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Predicting failures in hard drivers based on isolation forest algorithm using sliding window

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Abstract. With the surge in the development of cloud computing and big data, the scale of the data center is constantly expanding. The data missing caused by the damage of large data center disk has become a problem that cannot be ignored. Predicting the failures of the hard drivers can effectively improve the reliability and reduce the maintenance cost of the data center. The SMART data is volume and multi-dimensional, as well as the high dynamic characteristics of data center hard disk accessing, so we propose an algorithm based on isolation forest using sliding window. The experiments show that this algorithm can effectively save the time of modeling and ensure high prediction accuracy.

1. Introduction

With the surge in the development of cloud computing and big data, the scale of the data center is constantly expanding, and data center downtime costs are increasing significantly. In 2016, Emerson Network Power released "Cost of Data Center Outages in 2016", which shows that the cost per minute of data center failure is close to $9,000 in the U.S [1]. IT equipment failure is the main cause of data center downtime, one of them is hard drive failure. It has been estimated that 78% of the hardware replacements are caused by hard drive failures [2]. Predicting the failures of the hard drives can effectively improve the reliability and reduce the maintenance cost of the data center.

Hard disk failure prediction methods including threshold method, the statistical methods, the Bayesian methods, the Support Vector Machine (SVM), decision tree, and the Hidden Markov Model (HMM) [3]. Most of them may not get good results, on the one hand, the data sets are small, which are far from the data of data center in real word, on the other hand some methods were used in many years ago, which were not quite effective [12].

In recent years, many researchers have proposed some improved algorithms. Zhao et al. [4] regard SMART attribute value as time series data, and used Hidden Markov Model (HMM) and Hiddle semi-Markov Model (HSMM) to the failures of the hard drives, which obtains zero false alarm rate and 52% prediction accuracy in Hughes data set. Song et al. [5] propose to use SMART data to predict hard disk failure based on the Support Vector Machine (SVM) Classification using IOcal clusteringG with Over-Sampling (COG-OS) framework. Compared with the traditional SVM algorithm, it improved the recall ratio of failure class prediction, while leads to accuracy of failure class prediction and performance of normal class prediction decline. The authors of [6] propose an attribute selection method based on neural network weight matrix, combining with three kind of non-parametric
statistical methods (the Rank Sum test, the RAT reverse arrangement test, Z-Score) to select useful attributes for building prediction models based on two kinds of machine learning methods (CART decision tree and BP neural network), which obtain very good performance, the experimental results also show that the accuracy may decline when applying this method to unbalanced data.

The SMART data set of data center has the characteristics of huge amount and multi-dimension. According to the research of BACKBLAZE data centre, there are about 8.95 million pieces of data in the data set of the second quarter of 2018 (SMART Attribute values are read per day for each disk) [7]. So the prediction algorithms must have the ability of dealing with volume and multi-dimensional data set. Compared with other prediction algorithms, the isolation forest algorithm predicts the failure through compute the path length of data in iTree, which reduces the calculation cost, has a linear time complexity with low constant and a low memory requirement. So this algorithm has the capacity to scale up to handle extremely large data size and high-dimensional problems.

The access to the hard disk in the data center is highly dynamic, resulting in large fluctuations in some SMART properties. Therefore, it is difficult to accurately determine the failure of the hard disk through SMART data at a single point in time series. The algorithm based on sliding window comprehensively considers the prediction results of multiple time points in the window and reduces the false alarm rate of single point prediction.

In this paper, Aiming at the characteristics of disk driver predictions of large data centers, we proposes an isolation forest algorithm based on sliding window, which can make best use of the advantages of isolation forest algorithm and sliding window algorithm. We also apply it to the SMART data of a real large data center for failure prediction, to verify the availability and efficiency of the algorithm.

The rest of this paper is organized as follows: Section 2 briefly introduces the related work. The algorithm based on isolation forest using sliding window is described in Section 3. In Section 4, the experimental results and analysis are presented. Finally, Section 5 concludes the whole paper.

2. Related Work

In this section, the brief introduction of SMART, the basic principle of the isolation forest algorithm and the general framework of sliding window will be presented.

2.1. Introduction of SMART

The SMART (self-monitoring, analysis and reporting technology) detect hard driver failure by monitoring the hard driver heads, platters, motor, circuit operation data (such as temperature, read data error rate, start-stop times, temperature, etc.) [8]. Each drive manufacturer defines a set of attributes, and sets threshold values beyond which attributes should not pass under normal operation, if exceed those threshold, the system can automatically send warning information. Although the accuracy of the SMART technology is low and the SMART warning-time goal is 24 hours before driver failure, the monitoring data of SMART technology provides the basis for other prediction algorithms.

2.2. Principle of isolation Forest

The core idea of the isolation forest algorithm is that the number of abnormal points is usually small, and there are significant differences between normal points in attributes. Therefore, when the points are partitioned by iTree, the path length of normal points is greater than the path length of abnormal points [9]. As shown in Figure 1, the Figure 1(a) contains 7 normal points and 1 abnormal point. After a randomly generated iTree (as shown in Figure 1(b)) partition, the path length of the abnormal point in iTree is significantly smaller than that of other normal points.

2.3. General Framework of sliding window

In this paper, the algorithm based on sliding window comprehensively considers the prediction results of multiple time points in the window. The general form of SMART data can be described as follows: $V = \{v(1), v(2), \ldots, v(t), v(t+1), \ldots\}$
where $v(t) \in R^N$ for $t \geq 1$.

The prediction window at time $t$ can be described as follows:

$$P_{\text{window}}(t) = \{v(t-1), v(t-2), \ldots, v(t-k+1)\}$$

where $k$ denotes the size of sliding window.

