Anomaly Detection of Aerospace Facilities Using Ganomaly

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ABSTRACT
In the field of aerospace, the abnormal detection of data is of great significance. The rapid and effective detection of abnormal parameters is key to find potential failures of spacecraft. Traditional methods of anomaly detection need much manual labour and material resources but cannot satisfy the requirements of real-time accuracy. At the same time, there are far more normal samples than abnormal samples, and the original classification methods cannot be applied. In this paper, we propose a GANomaly-based framework for anomaly detection of aerospace data. GANomaly is a framework that analyzes the underlying relationships of data using potential space, which is more in line with the characteristics of the payload data and the actual scenarios for anomaly detection. This article compares GANomaly with other anomaly detection methods on the public aerospace dataset and payload dataset respectively. The results show that the GANomaly-based anomaly detection framework has good capabilities for detecting abnormality of aerospace datasets.

CCS Concepts
• Information systems →Information systems applications →Data mining →Data stream mining

Keywords
Anomaly detection; space payload; GANomaly; GAN

1. INTRODUCTION
With the rapid development of the aerospace industry, the space station is more and more widely usedwhere the structure and function of the payload are more complex, and the requirements for its robustness and stability are higher. A large amount of on-orbit real-time monitoring data generated by the payload is transmitted from space to the ground system. which contains a large amount of operating status information, which reflects the working status of the space payload. At the same time, the design, manufacture and in-orbit operation of space payloads will cost a lot of manual labor, material and financial resources. This paper proposes a framework based on GANomaly for anomaly detection of load data.

1.1 Related Work
In anomaly detection, the most traditional method is to distinguish normal from abnormal based on the threshold value and expert experience. This method is highly efficient and sufficient for daily detection. However, it is difficult to distinguish anomalies that do not exceed the threshold, and the flexibility is not enough. It is difficult to obtain expert experience for different situations at the same time. In recent years, deep learning has developed rapidly, and more and more deep learning based methods have been applied to anomaly detection. The accuracy of deep learning detection is higher, and more complex relationship between data can be learned. Many deep learning methods are applied to anomaly detection. However, because of an imbalance between the data of different categories, there are far more normal samples than abnormal samples. Therefore, most researches are based on semi-supervised and unsupervised anomaly detection and generating models have become one of the most popular technologies. The generative model refers to a model that can learn its distribution by extracting the underling features and generate similar samples. Early researches proposed using a Restricted Boltzmann machine (RBM) [1], Autoencoder (AE) [2] and other generative models as a feature learner to speed up training via the network [3]. In 2014, Goodfellow proposed GAN. Then GANs are more used for anomaly detection although their application has been only recently explored [4-6]. Anomaly detection using GANs is the task of modeling the normal behavior using the adversarial training process and detecting the anomalies by means of an anomaly score [4]. AnoGAN[4] is the first proposed model applied on anomaly detection, it uses a standard GAN to train with positive samples, learn a mapping from latent variables z to real samples, and use this learning representation to map new samples back to latent space. Efficient GAN-Based Anomaly Detection (EGBAD) [5] utilize the BiGAN architecture into anomaly detection. In particular, EGBAD tries to address the disadvantages of AnoGAN reffering to the works of Donahue et al. [7] and Dumoulin et al. [8] that allows an encoder able to map input samples to their latent representation during the adversarial training. GANomaly [6] makes another improvement, using latent coding space to compare images. For normal data, the gap between the latent space obtained by encode-decode-encode structure and the latent space obtained by the first encoding will not be that large. However, if the gap in the latent space of the

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input abnormal data is large. When this distance exceeds a certain threshold, it is determined as an abnormal sample.

In this paper, we compare the effectiveness of the GANomaly algorithm in detecting anomalies in public and payload datasets. The experimental results show that the proposed framework can accurately detect anomalies on aerospace data, which has practical significance.

