CRATOS: Cognition of Reliable Algorithm for Time-series Optimal Solution

Ziling Wu
School of Electronics and Information Technology
Sun Yat-sen University

Ping Liu
Huawei Technologies Co.

Zheng Hu
Huawei Technologies Co.

Jun Wang
School of Electronics and Information Technology
Sun Yat-sen University

Abstract

Anomaly detection of time series plays an important role in reliability systems engineering. However, in practical application, there is no precisely defined boundary between normal and anomalous behaviors in different application scenarios. Therefore, different anomaly detection algorithms and processes ought to be adopted for time series in different situations. Although such strategy improve the accuracy of anomaly detection, it takes a lot of time for engineers to configure millions of different algorithms to different series, which greatly increases the development and maintenance cost of anomaly detection processes. In this paper, we propose CRATOS which is a self-adapt algorithm that extract features for time series, and then cluster series with similar features into one group. For each group we utilize evolution algorithms to search the best anomaly detection methods and processes. Our methods can significantly reduce the cost of development and maintenance. According to our experiments, our clustering methods achieve the state-of-art results. Compared with the accuracy (93.4%) of the anomaly detection algorithms that engineers configure for different time series manually, our algorithms is not far behind in detecting accuracy (85.1%).

1 Introduction

Outlier detection has become a field of interest for many researchers and practitioners and is now one of the main tasks of time series data mining. Although various anomaly detection algorithms have been investigated, there is no universal algorithm to deal with all the anomaly detection tasks in time series. In most cases, appropriate anomaly detection algorithms are manually configured to a KPI based on the nature of it. Especially, the inappropriate adaptation which frequently happens will lead to serious problems such as false positive, false negative and untimely alarm. Moreover, time series in cloud computing data centers is considerably huge. Therefore, it is pretty tedious for engineers to manually adapt the detection process for different time series.

In order to solve the problem mentioned above, Li et al. [16] proposed a KPIs clustering method in which the complicated time series is gathered into one cluster according to similarities, and then uniform anomaly detection algorithm is adapted to these clustered time series. However, most existing clustering methods based on the waveform similarity hardly take use of this idea because such clustering methods are not designed for anomaly detection on purpose. The results gotten from those methods are sometimes not suitable for any anomaly detector, or clusters suitable for the same one detector does not reduce the workload of engineers very much.

In this paper, we propose CRATOS which can self-adapt algorithms for anomaly detection. Firstly, the features of a large number of input time series are extracted, and then targeted hierarchical clustering for the extracted features are made. Then we use evolutionary algorithm (EA) to find the most appropriate anomaly detection algorithm and corresponding parameters for each cluster. After the off-line training process above, a trained anomaly detection mode can be obtained as: a) determine the cluster of the input time series; b) use the previously trained anomaly detection process which is suitable for the cluster the input time series belonging to to detect outliers in the input time series. The above processes can significantly improve the efficiency of algorithm adaptation and maintenance for large-scale time series anomaly detection.

In summary, the contribution of the paper consists of:
1) We propose three features for clustering and suggest to cluster time series with these features.
2) We utilize evolutionary algorithms to select appropriate anomaly detection algorithms and parameters for different KPIs clusters.
3) We suggest a self-adapt algorithm processes for anomaly detection, which we name CRATOS.

2 Related works

One strategy of anomaly detection for univariate time series is to predict the expected value of a point and then compare the difference between the ground truth value of that point and the expected value. In [6,7,22,27], values both before and after a point was proposed to be used for predicting the expected value of that point. After obtaining the expected value, Carter and Streilein [6], Chen et al. [7] and Reddy et al. [22] directly calculate the difference between the real value and the predicted value and Song et al. [27] use slope constrains to detect anomalies. Besides, there are some methods predicting the expected value by simply using the value before that point. For instance, Basu and Meckesheimer [4] use the mean value before this point to predict the expected value of
In the section of offline training, we first cluster KPIs into a number of clusters, then we configure parameters and algorithms for each cluster with evolution algorithm. In the section of online predicting, we determine which cluster a new KPI belongs to and then we use the anomaly detection processes for the cluster to detect outliers in the new KPI.

Hill and Minsker [10] predict the change interval of the expected value with an auto-regressive model. Ahmad et al. [2] use the Hierarchical Temporal Memory (HTM) network which updates incrementally as new observations arrive.