For example, the SMART data of the hard driver at time 10 is $v(10)$, the time interval is 1, and the window size is 3, then the prediction window of the hard driver at time 10 is $P_{\text{window}}(10) = \{v(10), v(9), v(8)\}$, and the prediction window at the next moment is $P_{\text{window}}(11) = \{v(11), v(10), v(9)\}$.

#### 3. The Algorithm Based on Isolation Forest using Sliding Window

In the training, isolation forest is composed of a certain number of isolation trees. In the process of constructing an isolation tree, first, we extract $N$ pieces of data from the training data set by uniform sampling, it can be used as the training data of the isolation tree. Second, we randomly select an attribute and a value within the range of all values of this attribute (between the minimum value and the maximum value), then divide the data by selected attribute and value, if the value of data’s attribute less than the selected value, it will be divided into the left of the node, contrarily, it will be divided into the right of the node. Finally, we can obtain a split condition and two depending cubes, and then repeats the partition process on two depending cubes, until only one record is in the data set or the height of the tree is reached. The algorithm can reference to [9].

In the predicting, we assume that the prediction algorithm is $f(v_i)$, The general form of hard driver’s state can be described as follows:

$$\sum_{i=0}^{k-1} f(v_{i-1}) > \sigma$$

the state of hard driver is failure.

$$\sum_{i=0}^{k-1} f(v_{i-1}) \leq \sigma$$

the state of hard driver is failure.

where $f(v_i) = 1$ denotes that the predicted state is abnormal, $f(v_i) = 0$ denotes that the predicted state is normal, $\sigma$ is the abnormal threshold. The algorithm is shown in Figure 2.
4. Result And Discussion

All samples [11] were collected from an enterprise-class disk model of Seagate named ST31000524NS. There are samples from 23,395 disks in the dataset. Each disk was labeled good or failed, with only 433 disks in the failed class and the rest of disks (22,962) in the good class. Each SMART data contains 10 SMART attributes. In the experiment, we construct 11 training data sets and 1 test data set, as shown in Table 1.

| Name            | Number of Hard Driver | Name            | Number of Hard Driver |
|-----------------|-----------------------|-----------------|-----------------------|
| good            | failed                | good            | failed                |
| Train_Data_1    | 1000                  | 100             | Train_Data_2         | 2000                  | 100             |
| Train_Data_3    | 3000                  | 100             | Train_Data_4         | 4000                  | 100             |
| Train_Data_5    | 5000                  | 100             | Test_Data            | 1000                  | 333             |

In the first experiment, we chose 6 data sets (Train_Data_1, Train_Data_2, Train_Data_3, Train_Data_4, Train_Data_5) to train prediction model. Then, we use the test data set (Test_Data) to test the model. We use accuracy and false alarm rate to evaluate the classifier’s performance, the Table 2 shows the result.

| Name            | Accuracy | false alarm rate |
|-----------------|----------|------------------|
| Train_Data_1    | 93.79%   | 5.48%            |
| Train_Data_2    | 93.92%   | 5.40%            |
| Train_Data_3    | 94.22%   | 5.25%            |
| Train_Data_4    | 95.05%   | 4.28%            |
| Train_Data_5    | 94.52%   | 4.72%            |

In the second experiment, we use the open-source data mining tool WEKA 3.8.3, and the test environment is Intel(R) Core(TM) i3-6100 CPU @3.70GHZ with 4GB of RAM. We chose Random Forest, Bayesian network, BP neural network, LibSVM and isolation Forest to train prediction model.
in 5 data sets (Train_Data_1, Train_Data_2, Train_Data_3, Train_Data_4, Train_Data_5). The training times of five kinds of algorithm in each data set are shown in Table 3.

Table 3. The training time of five kinds of algorithm in each data set.

| Algorithm          | Train Time 1 | Train Time 2 | Train Time 3 | Train Time 4 | Train Time 5 |
|--------------------|--------------|--------------|--------------|--------------|--------------|
| Random Forest      | 61.05 S      | 131.06 S     | 211.25 S     | 281.02 S     | 394.72 S     |
| Bayesian network   | 1.33 S       | 2.97 S       | 5.00 S       | 6.22 S       | 9.93 S       |
| BP neural network  | 154.40 S     | 281.59 S     | 403.56 S     | 515.53 S     | 667.74 S     |
| LibSVM             | 1129.21 S    | 1325.21 S    | >1500 S      | >1500 S      | >1500 S      |
| isolation Forest   | 0.68 S       | 1.81 S       | 3.11 S       | 4.48 S       | 5.89 S       |

The first experiment shows that the average accuracy of the algorithm is 94.30%, and the average false alarm rate of the algorithm is 5.03%. The algorithm has higher accuracy and lower false alarm rate. The Second experiment shows that the training time of isolation forest algorithm in each data set is least, while the algorithm of LibSVM costs most time. The Figure 2 shows the relationship between train time and the size of data set. As the number of data increases, the training time increases linearly.

![Figure 2. The relationship between train time and the size of data set.](image)

Compared with other prediction algorithms, the algorithm based on isolation forest using sliding window reduces the calculation cost, has a linear time complexity with low constant and a low memory requirement. So this algorithm has the capacity to handle extremely large data size and high-dimensional problems.

5. Conclusion

In this paper, we propose an algorithm based on isolation forest using sliding window for predicting the failures of the hard drivers. We also applies it to the SMART data of a real large data center for failure prediction, to verify the availability and efficiency of the algorithm. The experiments show that this algorithm can effectively save the time of modeling and ensure high prediction accuracy.

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