# AN EFFECTIVE WAY TO DETECT COMPUTER NETWORK ANOMALIES

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#### ABSTRACR

With increased threat on the network, the detection of network anomalies is becoming more complicated. This thesis looked at anomaly detection by modeling a computer network as a temporary network.

**Keywords:** Anomaly detection, network level detection, app level detection, mobile security, Android security.

In general, according to the cardinalities of Nature, Environment, behavior and correlation, the anomalies of the Computational Network can be divided into 3 categories: point anomalies, natural anomalies, integrated anomalies.

The technology for detecting current anomalies can be divided into 4 categories, namely classification methods, statistical methods, clustering methods and information theory method.

Among them, the development of statistical theory and computer network science has greatly helped to detect network anomalies. An algorithm for analyzing localized key components has been used to continuously monitor the properties of the network area. A fault detection algorithm based on Xos vectors has been proposed and applied to a multilayer web network system represented by Time series graphs. The computer network was modeled as a dual graph and then a dual graph was projected as a directed weighted graph. Unlike these methods, in this thesis, an active subnet was isolated from the network. We divide it by the specified time frame. We divide into networks with directed weighted graphs in the time sequence. Then we carry out the decomposition of the properties separately for each network segment. In the first part of the work, the identification of active sub-networks is obtained from the network. In the second part, the process of detecting anomalies is carried out. At the end of the work, the results are considered.

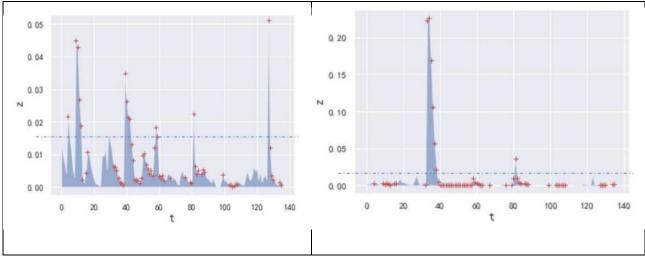
### **IDENTIFICATION OF ACTIVE SUBSETS**

At work, we model the time-lapse communication record in two parts, including Source IP and Destination IP. The "Source IP" part represents all nodes sending a connection message in the time section, and the "Destination IP" part represents all nodes at the time the message is received. Some nodes in "Source IP" only send connection messages, some nodes in "Destination IP" receive messages, while nodes present in "Source IP" and "Destination IP" not only send but receive messages. Therefore, we can use the "Source IP" or "Destination IP" communication state to indicate the communication state of the entire network. This causes some of the contact information to be lost. But significantly reduces the computational complexity.

### **RESULTS OF DETECTION OF ANOMALIES**

In the experiment, we used W = 7 as an examination of the experiment. On this basis, we mark different moments after the division. If there is a case where there are entries within a marked as an anomaly, this case is defined as an anomaly. Both the Source IP address and Destination IP address of this entry, currently designated as an anomaly, are defined as anomalies at the same time.

Figure 1 shows the value of deviations at different times in the given window. In the figure, the time marked "+" is the time when the anomalous record is set in the data set.



# Figure 1. Change of information exits

As can be seen from the picture, after giving a certain limit, it is possible to assess whether an anomaly occurs at the moment, depending on whether it exceeds the limit. Table 1 shows anomaly detection results with dual projection results under the priority of accuracy.

Table 1. Anomary detection results				
Anomaly types Signal	Anomaly types Signal	Anomaly	Anomaly	Anomaly types
number accuracy recall	number accuracy recall	types Signal	types	Signal number
ratio	ratio	number	Signal	accuracy recall
		accuracy	number	ratio
		recall ratio	accuracy	
			recall ratio	
Off-level joint projection	Off-level joint	Off-level	Off-level	Off-level joint
unspecified anomalies,	projection unspecified	joint	joint	projection
internal access, HTTP	anomalies, internal	projection	projection	unspecified
service denial,	access, HTTP service	unspecified	unspecified	anomalies,
	denial,	anomalies,	anomalies,	internal
		internal	internal	access, HTTP
		access,	access,	service denial,
		HTTP	HTTP	
		service	service	
		denial,	denial,	
Distributed denial from	Distributed denial from	Distributed	Distributed	Distributed
IRC botnet service, brute	IRC botnet service,	denial from	denial from	denial from
force Cracking of SSH 12 1	brute force Cracking of	IRC botnet	IRC botnet	IRC botnet
0.188	SSH 12 1 0.188	service,	service,	service, brute
		brute force	brute force	force Cracking
		Cracking of	Cracking	of SSH 12 1
		SSH 12 1	of SSH 12	0.188
		0.188	1 0.188	
Level joint projection	Level joint projection	Level joint	Level joint	Level joint
internal access, distributed	internal access,	projection	projection	projection
rejection from IRC botnet	distributed rejection	internal	internal	internal
Service 7 1 0.109	from IRC botnet	access,	access,	access,
	Service 7 1 0.109	distributed	distributed	distributed
		rejection	rejection	rejection from
		from IRC	from IRC	IRC botnet
		botnet	botnet	Service 7 1
		Service 7 1	Service 7 1	0.109
		0.109	0.109	

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