



Detecting Rare and Collective Anomalies in Network Multivariate Data using Summarization

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Abstract

Identifying interesting patterns from a huge amount of data may be a challenging task across a wide variety of application domain. Especially, for cyber security being able to identify rare types of network activities or anomalies from network traffic data is an important but time-consuming data analysis task having moderate computing resources. Existing research has shown that it is possible to detect rare anomalies from the summarized version of big data. Therefore, summarization is an effective preprocessing function before applying anomaly detection techniques. The aim of this paper is to improve and quantify the scalability and accuracy of the anomaly detection techniques by using summarization. Hence, we propose a sampling-based summarization technique that is computationally effective than the existing techniques and also performs better in identifying rare anomalies from twelve benchmark network traffic datasets. The experimental results show that, instead of using original dataset, a summary of the data yields better performance in terms of true positive and false positive rates, once used for anomaly detection with less time needed.

Keywords: Anomaly detection, data summarization, sampling, clustering, SCADA, network traffic.

INTRODUCTION

Internet traffic is being generated at a very fast rate that makes it a challenging task to monitor any network in real time. Different network applications produce big data, which cannot be fully analyzed in real time. Anomaly detection techniques are applied to this huge amount of data, however, there are often several hundreds or thousands of instances of anomalous network traffic that require the attention from cyber security personnel. In practice, it is only possible looking at only a few pages of results that cover a portion of the anomalies detected. The lack of analysis of the complete list of anomalies detected from the huge

amount of network traffic leaves the network vulnerable. At the same time anomaly detection on big data is computationally expensive. If the important realities has each normal and unordinary irregularities and the diagram contains of truly plenty of regular instances, at that thing it's miles vain to make use of anomaly recognizable evidence on such once-over. Idiosyncrasy notoriety methods change usually as an outcome do the once-over structures. The scattering of irregularities in the number one records and the summation is not for the maximum part the equivalent. Hence, the advent of peculiarity disclosure processes will fluctuate. We want to track down the reasonable blend of precis methodology and quirk locale



method. For peculiarity recognizable evidence, an first-rate once-over want to contain inconsistencies from the primary statistics but, concurrently, the summary should be conservative. Along these follows, perceiving the appropriate define length is an essential piece of the as soon as-over cycle.

RELATED WORK

There are many existing tools that can generate reports to summarize network traffic such as cFlowd: Traffic Flow Analysis Tool, Flow-tools, Network Visualization Tools, Network Monitoring Tools. A graphical report is created using the variations in traffic measurements, such as network bandwidth, latency and utilization etc. The report can be based on the heaviest users of services, such as the top five heaviest users of the network or the top five application protocols present in the traffic. The limitations of these tools are that they only aggregate and characterize traffic instances based on a single attribute at a time, e.g., source/destination address or protocol. As a result, further processing on the summaries produced by these tools such as anomaly detection is difficult [10]. The objective of a summary is to provide a precise report of the traffic patterns in the network and to do so, summarization technique should be able to identify traffic patterns based on arbitrary combinations of attributes in an efficient manner. In [8], an extensive survey on data summarization is conducted. Within the scope of this paper, only structured data summarization techniques are considered as network traffic is an example of structured data. Figure 1 demonstrates a simple taxonomy of structured data summarization. The summarization techniques suffer from a number of problems as follows:

- These techniques depend on an expert to determine the summary size, but currently there is

no solution that can automatically suggest the best summary size based on a number of important factors for summarization, including, information loss, and computational complexity e.g., memory size and time for solution.

- Moreover, the summaries produced using techniques such as clustering, frequent item sets only capture frequent items in the summaries; they ignore or leave out anomalies which may be infrequent. Consequently, anomaly detection techniques do not perform well on summaries as they do not contain any anomalies.

- In the case of clustering, the centroids may not be a part of the original data.

- In the case of frequent item sets, it misses the value of attributes in summary when they are not identical. As a result, a summary produced according to these approaches cannot be directly used as input for anomaly detection purposes.