In terms of multivariate time series, Papadimitriou et al. The anomaly detection methods of single KPI was applied to multivariate time series after eliminating the correlation between different KPIs. Principal Component Analysis (PCA) is proposed to reduce the dimension of multivariate time series and eliminate the correlation between KPIs [21]. Galeano et al. [9] suggest reducing the dimensionality with projection pursuit, which aims to find the best projections to identify outliers. Baragona and Battaglia [3] propose using Independent Component Analysis (ICA) to obtain a set of independent time series of non-gaussian distributions. Lu et al. [18] and Shahriar et al. [26] simplify the input multivariate time series into a single time series instead of a set of unrelated series. It should be noted that methods proposed by Galeano et al. [9] and Lu et al. [18] are only applicable to data dimensionality reduction in the field of anomaly detection instead of other fields. There are also some methods that directly detect anomalies on multivariate time series without reducing dimension. They can simultaneously predict the expected value of all KPIs to obtain an expected value vector, and calculate the distance between the expected value vector and the ground truth to detect anomalies. For example, in [15,29], auto-encoder is proposed to predict the expected value of all KPIs because the abnormal points often contain some non-representative features and auto-encoders fail to reconstruct these features at the decoding ends, which will result in a significant difference between the input and output of the auto-encoder at the anomaly point. So that's the reason why we can interpret the output of the decoding end of the auto-encoder as a prediction of the expected value of all KPIs. Su et al. [29] extract the correlation of volatility features of different curves (whether volatility is correlated, whether the backward order of volatility is consistent with the direction of volatility) for anomaly detection and diagnosis.

To detect subsequence outliers of univariate time series, Keogh et al. [14] and Lin et al. [17] compare the difference between a subsequence and the other subsequences in the time series. However, such strategy requires an artificially predetermined length of the subsequence. To address this problem, Senin et al. [25] utilize Piecewise Aggregate Approximation (PAA) to calculate the length of subsequences automatically.

For subsequence outliers in multivariate time series, compared with univariate time series, it is often necessary to consider the correlation between KPIs. One strategy directly applies univariate techniques to each time-dependent variable in multivariate time series. For instance, Jones et al. [12, 13] apply the exemplar-based method to each variable of the multivariate time series by setting a normal subsequence as the reference and compare other subsequences with the reference during detection. Wang et al. [30] reduce the dimension of the data before detection, eliminating the correlation between the indicators. Different from applying univariate techniques to each time-dependent variable in multivariate time series, some methods can directly detect the anomaly sequences in multivariate time series. Munir et al. [19] use CNN to predict the expected value of the upcoming subsequence and compare it
with the ground truth value to detect outlier subsequence.

In recent years, deep learning has been widely used in computer vision, natural language processing and other fields, as well as in the field of anomaly detection. This is because deep learning has better performance than traditional methods and can be applied to large amounts of data. Besides, deep neural network can automatically extract the features of data hierarchically without manual feature extraction, which can approach end-to-end anomaly detection. Hundman et al. [11] propose using the Long Short-Term Memory (LSTM) to predict spacecraft telemetry and find point outliers by the difference between expected values and ground truth. Salinas et al. [21] propose a supervised learning algorithm suitable for time series prediction by using Recurrent Neural Network (RNN) to generate point prediction and probability prediction, which has higher prediction accuracy than traditional prediction techniques such as Autoregressive Integrated Moving Average model (ARIMA) and exponential smoothing. The MSCRED proposed by Zhang et al. [31] converts the multivariate time series data into the multi-resolution feature matrix, which serves as the input of convolution LSTM, by calculating the covariance between the pairs of multivariate time series, enhances the fitting ability of the network and can realize the detection and diagnosis of anomalies in multivariate time series at the same time. However, since the boundary between abnormal and normal behaviors is not clear defined in different data domains, as we explained in the introduction, and there is no enough labeled dataset for supervised learning, despite deep learning has better performance than traditional methods, deep learning cannot replace the traditional methods in anomaly detection.

Since boundaries between normal and abnormal behaviors are not consistent in different application scenarios, even though many state of art anomaly detection algorithms have been proposed, we still need to configure different anomaly detection techniques to different application scenarios. One of the solutions to this problem is to divide a large number of KPIs into different clusters, and the KPIs in a single cluster have much in common. Then, a unified anomaly detection algorithm can be adapted to a single cluster, so as to avoid configuring anomaly detection algorithms to a large number of KPIs one by one. This idea requires us to make a classifier of massive KPIs and a matching strategy of algorithms. As for the KPIs classifier, the application of supervised learning method is not effective since there is no clear classification of KPIs categories in the industry and there is also a lack of labeled data sets for KPIs classification. Therefore, many scholars have focused on clustering, which is an unsupervised learning strategy. Ding et al. [5] proposed YADING which can cluster large scale time series. By randomly extracting time series and using PAA to compress time series, it can reduce the computation quantities of large scale KPIs clustering. By taking L1-norm between compressed time series as the distance of time series, it cluster compressed time series with multi-DBSCAN. Li et al. [16] proposed ROCKA which can also cluster large scale time series. Similar to YADING, ROCKA also uses DBSCAN for clustering. The difference is that ROCKA uses shape-based distance (SBD) distance to measure the distance between time series. However, both ROCKA and YADING have drawbacks. The PAA used by YADING is essentially mean filtering with strides bigger than 1, and the series that are finally clustered are the smoothed series. ROCKA removes impulses and extracts baselines through mean smoothing before clustering. Therefore, both YADING and ROCKA cannot distinguish the amplitude and impulses density of KPIs. In addition, it is inevitable to identify some KPIs as noise with DBSCAN, to be more specific, these KPIs do not belong to any cluster, which leads to insufficient use of data.

