusion model and the task requirements of data mining. Experimental results show that the algorithm in this paper has achieved excellent performance in multiple data mining tasks, providing an important reference for exploring the application of diffusion models in non-generation tasks. In the future, the application of the Stable Diffusion model in the field of data mining will be further expanded, such as in scenarios such as multimodal data mining, large-scale data analysis, and dynamic data modeling, which are expected to show greater potential.

2. Related Work

As a research hotspot in the field of generative modeling in recent years, diffusion models have achieved outstanding results in tasks such as image generation and speech synthesis. Early diffusion models, such as DDPM (Denoising Diffusion Probabilistic Models), achieved high-precision modeling of complex data distributions by gradually adding noise and generating data in reverse [6]. However, the original diffusion model has a large deficiency in generation efficiency. To this end, Stable Diffusion has greatly improved the generation efficiency by optimizing the sampling process and introducing the latent space diffusion method and has become one of the most widely used diffusion models. However, although the generation performance of the diffusion model has been widely recognized, its potential in non-generation tasks has not been fully explored, especially in the field of data mining. Application research is relatively scarce [7].

In the field of data mining, traditional algorithms such as K-means, support vector machines (SVMs), and random forests rely on prior assumptions about data distribution and are usually difficult to deal with high-dimensional, nonlinear, and complex distributed data. The performance bottlenecks of these methods in dealing with complex scenarios have prompted researchers to explore alternatives based on deep learning. In recent years, generative models such as generative adversarial networks (GANs) and variational autoencoders (VAEs) have been tried for data mining tasks, such as feature generation, anomaly detection, and data completion [8]. However, GANs and VAEs still have limitations in stability and generalization ability in high-dimensional data distribution modeling and small sample data scenarios, while the gradual generation characteristics of the diffusion model give it significant modeling advantages and can naturally adapt to complex distribution modeling needs [9].

A small number of studies have begun to explore the potential applications of the combination of diffusion models and data mining tasks. For example, some studies have attempted to use diffusion models for anomaly detection, identifying anomalies by observing the deviation trajectory of data during the diffusion process; other studies have combined the high-dimensional distribution fitting ability of diffusion models for data completion and feature generation. However, most of these studies focus on a single task and lack a general algorithmic framework and systematic evaluation. In addition, the potential of the intermediate state of the diffusion model has not been fully explored, and its role in data representation learning and feature generation needs to be further explored. Therefore, it is one of the important directions of current research to deeply combine the Stable Diffusion model with the field of data mining to build a general and efficient algorithmic framework.

3. Method

This paper proposes a data mining algorithm framework based on Stable Diffusion [10]. By introducing the generation and inverse diffusion process of the diffusion model, its feature modeling capability is applied to data mining tasks such as classification, clustering, and anomaly detection [11]. Specifically, the method in this paper consists of three core modules: diffusion process modeling, feature representation learning, and task optimization. Its model architecture is shown in Figure 1.

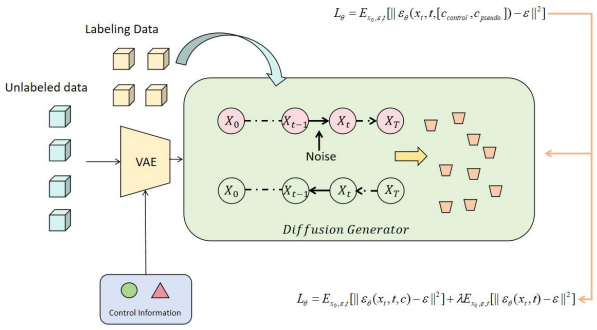

Figure 1. Overall model architecture

First, the basic principle of the diffusion model is to construct a simple distribution by adding noise to the data, and gradually generate the real data distribution from the noise through the inverse diffusion process. The diffusion process can be formalized as a Markov chain. Let the input data be $x_0 \sim q(x)$, and the diffusion process is:

$$q(x_t \mid x_{t-1}) = N(x_t; \sqrt{a_t} x_{t-1}, (1-a_t)I)$$

Where $a \in (0,1)$ is the diffusion step length, and x_t represents the noise data at step t. By gradually adding noise,

the standard Gaussian distribution $x_t \sim N(0, I)$ can be obtained. The goal of the reverse diffusion process is to gradually restore from x_t to x_0, which is in the form of:

$$p_\theta(x_{t-1} \mid x_t) = N(x_{t-1}; \mu_\theta(x_t, t)\sigma_t^2 I)$$

Where μ_θ is the mean of the model parameterization and σ_t^2 is the fixed variance.