- Semantics based techniques do not produce summary which are part of original data.

- Statistical based techniques such as sampling do not guarantee the representation of anomalies in the summary.

IMPLEMENTATION

Capable and lively evaluating based framework estimation is proposed that is modest for irregularity persona on network visitor's datasets. The proposed abstract approach could make strains which, when used as dedication to irregularity recognizable proof figuring's, yield near or favored execution over function occurrence executed on the critical information. An advantage of the proposed count is that the time predicted to make define and anomaly put on the review is decrease than the irregularity notoriety on the number one facts.



The proposed as soon as-over computation relies upon analyzing. Analyzing is a powerful method for compacting enter statistics and has been explored in particular segments of huge business the chiefs, for instance, traffic assessment and specifying, guests depiction and interference area. The pioneer benefits of analyzing over whole character are the blurred cost and severely high-quality speed.

ALGORITHM

1: Such (Summarization Using Chernoff Bound)

Input : D, Dataset;

|Canomaly], Size of anomalous cluster;

δ , Probability for the sample to contain anomalous instances;

f, fraction of the dataset to be anomalous cluster.

Output: S, The summary of D

Begin

Calculate the summary size s using Chernoff bound (2)

$S \leftarrow$ random sample from D of size s

End

Chernoff Bound: For a cluster C in a dataset D, if the sample size s satisfies equation (1), then the probability that the sample contains fewer than $f \times |C|$ data instances belonging to the cluster C is less than δ , $0 \leq \delta \leq 1$. In equation (1), f defines the fraction of the cluster C, $0 \leq f \leq 1$.

2: Summarizing Infrequent Patterns in Smart Systems (SIPSS)

Input : D, dataset.

Output: S, summary of D

Begin

$C_1, C_2, \dots, C_n \leftarrow$ x-means (D,K)

for each cluster C_i , $i = 1:n$ do

$c_1, c_2, \dots, c_l \leftarrow$ x-means (C_i, K_i)

for each cluster c_j , $j=1:l$ do

$S_j \leftarrow$ P samples as summary instances

end

end

$S \leftarrow S_n \cup S_j$

End

Algorithm 2 shows the SIPSS method in which x-means clustering is first applied on the dataset (D) and then on each of the clusters produced. Using the combination of mutual information, SSE and cluster size, a proportion of the data instances from each recursive cluster is sampled.

RESULTS & DISCUSSION

```
user@node:~$ start-all.sh
This script is deprecated. Instead use start-raft.sh and start-raft.sh
22/02/20 11:14:29 user@node:~/hadoop$ ./start-all.sh
Starting namenodes on [localhost]
localhost: starting namenode, logging to /usr/local/hadoop-2.8.4/logs/hadoop-user/namenode-node.out
localhost: starting datanode, logging to /usr/local/hadoop-2.8.4/logs/hadoop-user/datanode-node.out
Starting secondary namenodes [localhost]
22/02/20 11:14:31 user@node:~/hadoop$ ./start-all.sh
Starting namenodes on [localhost]
localhost: starting namenode, logging to /usr/local/hadoop-2.8.4/logs/hadoop-user/namenode-node.out
localhost: starting datanode, logging to /usr/local/hadoop-2.8.4/logs/hadoop-user/datanode-node.out
Starting secondary namenodes [localhost]
22/02/20 11:14:31 user@node:~/hadoop$ ./start-all.sh
Starting namenodes on [localhost]
localhost: starting namenode, logging to /usr/local/hadoop-2.8.4/logs/hadoop-user/namenode-node.out
localhost: starting datanode, logging to /usr/local/hadoop-2.8.4/logs/hadoop-user/datanode-node.out
Starting secondary namenodes [localhost]
user@node:~$
```

```
user@node:~$ jps
3489 ResourceManager
3915 Jps
3300 SecondaryNameNode
3000 NameNode
3125 DataNode
3616 NodeManager
2707 org.eclipse.equinox.launcher_1.3.0.v20140415-2008.jar
user@node:~$
```




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