In terms of configuring strategies of algorithms, Bergstra et al. [5] suggest that the traditional search strategy (grid search) is often less effective than the random search because there are many dimensions in the search space that have little impact on the results, and it is difficult to determine which of these dimensions have little impact on a specific problem, while grid search wastes a lot of time searching on these useless dimensions. In [1], genetic programing is utilized to search for the most suitable algorithm for different specific problems.

In summary, anomaly detection algorithms based on data analysis has been developed and applied in industry for a long time. However, there are still some problems in the self-adapt algorithm of millions of time series data in the cloud scenario, as we explained in the introduction, and there is no enough labeled dataset for supervised learning, despite deep learning has better performance than traditional methods, deep learning cannot replace the traditional methods in anomaly detection.

### 3 Proposals

Similar interval tendency, amplitude, impulses density are the main factors that we consider most when we configure algorithms for a KPI. For example, dynamic threshold method makes sense when dealing with time series with periodicity or similar interval tendency as shown in Figure 2(a)(b). On the other hand, it is not necessary to consider historical trends when dealing with nonperiodic signals as shown in Figure 2(c)(d). Besides, as shown in Figure 2(a)(b), since the amplitude of the two curves is different due to the noise, different tolerances are needed to detect steep drops. In addition, there are always sparse or dense impulses in time series, as shown in Figure 2(c), such waveforms are suitable for median smoothing in the pre-processing step because these sparse impulses are not abnormal and are caused by many transient behaviors in practice, such as system jamming and JVM garbage collection. On the contrary, for the case shown in Figure 2(d), these dense impulses are the normal state of the system instead of anomalies, so it is necessary to use mean smoothing in the pre-processing step. Therefore, different anomaly detection algorithms and detection processes should be adapted to time series with different properties.

In this section, we propose a framework from clustering to matching appropriate detection algorithms for different clusters of time series, as shown in Figure 4.

#### 3.1 Clustering

In order to ensure that the clustering result can be a perfect match corresponding anomaly detection algorithm, we hope that the clustering results can distinguish time series significantly in the three properties of periodicity, amplitude and
It should be noted that when we extract Swing feature, before extracting Swing feature, we should pre-process the data first to remove impulses from the data. Therefore, we suggest that it is an effective way to extract different features for these three properties and conduct targeted hierarchical clustering. In this section, we will expound the features required for hierarchical clustering.

3.1.1 Clustering methodology

Both ROCKA and YADING choose DBSCAN as the clustering method. The reason is that it is not clear which categories the time series of clustering belong to. However, we use hierarchical clustering to classify the categories according to the periodicity, amplitude and impulse density, so the number of clusters are very clear. Therefore, we use k-means for clustering, and set k to 2 for each layer of clustering.

3.1.2 SectionSign feature

Inspired by local binary patterns (LBP) \[20\] which is widely used in digital image processing and computer vision, we propose a new feature named SectionSign. Compared with applying LBP directly to time series, our SectionSign feature is faster to calculate and can effectively distinguish the time series with or without periodicity.

A. Pre-processing

Before extracting SectionSign features, we should pre-process the data first to remove impulses from the data. We recommend taking 1.01 times the 99 percentile in a single time series as the upper bound, and 0.99 times the one percentile as the lower bound, replacing all values greater than the upper bound with the upper bound, and all values less than the lower bound with the lower bound.

B. Extracting SectionSign features of KPIs

We define the set composed of multiple time series after pre-processing as \( T = \{T_1, T_2, T_3, ..., T_n\} \). A time series of length \( l \) is defined as \( T_i = [T_{i1}, T_{i2}, T_{i3}, ..., T_{il}] \), \( T_i \in T, i \in [1, n] \). In order to extract the SectionSign feature of \( T_i \), we use a slide-window with length \( m = 90 \) to slide from the beginning of \( T_i \) to the end of \( T_i \) with the stride \( s = 30 \). A time series segment covered by the slide-window is defined as: \( t_{ij} = [T_{i[j-1]+1}, T_{i[j-1]+2}, T_{i[j-1]+3}, ..., T_{i[j-1]+m}] \). With each sliding step, we extract the SectionSign features of \( t_{ij} \).

The method is as follows:

1) Define \( \text{med} \) as the value of the center point of \( t_{ij} \). \( \text{med} \) is calculated by equation 1:

\[
\text{med} = \begin{cases} t_{ij}\left\lfloor \frac{m}{2} \right\rfloor, & \text{if } m \text{ is even} \\ t_{ij}\left\lfloor \frac{m}{2} \right\rfloor + t_{ij}\left\lceil \frac{m}{2} \right\rceil, & \text{if } m \text{ is odd} \end{cases}
\]

2) Calculate \( \text{diff} \) which is defined as \( \text{diff} = [t_{ij}[1] - \text{med}, t_{ij}[2] - \text{med}, ..., t_{ij}[m] - \text{med}] \), then we divide \( \text{diff} \) into two parts of the same length, the left half is \( \text{left} \), and the right half is \( \text{right} \).

