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Intelligent Fault Analysis with AIOps Technology

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Abstract: ***With the deep integration of artificial intelligence (AI) and operation and maintenance management, AIOPS (Artificial Intelligence operation and maintenance), as an emerging technology in the field of operation and maintenance management, has gradually attracted wide attention. AIOPS is committed to improving the efficiency and quality of traditional operations management through the introduction of automation and intelligent technology, and has become a hot topic in the industry. The development of AIOPS is inseparable from the identification of patterns and anomalies in data, which requires the application of machine learning, deep learning and other technologies. The rise of AIOPS is also due to the development of big data, cloud computing and container technology. These new technologies make traditional operation and maintenance monitoring means and processing methods powerless. Traditional troubleshooting methods can no longer meet the needs of large-scale and complex system monitoring and problem positioning. Therefore, this paper combines the implementation process and case analysis of AIOps system on intelligent fault analysis under the background of artificial intelligence, so as to analyze the development prospects and improvement suggestions of AIOps.***

Keywords: AIOps; Fault analysis; Intelligent operation and maintenance.

1. INTRODUCTION

Back in 2016, Gartner added the term AIOps[1] to its vocabulary, at the time AIOps was short for Algorithmic IT Operations, which is literally an algorithm-based way of operating. Over the past two decades, advances in AI technology have intermittently affected the progress of ITOM[2], and AIOps is just the latest example of this influence. Therefore, for traditional enterprises, intelligent operation and maintenance is not a new concept, but the product of IT operations analysis/operation and maintenance management (ITOA[3]/ITOM) system combined with big data and artificial intelligence technology. AIOps intelligent operation and maintenance platform is based on the operation and maintenance big data collected by ITOM/ITOA system, and uses artificial intelligence and machine learning algorithms to conduct in-depth analysis of operation and maintenance data, covering IT monitoring, application performance management, external network monitoring, log analysis, system security and other aspects. At present, the main application scenarios of AIOps include abnormal alarm, alarm convergence, fault analysis, trend prediction, anomaly detection, root cause analysis, etc. In the process of intelligent fault management, fault discovery is the initial part of fault management. In the current scenario of massive indicators, automatic fault discovery and automatic anomaly detection are urgently required. It can greatly simplify the cost of R&D policy configuration, improve the accuracy of alarms, reduce alarm storms and false reports, and improve the efficiency of R&D.

2. RELATED WORK

At present, the IT challenge of digital transformation is to control IT costs on the one hand, and provide operations management capabilities to support higher complexity on the other hand. Traditional ITOM products are often under extreme pressure to handle large volumes, variety, and high-speed data. More importantly, these monitoring tools do not provide the multi-system data needed for horizontal business tracking and root cause targeting.

The quest for precise robot positioning within logistics automation has been a focal point in recent research endeavors. A multitude of techniques and methodologies have been explored to address this critical challenge.

2.1 Building AIOps

The term AIOps for IT Operations was coined by Gartner to refer to the application of artificial intelligence (AI) techniques, such as natural language processing and machine learning models, to automate and streamline operational workflows. Specifically, AIOps uses big data, analytics and machine learning capabilities to perform the following operations:

1) Collect and aggregate the massive amounts of data continuously generated by multiple IT infrastructure components, application requirements and performance monitoring tools, and service ticket systems

2) Intelligent screening to determine the "signal" from the "noise" and identify important events and patterns related to system performance and availability issues.

3) Diagnose the root cause and report IT to IT and DevOps teams so they can respond quickly and take remedial action, or in some cases resolve the issue automatically without human intervention.

When considering which tools to adopt within your organization to help improve intelligent Operations AIOps, you must ensure that these tools have the following capabilities:

Observability: Observability refers to software tools and practices that capture, aggregate, and analyze the continuous flow of performance data generated by distributed applications and the hardware and networks on which they run, enabling more efficient monitoring, diagnosis, and commissioning of applications to meet customer expectations for product or service experience, service level agreements (SLAs), and other business requirements. Predictive Analytics: Intelligent Operations AIOps solutions analyze and correlate data for better insights and automated operations to help IT teams stay on top of increasingly complex IT environments and ensure application performance. Proactive response: Some intelligent Operations AIOps solutions proactively respond to unexpected events, such as performance degradation and operational outages, combining application performance and resource management in real time.

2.2 AIOps Fault Detection

In general, we can locate the attribute value that causes the exception according to the root problem. From the perspective of abnormal event, we want to locate which index exception causes the event exception.

