MINING NETFLOW RECORDS FOR HOST BEHAVIORS

by

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STATEMENT OF THESIS APPROVAL

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ABSTRACT

Network administrators perform various activities every day in order to keep an organizations network healthy. They take the assistance of different tools to maintain these networks. The tools used by admins perform aggregation at different levels for performance management, security, maintaining the quality of service and others. Aggregating at port/application level to understand the behavior of flows is well studied whereas understanding the behavior of hosts and groups of hosts is less well studied. The latter in conjunction with the former is helpful to admins in making informed decisions regarding activities that include security policies and capacity planning among many others. Looking at flow level doesn't help us in understanding the total activities each host is undertaking and doesn't let us figure out which hosts are behaving alike as a flow is just an instance of communication between two hosts. Hence, we want to aggregate by hosts and group them by understanding their behavior.

As we have millions of flows and thousands of hosts to work on, we used data mining techniques to find the structure and present them to admins to help them make decisions and ease enterprise network management.

We have built a system that consumes flow records of a network as input and determines the host behaviors in the network and groups the hosts accordingly. We also built an accompanying tool to this system that analyzes the host behaviors in different dimensions. This approach of extracting behaviors from network data has helped us in gaining interesting insights into the users of the system. We claim that analyzing host behaviors can help in uncovering the vulnerabilities in network security that are not found through traditional tools. We also claim that hosts behaving similarly require a similar amount of network resources and this will be an efficient way for network admins to plan their network capacity compared to the present bandwidth monitoring techniques.

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CHAPTER 1

INTRODUCTION

Understanding the behavior of flows[1] at port level is well studied whereas understanding the behavior of hosts and groups of hosts is less well studied. The latter in conjunction with the former is helpful to network admins in making informed decisions in day to day activities. Network administrators perform various network management activities and equipping them with right information will lead to better performance. Our system analyzes daily network data and extracts host[2] behaviors out of it. Behavior of a host is an aggregate of the amount of traffic that it sends both in terms of packets and bytes, the set of destinations it tries to connect to, the set of protocols it uses over some time period. For the purposes of our study, the time period that we choose is a day. There is nothing inherent about choosing a day as a time frame but we expect that the way networks are used varies from the days to nights and a day would be long enough to capture all these variations. These behaviors help us in learning more about what is going inside the network. Presently, admins use the following techniques to manage networks.

- They perform aggregation based on ports, protocols, applications. This helps in identifying applications consuming the most bandwidth, ports that are being used heavily, consolidate flow data from multiple devices, monitor wireless network bandwidth.

- They perform deep packet inspection to know what is in the payload of a packet. This is generally performed to extract the URLs or sites that users are visiting. This is a fine-grained version of the above technique.

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[1] All packets with the same source/destination IP address, source/destination ports, protocol interface and class of service are grouped into a flow.

[2] A host in our system is defined as any unique IP address.

- Rule-based systems are generally incorporated by admins to secure the network from malicious users. In a rule-based system, a trigger is executed when specific actions occur. An example would be blocking the IP address of the user if he has more than 6 unsuccessful login attempts. Here the action is six unsuccessful attempts and the trigger is blocking the IP address.

Now, let us look at how does the present techniques differ from our proposed work. In the **Figure 1.1** on this page the left image represents a screenshot taken from Solarwinds[3] application when our data is passed through it. Here we can clearly see that the Solar-Winds tool listed top 10 applications being used. If we look at the blue colored section of the pie chart it says that 83.67 percent of the traffic is World Wide Web traffic on port 80.

Moving on to the right side of the figure, it is a screenshot from the system we developed. Consider the hosts which are behaving as scanners on a Jan 3rd they were 1221 of them and on Jan 4th they are 1461 with an increase of 29 percent. One can clearly observe

[3]Solarwinds is an application that performs network monitoring using aggregation techniques when NetFlow data is passed as input.