3) The SectionSign feature of \( t_{ij} \) is defined as: \( S_{ij}, S_{ij+1} = \text{mean}(\text{sign}(\text{left})), \text{mean}(\text{sign}(\text{right})) \), the SectionSign feature of \( T_i \) is defined as: \( S_i = [S_{i1}, S_{i2}, S_{i3}, S_{i4}, ..., S_{i(2h)}] \), \( h = \left\lfloor \frac{m}{2} \right\rfloor + 1 \), \( \text{mean} \) is to calculate mean value, \( \text{sign} \) is defined in equation 2.

\[
\text{sign}(x) = \begin{cases} 1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases}
\]

Intuitively, both SectionSign feature and LBP are looking for trends within a segment. Therefore, the SectionSign features can effectively extract the difference between cyclical trends and aperiodic trends to classify time series. After extracting the feature sequence \( S_i \) of all \( T_i \) in \( T \), we utilize \( k - \text{means} \) to cluster \( T \) and obtain the periodic sequence set \( T_{\text{L}} \), the non-periodic sequence set \( T_{\text{D}} \). The results of clustering with SectionSign feature is shown in Figure 3.

3.1.3 Swing feature

To distinguish the amplitude of time series, we propose Swing feature. Time series set \( T \) has already been divided into two parts \( T_{\text{L}} \) and \( T_{\text{D}} \) before extracting Swing feature. We use Swing feature to distinguish the amplitude of \( T_{\text{L}} \) and \( T_{\text{D}} \), respectively. It should be noted that when we extract features, the data pre-processing processes of different features are different and independent of each other because the information that messes the extraction result of a feature may be the key information desired by other features. For instance, the impulses and Gaussian noises affect the result of SectionSign feature extraction and need to be filtered out are important factors deciding the amplitude of time series and should be retained. The result of distinguishing the amplitude of \( T_{\text{L}} \) from \( T_{\text{D}} \) is shown in Figure 4.

A. Pre-processing

The pre-processing of Swing feature also requires the removal of up and down impulses from the data, in a manner consistent with SectionSign features, and then followed by maximum-minimum normalization.

B. Extracting Swing features of KPIs

Similar to SectionSign feature, we define the set composed of multiple time series after pre-processing as \( T = \{T_1, T_2, T_3, ..., T_n\} \). A time series of length \( l \) is defined as \( T_i = [T_{i1}, T_{i2}, T_{i3}, ..., T_{il}] \), \( T_i \in T, i \in [1, n] \). Then we calculate the first difference of \( T_i \) as \( D_i = [D_{i1}, D_{i2}, D_{i3}, ..., D_{i(l-1)}] \). We use a slide-window with length \( m = 90 \) to slide from the beginning of \( D_i \) to the end of \( D_i \) with the stride \( s = 30 \). A time series segment covered by the slide-window is defined as: \( d_{ij} = \).
threshold late

$h = \frac{div}{2}$ set three attenuation coefficients $T$ of $D$ as absolute value as $d$ slide-window with length $m$

DiffThres features of $D$. The method is as follows:

1) calculate the deference between the $80^{th}$ and $20^{th}$ percentiles of $d_{ij}$ as $w$.
2) define the Swing feature of $d_{ij}$ as $w_{ij} = w$, and the Swing feature of $T_i$ is: $W_i = [w_{ij}, w_{i2}, w_{i3}, ..., w_{ih}]$, $h = \left\lfloor \frac{l+1-m}{s} \right\rfloor + 1$. We use a slide-window with length $m = 180$ to slide from the beginning of $D_i$ to the end of $D_i$ with the stride $s = 30$. A time series segment covered by the slide-window is defined as: $d_{ij} = [D_{i(j-1)s+1}, D_{i(j-1)s+2}, ..., D_{i(j-1)s+m}]$, $j \in [1, \frac{l+1-m}{s} + 1]$. With each sliding step, we extract the Swing features of $d_{ij}$. The method is as follows:

Its easy to understand that Swing feature is similar to variance, essentially measuring the volatility of a time series to determine the amplitude.

3.1.4 DiffThres feature

We propose the DiffThres feature to classify the density of impulses in time series. It is located in the last step of hierarchical clustering. The sequence sets after Swing feature classification are respectively clustered. The clustering results is shown in Figure 3.

Its not necessary to pre-process the data before extracting DiffThres feature because impulses whose density is what we care about shouldnt be filtered. We define the set composed of raw multiple time series as $T = \{T_1, T_2, T_3, ..., T_n\}$. A time series of length $l$ is defined as $T_i = [T_{i1}, T_{i2}, T_{i3}, ..., T_{il}]$. Then we calculate the first difference of $T_i$ and take the absolute value as $D_i = [D_{i1}, D_{i2}, D_{i3}, ..., D_{i(l-1)}]$. We use a slide-window with length $m = 180$ to slide from the beginning of $D_i$ to the end of $D_i$ with the stride $s = 30$. With each sliding step, we extract the DiffThres features of $d_{ij}$. The method is as follows:

1) define $max$ as the maximum value of $d_{ij}$.
2) set three attenuation coefficients $div = [2, 3, 4]$ and calculate threshold $= \frac{\max - \max}{2, \frac{3}{2}, \frac{4}{2}}$.
3) for $k \in [2, m - 2]$, when $d_{ik} < threshold < d_{ijk}$ or $d_{ijk} < threshold < d_{ij(k-1)}$ happens, it is considered that an impulse has occurred.