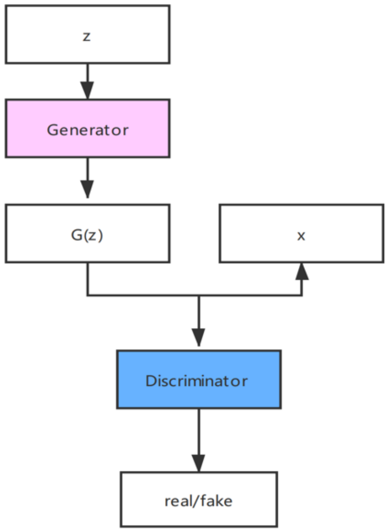

Figure 1. The architecture of GAN

1.2 Outline

The remaining of article is organized as follows. The second part reviews the principles and basic framework of GAN and GANomaly. The third part presents the process of GANomaly for anomaly detection of aerospace data. The fourth part mainly introduces the data and experimental results, and compares GANomaly with other methods. The fifth part summarizes the paper and looks forward to the key direction of the future work.

2. THEORETICAL BACKGROUND

2.1 Overview of GAN

Generative Adversarial Networks (GANs) was proposed by Ian Goodfellow [9] and it is a framework for estimating generative models via an adversarial process. The system consists of two models, a generator network G and a discriminator network D that are trained simultaneously. G captures the actual distribution of the real dataset, with the goal of mapping a latent space to the data distribution. D can judge the authenticity of the input data, aiming to estimate the probability that a sample came from the training data rather than G. The purpose of generator network is to fool the discriminator into believing that the generated data comes from the actual data distribution. The optimization of GAN is a "minimax two-player game", through the two network alternate training. So the resulting discriminator D network can learn to distinguish between generated data and real data, which makes the generator network in GAN no longer, requires a priori knowledge of real data. It can also be independent distribution approximation to study the result of real data. The generative network G can estimate the distribution of sample data, and the final result is that the data can be distinguished as false or true. In other words, it is difficult to distinguish the authenticity of data from the discriminator network directly. During the training phase, GAN can find a unique equilibrium solution, where G can generate the same distribution as the training sample, while the probability of D is 1/2 everywhere after the Nash-equilibrium of the training process. Figure 1 shows the architecture of a GAN.

To learn a generative distribution, p_g builds a mapping from a prior noise distribution p_z to a data space as $G(z;\theta_G)$, where θ_G are the parameters of the generator. The discriminator outputs a single scalar value defined as a measure of probability for the credibility of the x coming from real data rather than from p_g. The generator function is denoted with $D(x;\theta_D)$, where θ_D are the parameters of the discriminator. In order to train two models, the generator and discriminator both want to minimize their own cost function, $J_G(\theta_D,\theta_G)$ and $J_D(\theta_D,\theta_G)$respectively, by only adjusting their own parameters. The solution is a tuple (θ_D,θ_G) that minimizes J_D and, J_G. The training process utilizes a strategy called stochastic gradient descent. In the network, the input is divided into two parts, one that consists of values x from the real dataset, and the other that is drawn from the model's prior over noise variables. The iterative steps that update θ_D to reduce J_D and θ_G to reduce J_G are made at the same time. The cost used for the discriminator is:

$$J_D(\theta_D,\theta_G) = -\frac{1}{2}E_{x\sim p_{dt}}[\log D(x)] - \frac{1}{2}E_z\left[\log\left(1-D\big(G(z)\big)\right)\right] \quad (1)$$

The cost for the generator is $J_G = -J_D$. We define $V(\theta_D,\theta_G)= -J_D(\theta_D,\theta_G)$. Thus, models D and G are simultaneously optimized through the two-player minimax game with value function $V(\theta_D,\theta_G)$ as shown by (2).

$$\min_G \max_D V(D,G) = E_{x\sim p_{dt}}[\log D(x)] + E_z\left[\log\left(1-D\big(G(z)\big)\right)\right] \quad (2)$$

2.2 Overview of GANomaly

The GANomaly method is introduced by Akcay et al [6], where the generator consists of encoder-decoder-encoder sub-networks, which results in a direct feature space representation, and another sub-network is discriminator network, which aims to distinguish the input data from the real dataset or generator network. GANomaly utilizes an improved structure based on standard GAN architecture contained a generator network, which trains normal samples x by using an autoencoder trained to learn how to encode the data in their latent representation z efficiently. Then decoder generates samples $\hat{x}$ to complete an autoencoder process at the same time transforming $\hat{x}$ into $\hat{z}$ by another encoder network, and a discriminator receives fake samples produced by the generator and real samples from the original dataset for discrimination if the incoming sample is from the normal samples x. Figure 2 shows a visual representation of the architecture GANomaly [4].