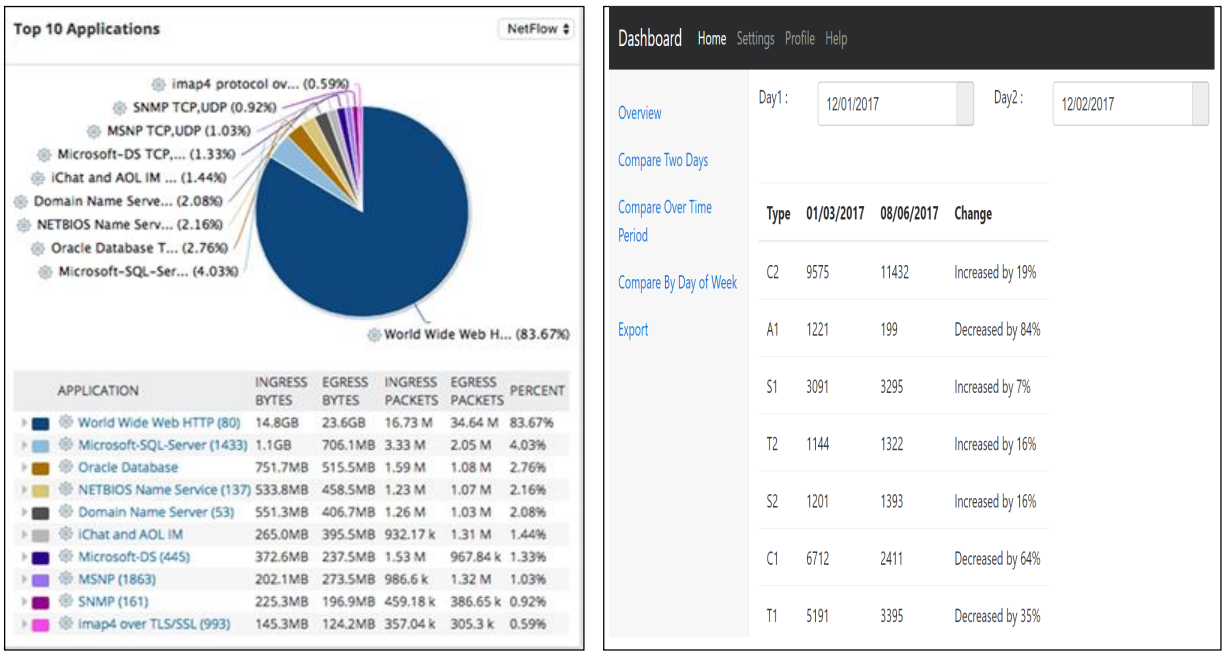

Figure 1.1. SolarWinds in comparison with our system

the difference between the two screenshots. While one views at the top applications and which ports make up the majority of traffic. The other views at the types of hosts and how they are changing over time. These are two different views of the same network data.

The obvious question that arises is why do we need an other view of network data and the answer is because the existing views are no more sufficient to perform different network management activities and our proposed approach helps in identifying behaviors that are not detected by traditional techniques. From the **Figure 1.1** on the previous page in the aggregation based techniques on the left side we are able to know that 86 percent of the traffic is web-based. But what do we know about the hosts that are originators of this traffic. There could be hosts which are doing both DNS and WWW traffic. There could be hosts that are carrying out a minimal amount of web traffic to evade from an anomaly event that they are performing. This information is not obtained from the SolarWinds or any other tool that uses these aggregation techniques. This is where we want our system to complement these existing techniques by providing hosts behaviors. Also, a major issue in network traffic analysis is classifying and characterizing traffic. Performing an accurate classification is indeed essential in various respects, such as traffic control, application identification, defense against attacks, and anomaly detection. However, they are often observed to fail, either because of packet encryption, arbitrary or dynamic port use, or because different protocols or utilizations employ the same single port. We also claim that hosts behaving similarly require a similar amount of network resources and host behavior extraction will be an efficient way for network admins to plan their network capacity compared to the present bandwidth monitoring techniques. Some behaviors that could be of interest to the network admins are:

- If hosts are behaving as clients or servers. This gives the admin a clear picture of how the network is being used and who are the major contributors to the traffic.
- If there are a group of hosts that exchange a large number of packets containing small bytes then it is normal interactive traffic in the network.
- If a group of hosts is sending data to a single host. This could be an example of off-site backups and network admin can use this information to plan the bandwidth accordingly.

- If a group of hosts is trying to scan on multiple ports then it is highly likely that these could be users trying to infiltrate into the network and admins could take actions appropriately.

To extract these behaviors we have used data mining techniques. The reason for approaching these techniques is firstly the amount of data that we want to look into is huge. Secondly, we want to find behaviors/patterns a human may not have known to look in first place and data mining is a field of study that performs exactly the same task. It extracts patterns from a given data set and present it to the user in an understandable format. Specifically, we used an unsupervised approach called clustering to extract these behaviors. We also applied other data mining methods to measure the quality of our clustering and find the divergence of host behaviors over a given time.

1.1 Contributions

"By combining clustering and other data mining techniques we can produce a view of host behaviors that help network administrators to understand the behavior of the networks. This system complements existing network analysis tools to ease network management."

The following are the main contributions from this work which supports and provides evidence for the thesis statement.

1) We have built a system that uses data mining techniques to extract host behaviors from the given Netflow data.