The specific process is shown in Table 1.

3.2 Choosing anomaly detection algorithms and parameters for each cluster

After obtaining the results of the hierarchical clustering, we need to configure the anomaly detection process for each cluster, including pre-processing for time series such as normalization, smooth method, smooth window size, anomaly detector, selections of anomaly detectors and other hyper-parameters required by the anomaly detector. So it is tedious to manually configure the appropriate anomaly detection process for each cluster. Traversal search method can also lead to the problem of combination explosion. Therefore we suggest using evolutionary algorithms to select appropriate anomaly detection algorithms and parameters for different KPIs clusters. Compared with manually configuring and traversal search, evolutionary algorithms can significantly reduce the effort spent on configuring algorithm. In this section we will discuss how to apply evolutionary algorithms to the configuration of anomaly detection processes.

3.2.1 Configuring the process of anomaly detection

There are many factors to consider in the design of the algorithm detection process. Sometimes it is necessary to select one of two or more functions as one step in the entire anomaly detection process. For example, mean smoothing or median smoothing is needed in data pre-processing. Sometimes we need to design the execution sequence of various methods, such as whether the detector should detect the dynamic threshold first or the steep rise and fall first. Sometimes it is necessary to determine whether a step should be carried out, for example, whether data should be normalized before testing. In a word, the design of the detection process mainly faces three problems: a) the choice of function b) the setting of the execution order of multiple functions c) the setting of whether to execute a certain step. For evolutionary algorithms, how to solve these three problems, how to initialize the values of genes, and how to design methods for variation, are the crucial problems. Other aspects of evolutionary algorithms, such as reproduction and natural selection, are not covered in this paper. Next we will discuss the above issues separately.

A. Initialization
1) Initialize functions
   We can put all the functions to be selected into a set and randomly select one or more functions as the selected functions with the same probability when initialize functions.

2) Initialize sequence of multiple functions
   We can put all the methods in one set and shuffle them.

3) Initialize whether a method is performed
   We can randomly generate a Boolean value that is initialized to execute the method when it is true and not executed when it is false.

4) Initialize a specific parameter value
   For a specific value, we set its value range and data type (integer, float), and then generate it randomly. It is important that the above initialization steps can be nested within each other, for example, when multiple functions are selected from a number of alternatives, it is possible to consider the order in which the selected functions are executed. In addition, in order to prevent the parameters obtained from the evolutionary algorithms do not tally with the practical experience, even if the objective function were significantly improved, we should also manually limit the range of parameters according to practical experience before the parameters are initialized, so as to prevent the evolutionary algorithm from learning unreasonable parameter combinations and accelerate the convergence rate of the objective function during training.

5) Initialize the mutation rate
   We define a real number rate as mutation rate. The value range of rate is related to the value of specific need variation. When mutating the parameters that choose one or more functions from a set of functions, adjusting the execution order of multiple functions and whether a method is executed or not, rate ∈ (0, 1). As for a specific parameter value is mutated, the value range of rate is related to the order of magnitude of the parameter. rate is generated randomly during initialization. In addition, rate is also a mutable parameter, and its initialization strategy is consistent with the initialization strategy for a specific parameter value. It should be noted that the rate of rate cannot be mutated and needs to be set artificially.

B. Mutation
   For the sake of discussion, method selection, execution order, and whether to execute a function are collectively referred to as function selection.

1) The process of mutation in functions selection
   Mutation in functions selection is essentially a matter of deciding whether or not to mutate, in which case a random floating-point number r is generated, r ∈ (0, 1), if r > rate then mutate the functions selection. Therefore, for this kind of problems, the value range of rate should be within (0, 1). When mutating, we simply re-execute the initialization process for functions selection.

2) Mutation for the value of a specific parameter
   The mutation for a specific parameter value is essentially a process of generating a new random number with a probability density function, which is defined as a normal distribution model X ∼ N(μ, σ^2), where μ is the current value of the parameter value to be mutated, and σ is the mutation rate.
of the parameter. The normal distribution model is used as a probability density function to generate new random numbers, which can be used as the new values of the mutated parameters. The mutation strategy of rate should also be implemented according to this strategy.

#### 3.2.2 Objective function

For different business scenarios, the objective function is different, take HUAWEI Cloud BU for instance: we obtained 206 time series from HUAWEI Cloud BU, containing different cases. Some cases have anomaly which are hardly detected in traditional method, some normal KPIs are easy to false positives. Therefore, we have developed its own passing criteria for each time series, that is, no anomaly is missed, no delay in reporting and no false alarm. For a combination of parameters, we count the number of KPIs that meet this criteria during anomaly detection process as the objective function $pass_num$. We want to maximize this objective function as the evolutionary algorithm iterates.