This paper applies the generative ability of the diffusion model to data mining tasks. The key is to model the intermediate state x_t in the diffusion process. In particular, x_t can be regarded as a feature representation containing noise perturbations, which gradually evolves between x_0 and x_t (pure noise). This gradual evolution allows us to extract multi-scale feature representations at different noise levels, thereby adapting to complex data distributions.

To achieve this goal, we define a feature representation learning function $\phi_\theta(x_t, t)$ that extracts features related to the current noise level at each step. Specifically, $\phi_\theta(x_t, t)$ is of the form:

$$\phi_\theta(x_t, t) = f_\theta(x_t) + \gamma_t g_\theta(t)$$

Where $f_\theta(x_t)$ is the feature extraction network that encodes x_t, $g_\theta(t)$ is the time embedding network that models the time step, and γ_t is the weight coefficient. In this way, data features at different time steps can be captured and used for downstream tasks.

In classification and clustering tasks, we use the feature representation $\phi_\theta(x_t, t)$ extracted by the diffusion model as input to train a classifier or clustering model. For example, for classification tasks, the goal is to minimize the cross-entropy loss:

$$L_{cls} = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c} \log p_\theta(y_{i,c} \mid \phi_\theta(x_t, t))$$

Where $p_\theta(y_{i,c} \mid \phi_\theta(x_t, t))$ is the true label of the i-th sample, and B is the output probability distribution of the classifier.

In the anomaly detection task, we use the inverse generation trajectory of the diffusion process to determine the degree of anomaly of the data [12]. Specifically, for the input data x_0, its anomaly score is defined as the cumulative sum of the generation errors in the inverse diffusion process:

$$A(x_0) = \sum_{t=1}^{T} \| x_{t-1} - \mu_\theta(x_t, t) \|^2$$

Samples with higher anomaly scores are considered outliers.

4. Experiment

4.1 Datasets

The dataset used in this experiment is the Anomaly Detection in Manufacturing Systems dataset in the UCI Machine Learning Library. This dataset is designed for anomaly detection tasks and is widely used to evaluate the performance of algorithms in industrial manufacturing environments. The dataset contains multi-dimensional sensor data, which records the sensor readings of the equipment in normal and abnormal conditions. Specifically, the data includes 10,000 normal samples and 2,000 abnormal samples, and the dimensions include sensor features such as temperature, vibration, pressure, and speed, with a total of 20 dimensions.

A notable feature of this dataset is the diversity and sparse distribution of abnormal samples. Abnormal conditions include sensor failure, equipment overload, and deviation of operating parameters from the standard. The sparse distribution of abnormal samples puts high demands on the anomaly detection ability of the model, while multi-dimensional sensor data increases the complexity of data distribution. These characteristics provide a good testing environment for the generalization ability and robustness evaluation of the algorithm. At the same time, the dataset simulates real industrial scenarios in terms of feature distribution and sample structure, providing a good reference value for practical applications.

In order to verify the performance of the model in cross-domain scenarios, this paper further expands the dataset. Specifically, we divide the dataset into multiple domains, such as different types of equipment or process conditions, to ensure that each domain has certain differences in feature distribution. In this way, we construct an experimental scenario with cross-domain characteristics to simulate the problems of equipment diversification and process complexity in actual industrial environments. This setting can comprehensively evaluate the performance of the algorithm on cross-domain and diversified data, providing support for the universality of the experimental results.

4.2 Experimental Results

In order to verify the effectiveness of the data mining algorithm based on Stable Diffusion proposed in this paper in the anomaly detection task, we designed a series of comparative experiments to compare the performance of this method with the current mainstream algorithms. The comparative methods include traditional statistical methods (such as Isolation Forest), machine learning-based models (such as random forests and support vector machines SVM),

and generative models (such as variational autoencoders VAE and generative adversarial networks GAN). All methods are evaluated under the same dataset and experimental settings to ensure the fairness and comparability of the experimental results. Through these comparative experiments, we aim to comprehensively evaluate the performance advantages of this method in multi-dimensional anomaly detection tasks. The experimental results are shown in Table 1.