During operation and maintenance, after finding a high search response time, machine learning algorithms are used to find the cause and rule of the anomaly. The specific implementation has the following steps:

First of all, FOCUS uses the log data generated by the system every day to train the decision tree, and the conditions leading to high search response time (HSRT) can be analyzed from the decision tree. Since one decision tree will be trained by the data every day, multiple decision trees will be generated after several days. Then, similar conditions that cause high search response time (HSRT) are mined in multiple decision trees, and these conditions are repeated in many days, which can be judged as long-term possible conditions that cause high search response time (HSRT). Finally, the influence of each attribute in the mined conditions that trigger high search response time (HSRT) is evaluated, and a scheme to optimize system performance is derived.

$$ps(S) = \max\left(1 - \frac{d(\vec{v}, \vec{a})}{d(\vec{v}, \vec{f})}, 0\right) \tag{1}$$

According to the formula, if the dimension combination (A=a, *, *) is abnormal, then the dimension combination (A=a, B=b, C=c) will have abnormal changes in the same proportion. This work proposes an index called potential score to evaluate whether a combination of dimensions is the root cause.

2.3 AIOps Anomaly Detection Model

Operation and maintenance data involves business, database, middleware, network equipment and other logs and states: may be time series data, with time, trend, cycle and other characteristics, most machine learning algorithms can not be used directly; There may also be text data, meaning is rich, if the traditional way of pre-processing, will lead to a lot of information loss. In the algorithm selection strategy for anomaly detection of time series data, the algorithm selection is not arbitrary, nor is it obtained aimlessly by trial and error. Instead, after understanding the business and data, multiple candidate algorithms are selected, and then the optimal combination is selected through training and evaluation.

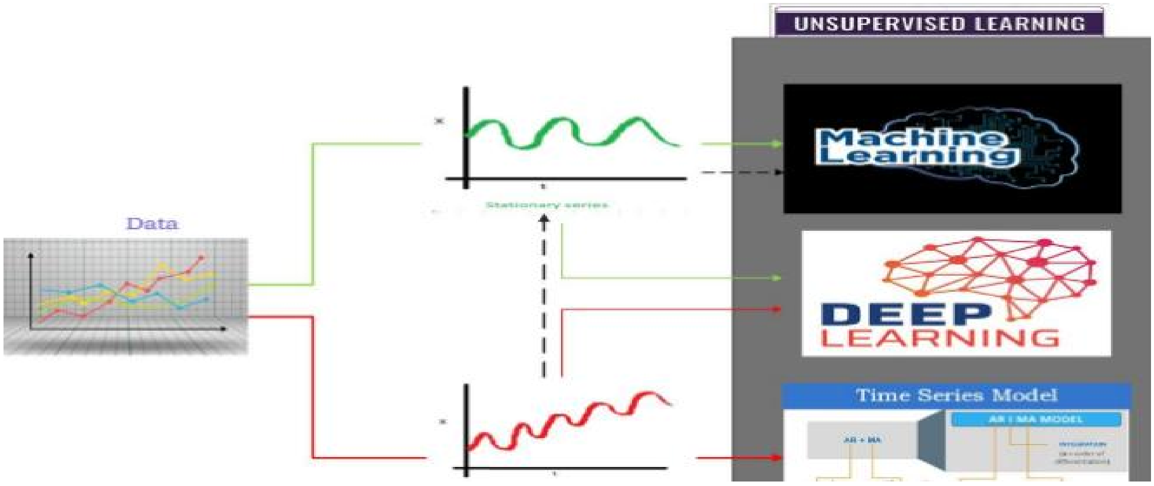

Figure 1: Unsupervised operation and maintenance anomaly detection model

stationary series: Machine learning algorithms (lonely forest, SVM, etc.) and deep algorithms (DeepLog, Auto-Encoder, etc.) can be used directly.

non-stationary series: Time series models (AR/MA/ARMA/ARIMA/Holt winters, etc.) and depth algorithms can be used directly.

3. METHODOLOGY

There are a lot of researches on anomaly detection and location of indicators, logs and trace data in the field of AIOps, and the anomalies in these works are more abnormal performance in time series indicators, which are far from the real faults, which are extremely sparse and not the same order of magnitude as the alarm quantity identified by the anomaly detection algorithm received by operation and maintenance staff every day. Therefore, this experiment is based on AIOps anomaly detection algorithm, and the following case analysis is done.