#### 3.3 Anomaly detection

In the previous process, we have obtained eight clusters through the hierarchical clustering, and then used evolutionary algorithm to determine the anomaly detection process and some key parameters for each cluster. Finally we will get a complete end-to-end anomaly detection model. It no longer requires artificial selection of matching algorithms and parameters for a certain time series. And we only need to input the new time series into the model, and obtain selected suitable anomaly detection algorithms and parameters based on the results of offline trained model. The specific process is as follows:

| Input: | Output: |
|--------|---------|
| $T_i$: input one single time series | features: DiffThres feature of the time series |
|         | $D_i$ = abs(diff($T_i$)) |
|         | cross2 = get_cross_feature($D_i$, div=2) |
|         | cross3 = get_cross_feature($D_i$, div=3) |
|         | cross4 = get_cross_feature($D_i$, div=4) |
|         | cross = concat([cross2, cross3, cross4], axis=1) |
|         | features = MinMaxScaler(cross) |

Table 1: The process of extracting DiffThres feature of a KPI.
Table 2: The overview of our datasets

| Similar interval trend (T is having similar interval trend) | Amplitude (T means having large amplitude) | Impulses density (T means having dense impulses) | The number of simulated data | The number of data from business scenario |
|-------------------------------------------------------------|--------------------------------------------|-------------------------------------------------|-----------------------------|----------------------------------------|
| F                                                           | F                                          | F                                               | 500                         | 50                                     |
| F                                                           | F                                          | T                                               | 500                         | 32                                     |
| F                                                           | T                                          | F                                               | 500                         | 5                                      |
| F                                                           | T                                          | T                                               | 500                         | 56                                     |
| T                                                           | F                                          | F                                               | 500                         | 1                                      |
| T                                                           | F                                          | T                                               | 500                         | 30                                     |
| T                                                           | T                                          | F                                               | 500                         | 0                                      |
| T                                                           | T                                          | T                                               | 500                         | 32                                     |

Table 3: The clustering results of k-means on a single feature.

4 Experiment

4.1 Dataset

4.1.1 Simulated data

In order to simulate the business data as much as possible, we adopted the method of extracting the baseline of the business data and adding Gaussian noise and pepper and salt noise to generate the simulated data or pseudo-data. The pseudo-data was only marked for the cluster of the time series, and no artificial anomaly was added. The specific process is as follows:

1) Select several representative business data.
2) Get baseline of these chosen business data by mean smoothing and median smoothing.
3) Add different levels of noise to the baseline to generate pseudo-data that can simulate business data, and label it based on the generation process.

The situation of the dataset is described in Table 2.

4.1.2 Data from business scenario

We obtained 206 KPIs with the length of 5760 from HUAWEI Cloud BU and marked their clusters and outliers. The situation of the dataset is described in Table 2. It should be emphasized that there are few businesses whose KPIs belong to the three clusters of TTF, TFF and FTF in business of HUAWEI Cloud BU, so there is a certain imbalance in the samples of these three clusters.

4.2 Evaluation standard

4.2.1 Evaluation standard for clustering

In order to measure the accuracy of clustering results, we introduced three indicators: precision, recall ratio and F1-score. First, we introduced three important concepts:

1) True Positive: the number of situation that curve $a$ is correctly classified into cluster $A$.
2) False Positive: the number of situation that curve $b$ is wrongly assigned to cluster $A$.
3) False Negative: the number of situation that curve $a$ is wrongly assigned to cluster $B$.

Therefore, for cluster $A$, its classification precision, recall ratio and F1-score are as follows:

\[
\text{precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (3)
\]

\[
\text{recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad (4)
\]

\[
F1\text{-score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (5)
\]

4.2.2 Evaluation standard for anomaly detection

As we said before, we obtained 206 time series from HUAWEI Cloud BU, containing different cases. Some cases have anomaly which are hardly detected in traditional methods, some normal KPIs are easy to false positives. Therefore, we have developed its own passing criteria for each time series instead of the precision and accuracy of anomaly detection. To be more specific, we measure the anomaly detection accuracy by the pass rate, which is defined as follows:

\[
\text{accuracy} = \frac{\text{Pass Number}}{\text{Total Number}} \quad (6)
\]

In equation 6, \(\text{Pass Number}\) is the number of series which pass the anomaly detection test without errors, \(\text{Total Number}\) is the total number of time series, and \(\text{accuracy}\) is the pass rate.