2.2.1 Generator Network

The generator G is composed of three factors in this sub-network, a completed autoencoder structure including an encoder G_E a decoder $G_D$and another encoder E.

The encoder G_E and another encoder E share the same framework. G_E encodes the input real image to get the encoded variable z.

Then z become the input to G_D which decodes z to get the output $\hat{x}$, the reconstructed x. Based on these, the generator network generates an image $\hat{x}$ by $\hat{x} = G_D(z)$ and $z = G_E(x)$. Finally, $\hat{x}$ is fed to the encoder E as a input to produces $\hat{z}$.

The structure of GANomaly has two main contributions. Firstly, the random noise of the original GAN input was used as the input to encode the normal data with the structure of autoencoder to facilitate anomaly detection, and the decoder was used to restore the representation to get the data more similar to the real data as the input of the discriminator. Secondly, Autoencoder uses z to generate normal data $\hat{x}$, when the input data is abnormal, because the generator always produces normal images, so the reconstructed data will have a very big difference with the input data.

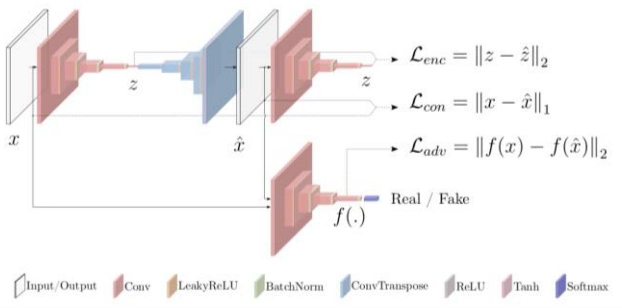

Figure 2. GANomaly architecture and loss functions.

2.2.2 Discriminator Network

The discriminator D is another part in the whole GANomaly system. With the former part the generator G , these two components form the standard GAN architecture. The discriminator D is used to discriminate real data and generate data to maximize the probability of assigning the correct label to both examples of real data and generated samples. When discriminator has difficulty distinguishing them, it means that the data the generator generates at this time is very similar to the real data.

The GANomaly architecture differs from AnoGAN [4] and from EGBAD [5]. In Figure 4 the three architectures are presented.

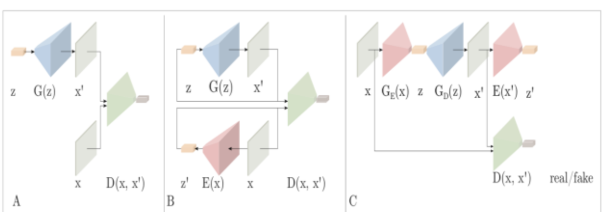

Figure 3. Architectures comparison. A) AnoGAN [4],

B) EGBAD[5], C) GANomaly[6].

2.2.3 The Composition of Loss

In addition to the three sub-networks, GANomaly makes a major contribution in the calculation of loss. The discriminator loss is the classical discriminator GAN loss; The generator loss of GANomaly is composed of three different losses, which optimizes the different parts of the whole architecture.

Including **Adversarial Loss** was chosen to be the feature matching loss proposed by Schlegl et al. [4] and pursued in Zenati et al.[5], where f is a layer of discriminator D to extract the characteristic representation of the input.

$$\mathcal{L}_{adv} = \mathrm{E}_{x\sim px}|f(x) - \mathrm{E}_{x\sim px}f(G(x))|_2 \tag{3}$$

Contextual Loss Isola et al.[10] was introduced to optimization to learn contextual information of input data,

$$\mathcal{L}_{con} = E_{x\sim px}|x - G(x)|_1 \tag{4}$$

and **Encoder Loss** This loss is used to let generator learn how to encode the features of an image generated for normal samples

$$\mathcal{L}_{enc} = E_{x\sim px}|G_E(x) - E(G(x))|_2 \tag{5}$$

The resulting generator loss will be the result of the sum of the three previously defined losses:

$$\mathcal{L} = w_{adv}\mathcal{L}_{adv} + w_{con}\mathcal{L}_{con} + w_{enc}\mathcal{L}_{enc} \tag{6}$$

Where w_{adv} , w_{con} and w_{enc} are weighting parameters that can be adjusted accordingly.