3.1 Data Input

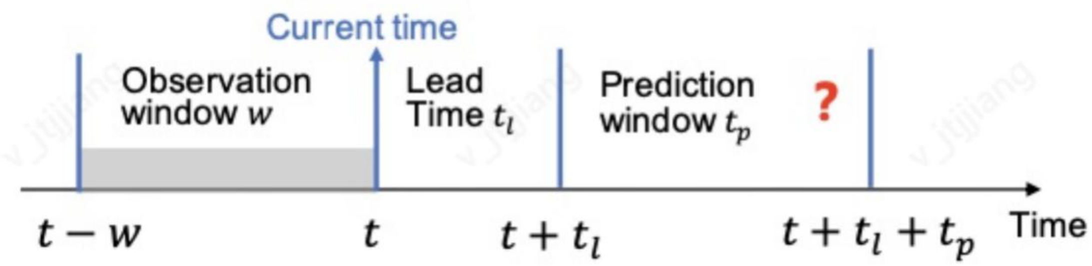

Figure 2: eWarn:Incident Prediction

As shown in the figure above, the purpose of the model is to predict whether there is a fault in the [t ten tl,t+tl+tp] window

ω: Observation window, using the observation alarm data in the "T-ω,t] chapter to predict whether there is a fault
tl: The time required by operation and maintenance personnel to prevent faults.
tp: If a fault occurs in the [t+tl,t+tl+tp] window, it is marked as an exception; otherwise, it is marked as normal
t: The size of the sliding window
ti: instance window, observation window ω will be divided into more fine-grained instance window.
Experimental parameter:
▲t=10min
ω=60min

tl=10min
ti=10min

The selection of tp= parameters will affect the model effect to a certain extent. The relationship between tp and F1-score is shown below:

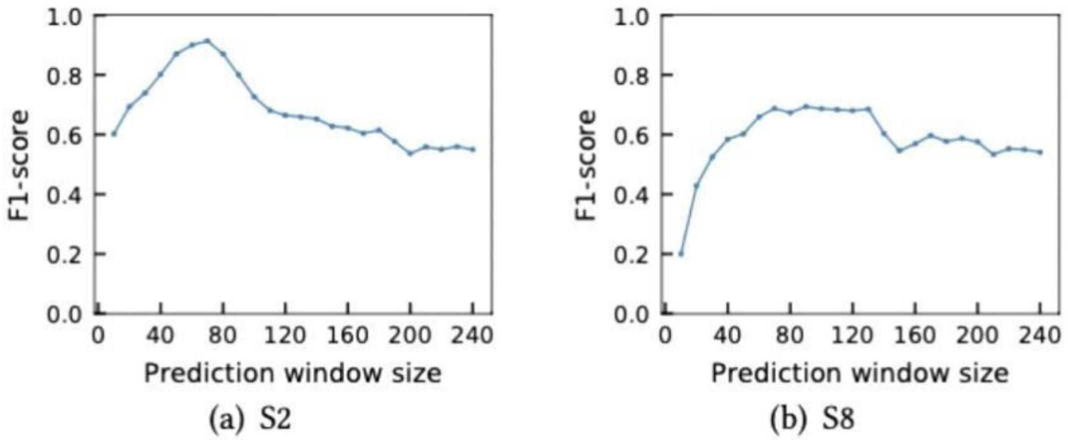

Figure 3: Two examples to show the efect of different prediction windows sizes (minutes) on F1-score

3.2 Model Structure

eWarn consists of four main steps:

1) Extract effective and interpretive features from alarm data through feature engineering;
2) Use multi-instance learning to distinguish useful alarms from noise alarms;
3) Based on the features extracted by feature engineering, use XGBoost for anomaly recognition;
4) Feedback fault prediction results to users, and use LIME (Local Interpretable Model-Agnostic Explanations) to interpret the prediction results of the Model:

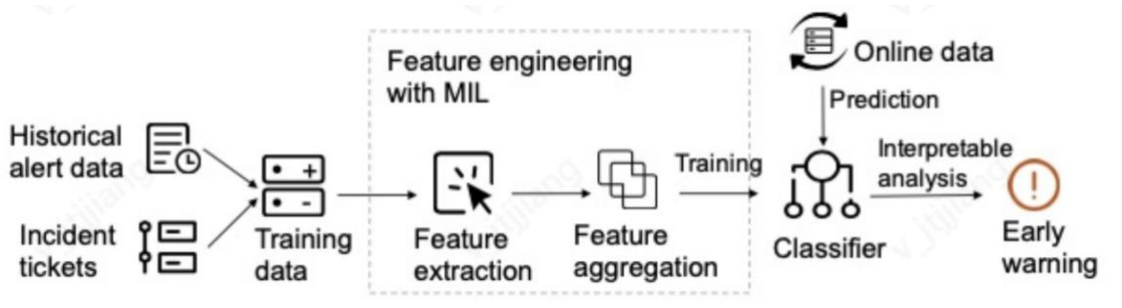

Figure 4: Overview of eWarn

3.3 Feature Extraction

Text features: Latent Dirichlet Allocation (LDA) is used to extract text features.