4.3 Results

4.3.1 Results on a single feature

First, we clustered time series with their SectionSign feature, Swing feature and DiffThres feature for similar interval trend, amplitude and impulses density and measured their performance respectively, as shown in Table 3.
Table 4: Performances of YADING, ROCKA and our method.

|       | YADING | ROCKA | CRATOS |
|-------|--------|-------|--------|
| FFF   | precision | 0.413 | 0.374 | 0.649 |
|       | recall   | 0.422 | 0.432 | 0.742 |
|       | F1-score | 0.417 | 0.401 | 0.692 |
| FFT   | precision | 0.381 | 0.381 | 0.637 |
|       | recall   | 0.278 | 0.312 | 0.782 |
|       | F1-score | 0.321 | 0.343 | 0.702 |
| FTF   | precision | 0.366 | 0.351 | 0.739 |
|       | recall   | 0.366 | 0.368 | 0.748 |
|       | F1-score | 0.366 | 0.359 | 0.743 |
| FTT   | precision | 0.377 | 0.377 | 0.733 |
|       | recall   | 0.326 | 0.356 | 0.742 |
|       | F1-score | 0.349 | 0.366 | 0.737 |
| TFF   | precision | 0.316 | 0.274 | 0.751 |
|       | recall   | 0.238 | 0.78  | 0.782 |
|       | F1-score | 0.271 | 0.406 | 0.766 |
| TFT   | precision | 0.32  | 0.317 | 0.717 |
|       | recall   | 0.114 | 0.154 | 0.76  |
|       | F1-score | 0.168 | 0.207 | 0.738 |
| TTF   | precision | 0.343 | 0.338 | 0.863 |
|       | recall   | 0.114 | 0.098 | 0.694 |
|       | F1-score | 0.171 | 0.152 | 0.769 |
| TTT   | precision | 0.256 | 0.369 | 0.886 |
|       | recall   | 0.716 | 0.138 | 0.622 |
|       | F1-score | 0.377 | 0.201 | 0.731 |

4.3.2 Comparison among different clustering methods

We chose ROCKA and YADING as the control group. Since the samples of our business data are not balanced, we used our method and the performance of these two methods on pseudo-data to illustrate the effectiveness of our algorithm. It should be noted that ROCKA and YADING are not clustering algorithms specifically for the similar interval trend, amplitude and impulses density. Therefore, for the convenience of comparison, we combined the clustering results generated by these two methods. The merging strategy is as follows:

1) count the number of KPIs of different categories in each cluster according to the labels.
2) for a cluster, take the category with the largest number in the cluster as the category of the cluster.
3) merge clusters of the same category into the final clustering results.

The final comparison results are shown in Table 4. Besides, as shown in Figure 3(a)(c), we obtained one of all clusters generated by YADING and ROCKA. It is obvious that ROCKA is able to cluster KPIs with similar waveform. However, YADING and ROCKA inevitably identify some time series as noises due to the principle of DBSCAN, which leads to underutilization of the dataset. Figure 3(b)(d) show noises generated by YADING and ROCKA. Compared them with the clustering results of CRATOS, as shown in Figure 3(e) and 5, we can see that CRATOS not only distinguishes the time series of different features well, but also do not identify some KPIs as noises during the clustering process.

4.3.3 Anomaly detection results

In this part, we use the data obtained from HUAWEI Cloud BU to cluster, and use the evolutionary algorithm to configure algorithms and parameters for each cluster. The use of business data can better reflect that our self-adapt anomaly detection algorithm meets the requirements of actual business scenarios. When setting up the evolutionary algorithm, we try to let the evolutionary algorithm configure the detection process for different clusters, including:

1) detector: dynamic threshold detector, global threshold detector, local steep drop detector, global steep drop detector and other detectors
2) smoothing: mean smoothing and median smoothing
3) some settings about parameter: smooth window size, sensitivity, etc

In addition, we initialize a population composed of different gene combinations with the scale of 200. After each iteration, only 40 gene combinations with the best performance were retained, and 160 offspring were propagated in the next iteration to control the population to remain at 200 with the purpose of controlling the computational complexity of the evolutionary algorithm at $O(n)$, which means the population size is positively correlated with the computational resources required by the evolutionary algorithm.

We used a server to train evolutionary algorithms and accelerated the training process in a multi-processes manner. In the experiment, each subprocess tested the pass rate of a gene combination for the entire time series. We made 100 subprocesses work at the same time. It took two hours for each iteration to compute. Generally, the solution of the optimal pass rate can be obtained after about 9 iterations. To ensure convergence, we iterated 40 times in total. Table 5 indicates the comparison of the final pass rate of the detection process in which the engineers manually configured the detection algorithm for each time series and the evolutionary algorithm configured for each cluster.

5 Discussion

From the experiment we can find that the results of clustering with evolutionary algorithm of configuration processes can automatically learn anomaly detection processes of each cluster in a short time and greatly saves the manpower. Ultimately there is not much difference between manually configuration and our proposed method. However, there are still some problems with our approach that deserve to be discussed and improved, which we will discuss separately in this section.

5.1 Improvement of clustering

From Table 5 we can find that although the self-adapt algorithm saves manpower, the pass rate is still lower than the manual configuration by engineers. There are two main reasons: first, the accuracy of clustering is not high enough; second, the self-adapt algorithm for each category is only based on the homogeneity of all time series in a cluster, and it lacks configuration for individual time series. In order to solve these two problems, we think that we can use the clustering algorithms based on shape similarity like ROCKA to perform
more elaborate clustering on the eight clusters. As shown in Figure 6(c), it is obvious that time series in a cluster generated by ROCKA have high similarity in appearance. Both further fine clustering based on the results from our clustering algorithm and the application of evolutionary algorithm to these more detailed clusters can improve the accuracy of clustering and the pass rate of anomaly detection, which is also one of our future work directions.

