IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
Volume 2, Issue 2, July 2022
Impact Factor: 6.252

Anomaly Detection for Web Log Data Analysis

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Abstract: *Many methods have been developed to protect web servers against attacks. Anomaly detection methods rely on generic user models and application behaviour, which interpret departures as indications of potentially dangerous behaviour from the established pattern. In this report, we conducted the use of a systematic review of the anomaly detection methods to prevent and identify web assaults; in particular, we utilised Kitchen ham's standard approach for conducting a organized analysis of literature in the computer science area. Logs that record system abnormal states (anomaly logs) can be regarded as outliers, and the improved PCA algorithm has relatively high accuracy in outlier detection methods. Therefore, we use improved algorithm to detect anomalies in the log data. However, there are some problems when using the improved PCA algorithm to detect anomalies, three of which are: excessive vector dimension leads to inefficient kNN algorithm, unlabeled log data cannot support the kNN algorithm, and the imbalance of the number of log data distorts the classification decision of kNN algorithm. In order to solve these three problems, we propose an efficient log anomaly detection method based on an improved PCA algorithm with an automatically labeled sample set. This method first proposes a log parsing method based on N-gram and frequent pattern mining (FPM) method, which reduces the dimension of the log vector converted with Term frequency. Inverse Document Frequency (TF-IDF) technology. Then we use clustering and self-training method to get labeled log data sample set from historical logs automatically. Finally, we improve the PCA algorithm using average weighting technology, which improves the accuracy of the PCA algorithm on unbalanced samples. The method in this article is validated on four log datasets with different types. The maximum recall rate & accuracy achieved for BGL dataset is 100 % & 97.62 % respectively. Similarly maximum F1-score achieved for Spirit dataset is 98.19 %. The accuracy, recall rate and F1-Score for Improved PCA Ensemble technique is 97.62 %, 100 % and 96.55 % for BGL/2 Log Set Data. Similarly, the accuracy, recall rate and F1-Score for Improved PCA Ensemble technique is 97.60 %, 98.79 % and 98.19 % respectively for Spirit/2 log set data.*

Keywords: Frequent Pattern Mining, PCA, KNN Algorithm

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