3. PROPOSED METHOD

3.1 The Framework of Improved GANomaly

Because the space environment is unknown and changeable, the structure and function of the space payload are extremely complex, and the inherent meaning between the downlink data is more complicated. Here we propose to use GANomaly to perform anomaly detection of the payload data in the space field. The framework of anomaly detection method based on GANomaly is shown in Figure 3 and the steps are shown as follows.

The specific steps of anomaly detection based on GANomaly are shown in Figure 4:

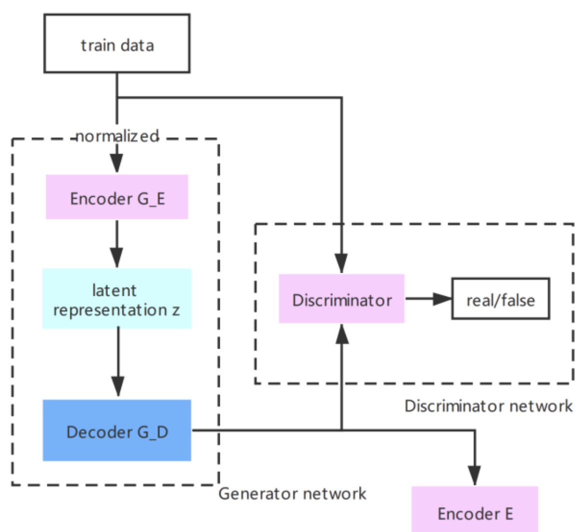

Figure 4. The framework of the improved GANomaly.

Step1, preprocess the raw load data. The training data should cover all working modes and uplink instructions in normal situation. The training data with the complete model is obtained for the next model training process.

Step2, we input the training data into GANomaly, using the generator network, the discriminator and the coding network to compete each other, and continuously calculate and optimize based on the three sets of loss functions. At the same time, use the backpropagation to update the parameters to gradually reduce the loss, and finally obtain a proper set of model parameters.

Step3, calculate potential spatial differences among the testing set containing normal data and abnormal data. If the data distribution differs greatly, the loss will exceed the set threshold range, and it will be determined as abnormal data. Otherwise, it is normal data.

3.2 Evaluation Criterion

There are some criteria to measure the performance of algorithms: precision, recall, F1 score. TP denotes the number of correctly detected anomalies, FP represents the number of normal samples that are considered as abnormal, FN denotes the number of undetected anomalies, and TN denotes the number of normal data judged to be normal. Where $F1$ represents the overall performance of the algorithm. And AUC-ROC curve is a performance measurement for classification problem at various thresholds settings. ROC is a probability curve and AUC represents degree or measure of separability, The ROC curve is plotted with TPR against the FPR where TPR is on the y-axis and FPR is on the x-axis. The formula is as follows:

$$Precision = \frac{TP}{TP+FP} \tag{7}$$

$$Recall = TPR = \frac{TP}{TP+FN} \tag{8}$$

$$F1 = \frac{2\times Precision\times Recall}{Precision+Recall} \tag{9}$$

$$FPR = \frac{FP}{FP+TN} \tag{10}$$

4. EXPERIMENTS

In this section, we first introduce the datasets used in the aerospace, then apply the proposed method and compared method on the datasets.

4.1 Dataset Introduction

The relevant situation of the data set used in this experiment will be introduced here. The dataset includes the public dataset Statlog Shuttle and the real dataset of the payload. The data characteristics of these two datasets will be introduced separately below.

Statlog Shuttle This dataset is a space shuttle dataset that describes the location of the radiator in the NASA space shuttle with 9 attributes, using anomaly detection. The "heatsink flow" is the normal category and the remaining 20% is a description of the original data anomaly. In order to reduce the number of anomalies, we chose Level 1 as the normal data and changed it to 2, 3, 5, 6, and 7 as abnormal data.