5.2 the reason why we propose evolutionary algorithm

So far, many optimization algorithms have been proposed, such as simplex algorithm, simulated annealing algorithm, gradient descent algorithm, evolutionary algorithm, etc. In many application scenarios, evolutionary algorithm is not the most appropriate optimization algorithm due to its limitation on computational resources and time consumption. However, we believe that evolutionary algorithm is the optimal method for the algorithm configuration problems discussed in this paper for the following two reasons.

5.2.1 Evolutionary algorithm can carry out multi-objective optimization, which is an advantage that other methods do not have

In our experiment, we set the objective function as pass rate, but it is possible that lower false positives and false negatives are also required in some other application scenarios, some application scenarios require lower false positives, while others require little false positives and false negatives. Such multi-objective optimization problems can be optimized by evolutionary algorithm.

5.2.2 Evolutionary algorithms is more flexible in editing genes

From the previous discussion, we can see that for each cluster of time series, we need not only to configure the parameter values for them, but also to select the appropriate anomaly detection functions for each cluster. As a result, our solution space is not a high-dimensional real solution space, but a complex solution space containing Boolean Numbers, discrete Numbers and continuous Numbers. In this space, it is difficult to calculate the gradient and find the optimization direction. We don’t want the learning process to fall into a local optimal solution with a high probability because of the uncertainty of solution space. However, evolutionary algorithm can freely define gene types and value ranges without being restricted by the algorithm solution process, so it is undoubtedly suitable for solving the problems we face.

Considering the above two aspects, we finally choose the evolutionary algorithm to optimize the anomaly detection processes and parameters of each cluster.

5.3 Improvement of evolutionary algorithm

However, evolutionary algorithms still inevitably face problems such as limited computational resources and excessive time consumption, so we suggest that we can optimize evolutionary algorithm from the following directions.

5.3.1 Surrogate model

Surrogate model is a widely discussed acceleration strategy in recent years. The main approach is to design a surrogate model such as deep neural network to simulate a complex process we want to execute, so as to achieve similar results to the execution of a complex model in less time. During the experiment, we found that the main training time of the evolutionary algorithm was spent in the process of executing the detection process for each gene. It can take up to an hour for a gene to run the test and get the output. Even if 100 processes were started simultaneously, only 100 different gene combinations could be calculated in an hour. It takes two hours for a population of 200 to iterate, and when the population doubles in size, the iteration time doubles, too. The larger the population, the more obvious the acceleration effect if we use gpu-accelerated deep neural network or other hardware acceleration methods as alternative models.

5.3.2 The intervention of human experience

In order to make the objective function of the evolutionary algorithm converge faster during training, or to prevent the results learned by the evolutionary algorithm from deviating greatly from the experience of engineers, it is necessary to add certain constraints to the genetic initialization of the evolutionary algorithm to prevent it from going astray during training. For example, the detection effect of dynamic threshold method applied to time series with similar interval tendency is usually better than that of global threshold method applied to them. Therefore, when algorithm selection is made for clusters with similar interval tendency, the selection range of alternative algorithm can exclude the global threshold method. Another example: to prevent smoothing windows from being too large or too small, we need to set variation ranges for them when initializing them.

5.3.3 Stop training early

From the experiment, we found that the evolutionary algorithm obtained the first optimal solution after only 9 iterations. After that we didn’t terminate the training iteration until more than 30 times. For accelerating the training speed of evolutionary algorithms, we can terminate the training process earlier. For example: when the objective function hasn’t reduced for n iterations, the training process should be terminated.

5.3.4 Sort multiple optimal solutions

From the experiments, we found that we often got multiple different optimal combinations of genes whose test results of
objective function are the same. So how to choose the best solution from these combinations of genes is a problem that needs to be solved. We suggest to make statistics on whether the genes in the gene combinations are consistent with human experience to choose the gene combinations that accord with human experience the most as the optimal solution.

6 Conclusion

In this paper, an KPIs clustering algorithm is proposed to conduct targeted hierarchical clustering for the features, including similar interval tendency, amplitude, and impulses density, required by the anomaly detection algorithm, so as to make our clustering results more easily match the anomaly detection algorithm. In addition, evolutionary algorithms is used to configure appropriate detection processes and parameters for each cluster in large batches. After that, we can obtain a complete online algorithm configuration process based on KPIs clustering, which can automatically match the appropriate anomaly detection algorithm for the new time series according to the results of the first two steps of offline training. The experiment proves that our cluster methods achieves the state-of-art results. Compared with the accuracy (93.4%) of the anomaly detection algorithms that engineers configure for different time series manually, our algorithms is not far behind in detecting accuracy (85.1%). Finally, we also discuss some possible optimization directions for our proposed algorithm.

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