2) We have built a tool to analyze the host behaviors in different dimensions and render it visually to help administrator take decisions.

3) We performed an extensive evaluation of our approach using emulated enterprise network data. This evaluation demonstrates the ability of our system to detect host behaviors under challenging conditions and to scale to enterprise-sized networks.

The rest of thesis is structured as follows. Section 2 gives a background of data mining. Section 3 discusses related work and plugs our work into context. Section 4 presents the design of our system. Section 5 provides the implementation details, while Section 6 evaluates our system and demonstrates our claims. Finally, we outline items for future work in Section 7.

CHAPTER 2

BACKGROUND

Gaining insights from the network data using Machine Learning(ML) and Data Mining(DM) is a trending research area. There is a lot of confusion in the literature about the terms ML, DM as they often employ the same methods and therefore overlap significantly. Hence, below we describe the process of ML and DM briefly and establish why we have chosen data mining for building our system.

Machine Learning is a method of generating rules from past data to predict the future. A Machine Learning approach usually consists of two phases: training and testing. The following steps are usually performed:

- Identifying attributes (features) and classes from training data.
- Choosing a subset of the attributes for classification.
- Choosing an ML algorithm to create a model using the training data.
- Use the trained model to classify the unknown data.

Data Mining is the process of extracting patterns and structures implicit in the data and provide them in an understandable format to the user. Data mining is generally considered as a step in the process of Knowledge Discovery from Data (KDD). KDD usually consists of the following steps:

- Selection of raw data from which knowledge has to be extracted.
- Preprocessing the data to perform cleaning and filtering to avoid noise.
- Transforming the data so that all the attributes in the raw data are aligned towards achieving the common goal.
- Applying data mining algorithms to find rules or patterns.

- Interpret the observations of the above step and validate them.

As outlined above though both the techniques have similar steps of preprocessing data they differ on the end goal while ML maps the data set to known classes DM tries to find patterns out of the data set.

The decision of the approach that we want to employ in our problem solving also depends on the type of data we have in hand. If the data is completely labeled, the problem is called supervised learning and generally the task is to find a function or model that explains the data. The approaches such as curve fitting or machine-learning methods are used to model the data to the underlying problem. The label is generally a meaningful tag that is informative and has relation to the collected data. When a portion of the data is labeled during acquisition of the data or by human experts, the problem is called semi-supervised learning. The addition of the labeled data greatly helps to solve the problem. In general case, the semi-supervised learning problem is converted to supervised learning problem by labeling the whole dataset using the known labeled data and again the same machine-learning methods can be employed here. In unsupervised learning problems, we don't have any labels in the given data set and the main task is to find patterns, structures, or knowledge from this unlabeled data.

The dataset that we used for addressing our problem is flow data collected at routers which is explained in detail in section 4. This flow data generally comes without any labels. As explained above if the data in hand doesn't have any labels the problem we are solving is called unsupervised learning problem. Also, in the introduction, we have mentioned that the main goal of this work is to extract host behaviors from the aggregate data. This problem falls under a category of finding implicit/unseen patterns. Thus, having unlabeled data and the problem that we are trying to solve led us to use data mining techniques in building our system.

2.1 Unsupervised learning

As we are approaching our problem using unsupervised techniques in data mining. Here is a brief explanation of different techniques within unsupervised learning. Unsupervised learning problems can be further grouped into clustering and association problems. A clustering problem is where you want to discover the inherent groupings in the data,

and find patterns. An association rule learning problem is where you want to discover rules that describe large portions of your data, such as given an event X there is a chance of event Y happening. Since we aim to find the inherent groupings our focus will be on clustering techniques. Clustering is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (in some sense or another) to each other than to those in other groups (clusters). Cluster analysis itself is not one specific algorithm, but the general task to be solved. It can be achieved by various algorithms that differ significantly in their notion of what constitutes a cluster and how to efficiently find them. Below we describe few of these techniques.

Connectivity models [23], work on the premise that data points close to each other exhibit higher similarity than those lying far away. Cluster formation in these models can be done in two ways. Either we can initially consider all the points as a single cluster and then divide them into multiple clusters based on the distance between data points or we can assume each data point is a cluster on its own and start merging them as the distance decreases. Hierarchical clustering algorithms fall under this category.

Centroid models, also use distance as their metric in grouping data points to a cluster. While connectivity models consider the distance between all points, centroid models measure the distance of a point from cluster centers so as to assign it to the closest center. These models are iterative in nature and come to a halt when the cluster centers don't change. There are different techniques to initially choose cluster centers. K-Means clustering algorithm [8] is a popular algorithm that falls into this category. K-Center, K-medoids also belong to the same family.

