Why topology helps to detect cyber-intrusions

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Abstract Cyber-intrusions are a big problems for communications. It is therefore desirable to continuously develop new methods for detecting intrusions. A recent paper has shown that in many cases, intrusions can be detected if we form an inclusion graph of all natural groups of computers with similar activities, and find the topology of this graph. Specifically, the appearance of a new cycle is, empirically, a good indication of an intrusion. In this paper, we provide an explanation for this empirical phenomenon.

1 Topology helps to detect cyber-intrusions: an empirical fact

Cyber-intrusions are a big problem. Cyber-intrusions are a big problem for communications. Economy-wise, they cost companies billions of dollars every year. They threaten national security. It is important to decrease their negative effects.

Why detecting cyber-intrusions is difficult. At first glance, since modern machine learning (AI) methods are so powerful, why not use them to detect cyber-intrusions? These methods have indeed been used, but their success is limited.

There are two main reasons for this limitation. First, machine learning means, in effect, recognizing the known patterns. Machine learning tools learn to recognize

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intrusions which are similar to the previous once, but adversaries are constantly coming up with new intrusion schemes, and machine learning tools cannot do much against such innovative attacks.

The second reason is the too-much-information problem. All the transactions are usually recorded, so after each intrusion, we have a very large amount of data. Some of this data may be relevant, some not – but we do not know this a priori. As a result, we have to submit all this information to the machine learning tool – and for such huge amounts of data, AI tools work very slowly and not very effectively.

Need to select relevant features. A natural way to overcome this problem is to select relevant features. Then, instead of using the whole record of an intrusion, we can use only these features.

How to select relevant features: a natural idea. Intrusion affects computer networks. We want to detect which computers have been affected – and are now under full or partial control of an adversary. All the computers in a network perform a lot of activities. So, a natural thing to do is to compare these activities – between different computers and between past and present activities of the same computer.

For new threats, past activities are probably not that helpful. So, if we have to select the smallest possible number of features, it makes sense to only use comparisons of different computers' activities.

Depending on the level of similarity, we can have clusters of computers that have some similarity level. For smaller levels of similarity, we have larger clusters; for larger levels of similarity, we have smaller clusters. A smaller cluster corresponding to a higher level of similarity is contained in a cluster corresponding to a lower level of similarity. Clusters with such an inclusion relation naturally form a graph, in which clusters are vertices and edges correspond to inclusion.

So, the question becomes: how can we detect cyber-intrusions based on this graph?

Empirical result: topology helps. It turns out – see [1] – that a very good indication of an intrusion is when we have a closed cycle in this graph, or, more generally, when we suddenly have an additional cycle in addition to whatever structure we had before.

The precise meaning of this comes from topology. Namely, we can represent each graph as a topological structure in space in which vertices are points, and edges are lines connecting the corresponding points. For this structure, cycles are described by the corresponding *homology groups*.

A natural question and what we do in this paper. A natural question is why additional cycles are a good indiction of a cyber-intrusion. In this paper, we provide a possible explanation for the relation between cycles and cyber-intrusion.

2 Our explanation

What happens in a normal situation. Usually, computers form a hierarchical structure. For example:

- a computer of a faculty from our university's Computer Science (CS) department is a part of CS domain;
- a computer of a faculty from the Department of Teacher Education (TED) is a part of a TED domain;
- both CS and TED domains are, in their turn, parts of general domain of our University of Texas at El Paso (UTEP), etc.

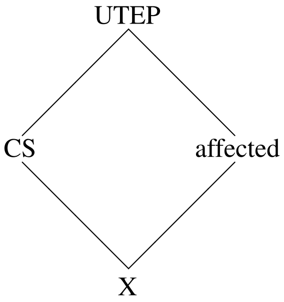
Every two clusters in this description are either included in each other or disjoint. If we make an inclusion graph, we get a tree, i.e., a graph without cycles.

What if we have an intrusion. Suppose now that we get an intrusion. As a result of this intrusion, some computers in different domains become affected. In this case, if we group computers into clusters – by similarity of their actions – then, in addition to the original hierarchical clusters, we get a new cluster: of affected computers. In this case, when we form an inclusion graph, we get a cycle: in addition to a usual hierarchy-related path from the room to the affected computer, we also have a different path – via the cluster of affected computers.

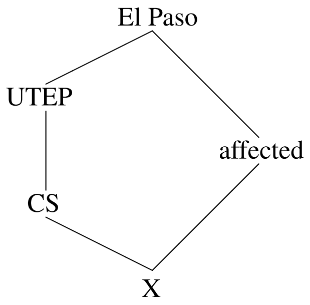
For example, suppose that one of CS computers (call it X) is affected (we hope not), and that the intrusion has affected only UTEP computers so far, including:

- some (but not all) computers from CS department and
- some (but not all) computers from the TED department.

Then we have the following cycle:



Similarly, if the intrusion has gone from UTEP to some other computers in our city of El Paso, we have a new cycle:



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