Similarly, the training and testing sets are in a large dataset, resulting in 46,464 instances with an anomaly rate of 1.89% ,878 exceptions appeared. This experiment selects 5000 data (including all abnormal data) as testing data.

Real Dataset of payload The dataset is the real load dataset for a payload on the spacecraft. The dataset is a 65-dimensional high dimensional data with time series features. During the period of normal working of the payload, we selected 80,000 samples as the training data for this experiment. At the same time, we also selected the data for a period of time before the failure of the payload and the failure samples, as the testing data. The testing set data consists of 3,581 normal data before failure and 3,080 anomaly data. There are no reusable samples in the normal data of the training set and testing set.

4.2 Experimental Results of Anomaly Detection

4.2.1 Results on Space Public Dataset

In the experiment, we performed a series of tests on the public dataset in Statlog Shuttle, including comparison of some classic methods (AE, LSTM AE, AnoGAN) and GANomaly-based methods in the detection of anomalies. We found that Ganomaly in the experiment performs well, have a good detection effect, and can detect most abnormal data. The specific experimental results are shown in Table 1.

Table 1. Evaluation results of different model on shuttle dataset

Model	Precision	Recall	F1	AUC
AE	0.963±6.7e-3	0.959±5.1e-4	0.961±6.1e-3	0.979
LSTM AE	0.745±3.6e-2	**0.964±3.7e-3**	0.768±6.1e-3	0.960
AnoGAN	0.959±4.9e-4	0.960±1.7e-4	0.959±2.4e-4	0.978
Our model	**0.985±1.5e-2**	0.962±3.5e-4	**0.978±1.4e-2**	**0.9840**

We can see that on the Shuttle dataset, the anomaly detection effect based on the GANomaly framework is relatively good, and each detection index has a high value. Compared with other methods, it can be seen that the accuracy of anomaly detection, F1 value and AUC have better performance.

4.2.2 Results on Space Payload

Next, we apply GANomaly to the actual payload dataset. This data set is an important parameter reflecting its working status.

Abnormal uplink commands and aging equipment may cause abnormal downlink data. First, we will compare the difference index of the potential space of the generator of GANomaly and the reconstructed potential space. The scores exceeding the threshold are regarded as abnormal samples. The results are shown in Figure 5.

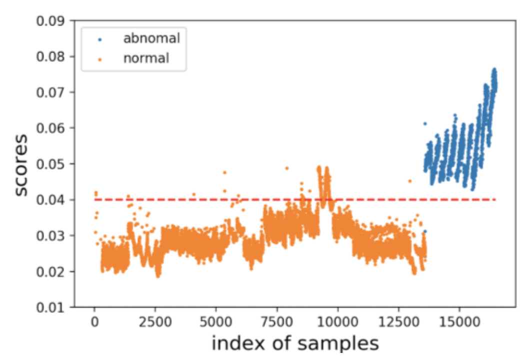

Figure 5. The distribution of scores on payload.

In Figure 5, orange is normal data, blue is abnormal data, and red dashed lines are thresholds. We can see that most normal samples are below the threshold and most abnormal samples are above the threshold, so this method has relatively good results.

Next, we compare GANomaly with several other methods on valid datasets, and prove that this model is effective in anomaly detection. The specific experimental results are shown in Table 2.

The GANomaly network is trained using normal data of the payload obtained in the real environment. From the experimental results in Table 2, it can be seen that the model can effectively and accurately detect unknown abnormal data and reflect the abnormal situation. There are far more normal data than abnormal data. In the aerospace field where anomalous data is scarce, this method has good applicability and has application value.