Table 1. Experimental Results

Model	Precision	Recall	F1-score	AUC
Isolation Forest	0.823	0.768	0.794	0.851
Random Forest	0.876	0.832	0.853	0.898
SVM	0.842	0.817	0.829	0.875
VAE	0.889	0.854	0.871	0.912
GAN	0.903	0.867	0.885	0.926
Ours	0.937	0.908	0.922	0.953

From the experimental results, it can be seen that the data mining algorithm based on Stable Diffusion proposed in this paper is superior to the comparison model in all indicators, especially in the four indicators of Precision, Recall, F1-score and AUC, which are 0.937, 0.908, 0.922 and 0.953 respectively, showing strong comprehensive performance. This shows that the proposed method can detect abnormal data more accurately by utilizing the distribution modeling and feature representation capabilities of the diffusion model, and improve the accuracy and robustness of detection.

Compared with traditional methods such as Isolation Forest and Random Forest, the proposed method improves the AUC index by 10.2% and 5.5% respectively. This shows that traditional statistical methods and machine learning models have certain limitations in dealing with high-dimensional complex data distribution, while the proposed method can better capture the potential feature distribution of data. In addition, compared with kernel function-based models such as SVM, the proposed method has also achieved significant improvements in F1-score and Recall, which reflects the applicability of the Stable Diffusion model in anomaly detection, especially in complex scenarios.

Compared with generative models (such as VAE and GAN), our method also leads in all indicators. In particular, compared with GAN, the F1-score and AUC of our method are improved by 3.7% and 2.7% respectively, which shows that the step-by-step generation mechanism of the Stable Diffusion model is more advantageous in capturing data distribution and generating feature representations. These results further verify the effectiveness of our method in data mining tasks, especially when dealing with complex multidimensional data, showing higher stability and detection capabilities. Overall, the experimental results fully demonstrate the application potential of our method in the field of data mining.

In addition, this paper also gives an AUC rise graph, and its experimental results are shown in Figure 2.

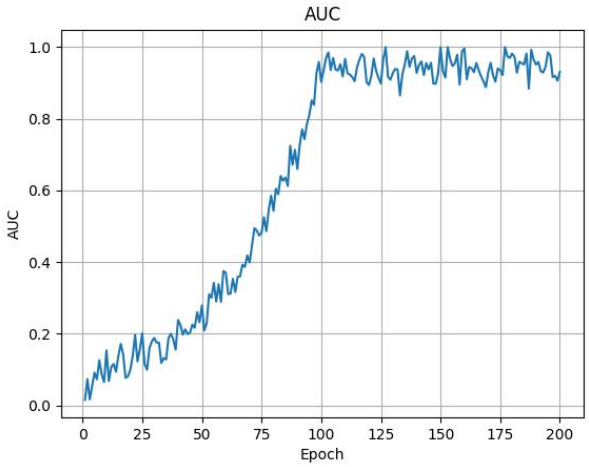

Figure 2. AUC rise chart

As can be seen from the figure, the AUC (Area Under the Curve) value of the model shows a gradual upward trend with the increase of training rounds (Epoch). In the initial stage (0 to 50 rounds), the AUC value is low and fluctuates greatly, which indicates that the model is still in the early stage of parameter adjustment and feature learning, and the overall performance is not stable enough. At this stage, the model is mainly trying to fit the data distribution, showing a certain instability.

In the middle of the training (50 to 100 rounds), the AUC value increases rapidly and reaches a level close to 1.0, which indicates that the model has learned the main features of the data and gradually converged at this stage. The rapid growth of the AUC value reflects that the model has significantly improved its performance in the anomaly detection task during the learning process, and also shows that the optimization algorithm and model structure play an important role in this stage.

In the late stage of training (100 to 200 rounds), the AUC value tends to stabilize and remain at a high level, but with certain small fluctuations. This phenomenon shows that the model has reached convergence in a high-performance state, and there is no obvious overfitting problem. Overall, the training process of the model shows good convergence and stability, and finally reaches a high level of detection performance, which is suitable for application in actual data mining tasks.