Statistical characteristics: Alarm quantity (Total alarm quantity, alarm quantity of different severity, alarm quantity of different types (such as application, database, memory, middleware, network, and hardware), window time (hour of the day, working day or weekend, day of the week, and whether business. hour, etc. Average alarm interval [whether frequent alarms are generated in the window].

The GBoost classification model uses SMOTE (Synthetic Minority Over-sampling TEchnique) to balance positive and negative samples, and then uses XGBoost for training. The results are as follows:

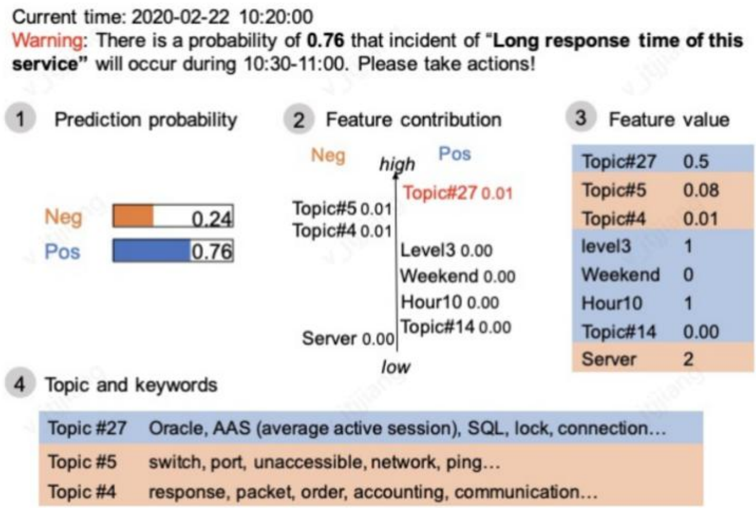

Figure 5: XGBoost training

According to the results, it can be seen that by comparing the detection results of the model on the test set with the real marked data, F-Score is calculated as the evaluation standard of the algorithm, and the accuracy and recall rate of the algorithm are investigated. In general, operation and maintenance personnel are only concerned about whether the anomaly detection algorithm can detect a certain continuous anomaly interval, rather than detecting every anomaly point in the anomaly interval. Therefore, for the continuous exception segment, the timeliness window is specified. As long as the exception point is detected in the window, the exception segment is counted as successful detection, otherwise it is judged as failure.

4. CONCLUSION

This paper discusses the development and application of artificial Intelligence Operation and maintenance (AIOps) in the field of operation and maintenance management. By introducing automation and smart technologies, AIOps is committed to improving the efficiency and quality of traditional operations management, becoming a hot topic in the industry. This paper focuses on the background of AIOps development, emphasizing the key role of data pattern and anomaly recognition, which requires the use of machine learning and deep learning techniques. At the same time, the rise of AIOps is also attributed to the development of big data, cloud computing and container technology, which makes traditional operations monitoring and processing methods powerless. In order to solve the needs of large-scale and complex system monitoring and problem location, this paper combines the implementation process and case analysis of AIOps system in intelligent fault analysis, and provides profound thinking for the future development of AIOps.

In the current era of rapid development of artificial intelligence, AIOps, as an emerging technology in the field of operation and maintenance management, presents a broad application prospect. This paper introduces the development process of AIOps, which starts from the algorithm foundation and gradually develops into an intelligent operation and maintenance platform based on big data and artificial intelligence technology. Especially in the application scenarios such as exception alarm, fault analysis, and trend prediction, AIOps has shown strong advantages. However, the paper also points out that the current challenges of AIOps, such as the effective monitoring of multi-system data and the accuracy of fault location, need to be further solved. With the continuous innovation of future technologies, AIOps is expected to play an increasingly important role in the field of intelligent operations and maintenance, improving operation and maintenance efficiency, and achieving more intelligent operation and maintenance management.

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Link to the article: https://doi.org/10.54097/qoseeQ5N

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