Table 2. Evaluation results of different model on space payload

Model	Precision	Recall	F1	AUC
AE	0.964±1.0 e-4	0.626±4.3 e-5	0.7588±6. 1e-5	0.872
LSTM AE	0.848±1.0 e-2	0.779±1.3 e-2	0.812±1.5 e-2	0.682
AnoGAN	0.386±2.4 e-2	0.901±1.5 e-2	0.541±2.7 e-2	0.7890
Our model	**0.981±2.5 e-3**	**0.967±2.4 e-4**	**0.982±4.4 e-2**	**0.989**

5. CONCLUSION

GANomaly is a method proposed in image anomaly detection. This paper applies it to the anomaly detection of aerospace data. We train the model with normal data to get a good detection model and appropriate thresholds. Then, we use including normal and abnormal data to determine whether the data is in an abnormal state using the value of the error. GANomaly perfectly takes the advantages of GAN and AE. By adding the loss function of latent features, three types of loss functions are obtained to update the model, so that the method can better learn the internal relationship between the data, the detection of GANomaly is more in line with the characteristics of the payload data and the actual scenarios.

Based on GANomaly, this paper conducts anomaly detection experiments on multiple sets of space data on public and payload datasets. The experimental results show that GANomaly can quickly and accurately detect anomalies. For solving the problem of anomaly detection under the influence of complex external environmental factors of the aerospace system, our proposed method has good accuracy, real-time and robustness, and has good performance in practical anomaly detection applications. In the future, we will continue to improve the algorithm to achieve a higher degree of adaptation. In addition, how to further improve this algorithm is also a valuable research.

6. ACKNOWLEDGMENTS

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7. REFERENCES

[1] Smolensky P. Information processing in dynamical systems: Foundations of harmony theory. Parallel Distributed Processing: Explorations in the Microstructure of Cognition. Cambridge, MA, USA: MIT Press, 1986.

[2] Hinton G E, Zemel R S. Autoencoders, minimum description length and Helmholtz free energy. In: Proceedings of the 6th International Conference on Neural Information Processing Systems. Denver, Colorado, USA: Morgan Kaufmann Publishers Inc., 1994. 3-10

[3] Bengio Y, Lamblin P, Popovici D, Larochelle H. Greedy layer-wise training of deep networks. In: Proceedings of the 21st Annual Conference on Neural Information Processing Systems. Vancouver, BC, Canada: MIT Press, 2007. 153-160

[4] Schlegl T, Seeböck P, Waldstein S M, et al. Unsupervised anomaly detection with generative adversarial networks to guide marker discovery[C]//International Conference on Information Processing in Medical Imaging. Springer, Cham, 2017: 146-157.

[5] Zenati H, Foo C S, Lecouat B, et al. Efficient gan-based anomaly detection[J]. arXiv preprint arXiv:1802.06222, 2018.

[6] Akcay S, Atapour-Abarghouei A, Breckon T P. Ganomaly: Semi-supervised anomaly detection via adversarial training[C]//Asian Conference on Computer Vision. Springer, Cham, 2018: 622-637.

[7] Donahue, J., Krhenbhl, P., and Darrell, T. Adversarial Feature Learning. abs/1605.09782, 2016. URL http: //arxiv.org/abs/1605.09782.

[8] Dumoulin, V., Belghazi, M. I. D., Poole, B., Lamb, A., Arjovsky, M., Mastropietro, O., and Courville, A. Adversarially learned inference. 2017. URL http://arXiv. org/abs/1606.00704.

[9] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, “Generative adversarial nets,” in Advances in Neural Information Processing Systems 27, 2014, pp. 2672–2680.

[10] Isola P, Zhu J Y, Zhou T, et al. Image-to-image translation with conditional adversarial networks[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2017: 1125-1134.

[11] Di Mattia F, Galeone P, De Simoni M, et al. A survey on gans for anomaly detection[J]. arXiv preprint arXiv:1906.11632, 2019.

[12] Wang Z, She Q, Ward T E. Generative adversarial networks: A survey and taxonomy[J]. arXiv preprint arXiv:1906.01529, 2019.

[13] Silva E, Lochter J. A study on Anomaly Detection GAN-based methods on image data[C]//Anais do XVI Encontro Nacional de Inteligência Artificial e Computacional. SBC, 2020: 823-831.

[14] Kliger M, Fleishman S. Novelty detection with gan[J]. arXiv preprint arXiv:1802.10560, 2018.

[15] Lee W, Xiang D. Information-theoretic measures for anomaly detection[C]//Proceedings 2001 IEEE Symposium on Security and Privacy. S&P 2001. IEEE, 2000: 130-143.