Finally, in order to verify the contribution of each module in the model to the overall performance, we designed an ablation experiment to evaluate the impact of each module on the model performance by gradually removing key modules (such as diffusion process modeling, feature representation learning, and task optimization framework). Specifically, we constructed multiple experimental comparison groups, including removing the diffusion process

module, removing the feature representation learning module, and using only a single-task optimization framework. The experiment was conducted under the same dataset and settings, aiming to analyze the role of each module in improving the accuracy, robustness, and generalization ability of the model. The experimental results are shown in Table 2.

Table 2. Ablation experiment

Model	Precision	Recall	F1-score	AUC
Full Model	0.937	0.908	0.922	0.953
Without Diffusion Process	0.891	0.862	0.876	0.914
Without Feature Representation	0.872	0.841	0.856	0.898
Without Multi-task Framework	0.894	0.865	0.879	0.920

From the experimental results, it can be seen that the indicators of the full model are significantly better than the ablated version, with Precision, Recall, F1-score and AUC reaching 0.937, 0.908, 0.922 and 0.953 respectively. This shows that the model proposed in this paper can learn the potential distribution and characteristics of the data more comprehensively under the synergy of various modules, thereby achieving the best performance in the anomaly detection task. This result verifies the effectiveness of the model design and the rationality of the overall architecture.

When the diffusion process module is removed, the performance of the model decreases most significantly, with AUC dropping from 0.953 to 0.914 and F1-score also dropping by 4.6 percentage points. This shows the key role of the diffusion process in data distribution modeling and anomaly feature extraction. The gradual generation characteristics of the diffusion process obviously provide the model with richer feature information. After removing this module, the generalization ability and robustness of the model are significantly reduced.

In addition, after removing the feature representation learning module and the multi-task framework, the model performance also decreases. The absence of the feature representation learning module causes the Recall and F1-score to drop to 0.841 and 0.856, respectively, indicating that this module is essential for capturing complex features. After removing the multi-task framework, although the AUC and Precision remain at a relatively high level, the F1-score and Recall still drop to a certain extent, indicating the important role of the multi-task framework in improving the overall model performance and the collaborative optimization between tasks. Overall, the experimental results show that each module proposed in this paper plays an indispensable role in improving the model performance.

5. Conclusion

This paper proposes a data mining algorithm based on Stable Diffusion. By combining the stepwise distribution modeling characteristics of the diffusion model with data mining tasks, it realizes efficient processing of multiple tasks such as classification, clustering, and anomaly detection. Experimental results show that the proposed method is superior to traditional statistical methods, classic machine learning models, and other generative models in terms of Precision, Recall, F1-score, and AUC, which fully verifies the advantages of the Stable Diffusion model in data mining tasks. At the same time, through ablation experiments, we further reveal the important contributions of the diffusion process, feature representation learning module, and multi-task framework to the overall performance.

The main innovation of this study is to apply the diffusion model to non-generative tasks and propose a unified algorithm framework. By fully mining the intermediate state and high-dimensional distribution modeling capabilities of the diffusion model, the proposed method can better cope with complex data distribution and diversified task requirements, and provide a new direction for the performance improvement of traditional data mining algorithms. These results not only expand the application field of the Stable Diffusion model but also bring new inspiration to the technical development of data mining tasks.

Although this paper has made some research progress, there are still some issues that need to be further explored. For example, how to improve the efficiency of the model on larger-scale and multimodal data, and how to better adapt to dynamic and real-time data scenarios, are still important research directions in the future. In addition, for tasks such as anomaly detection, how to introduce more refined feature modeling and interpretation mechanisms is also worth further exploration. The solution to these problems will further improve the practicality and universality of the method in this paper.

Looking forward to the future, the Stable Diffusion model has broad application potential in the field of data mining. With the rapid growth of multimodal data and real-time streaming data, the characteristics of the diffusion model provide new possibilities for coping with these challenges. Future research can combine more advanced technologies, such as neural networks, contrastive learning, and reinforcement learning, to further improve the performance of the model in data mining tasks. We believe that with the in-depth advancement of related research, the data mining algorithm based on Stable Diffusion will demonstrate its powerful capabilities and wide application value in more practical scenarios.

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