Distribution models[18], Datasets can be fit into different distributions (eg: Normal, Gaussian). The clustering models that group all the data points with similar distribution and generate clusters according to these distributions fall under this category. A well-known example of these models is Expectation-maximization algorithm.

Density Models [27], In these models clusters of data points, are determined based on the variation of density in the data space. Different density regions within the data space are found out and all those points that fall under same density region are assigned to the same cluster. Popular examples of density models are DBSCAN and OPTICS.

The choice of clustering model depends on the data in hand, amount of prior infor-

mation that we have about the data and the problem we ought to solve. In our case, we have chosen centroid models to solve our problem and specifically the K-Means algorithm. Before, discussing why K-Means in design section let us look at what K-Means algorithm is all about.

K-means [17] is a clustering algorithm that groups data points based on their feature values into K disjoint clusters. All the points that are classified into the same cluster are similar to each other when compared to those data points in the other clusters. The number of clusters K has to be specified in advance. Here are the four steps of the K-means clustering algorithm:

- Define the number of clusters K.
- Initialize the K cluster centers. We can arbitrarily choose K data points from the given data set as cluster centers or apply K-means++ [1] algorithm to find the initial K cluster centers. K-means++ helps in careful initial seeding that can output better clusters.
- Iterate over all data points and compute the distances to the centers of all clusters. Assign each object to the cluster to which it is nearest.
- Recalculate the cluster centers after the above assignments.
- Repeat step 3 until the cluster centers do not change anymore.

A distance function is required in order to compute the distance (i.e. similarity) between two objects. The most commonly used distance function is the Euclidean one which is defined as:

$$d(x, y) = \sqrt{\sum_{i=1}^{m} (x_i - y_i)^2}$$

where $x = (x_1, ..., x_m)$ and $y = (y_1, ..., y_m)$ are two input vectors(data points) with m features. In the Euclidean distance function, each feature is weighted equally. However, in our data set different features are usually measured at different scales. Hence, they must be normalized before applying the distance function.

CHAPTER 3

RELATED WORK

In this chapter, we review works that relate to usage of Machine Learning (ML)/Data Mining (DM) techniques in the area of networking and discuss in detail how researchers are using these methods for different purposes. We also put into the context how our problem statement and solution differ from the existing work and advances the state of the art.

First, we review the different ML/DM approaches that are being used for traffic classification and intrusion detection in the area of cybersecurity.

Second, we survey the vast body of work that does packet based inspection and also analyze the shift of research focus towards inspecting at higher granularities specifically the flow based inspection techniques.

Finally, we discuss how unsupervised approaches are being used to look at network data at higher granularities and compare our solution with the prior work.

3.1 Data Mining and Machine Learning techniques for intrusion detection

There are many papers published in the area of cybersecurity describing the different ML/DM techniques used. Buczak et al [6] provided a survey of the popular techniques used and thoroughly describe ML/DM methods which provides a good starting point to people who intend to do research in the area of ML/DM for intrusion detection.

The survey by Buczak et al [6] has been mainly on explaining the ML and DM methods whereas Bhuyan et al. [4] in his paper described different techniques used for network anomaly detection in detail. Garcia's work [15] also explained different intrusion techniques in detail. He extended his work to use machine learning techniques for anomaly detection with a focus on signature-based intrusion-detection. Narayan et al. [25] proposed a hybrid classification method utilizing both naive bayes and decision trees for intrusion

detection. While their findings had higher accuracy applying these supervised techniques to our dataset was not feasible as we had very less labeled data.

Wired networks generally have multiple layers of security before the intruder enters the network. But, the wireless networks are more vulnerable to malicious attacks. They add a whole new semantics to the network security such as dynamically changing topology, different authentication techniques and ad-hoc formation of networks. The process followed in this paper works in the context of both wired and wireless networks. Zhang et al. in his work [30] provide a perspective focused only on wireless network protection.

3.2 Machine Learning for traffic classification

Apart from using ML/DM techniques for intrusion detection, one other field where these have been extensively used is to classify the network data. The survey [24] lists the prominent ML/DM techniques used to classify the data and describes the need for traffic classification. In order to provide the promised quality of service and be liable to the government laws, network administrators should be able to distinguish the traffic on their network.

Traditional well-known port number based classification is not sufficient on its own to distinguish different applications as different services are using HTTP protocol to send their data and obfuscate from the traffic classifiers. Also, papers such as choicenet [29] point out that to develop an economy plane for the internet similar to the implicit content based billing architecture in mobile architecture there is a need for network administrators to classify the network data.

Naive Bayes form is the simplest technique used for this type of classification and has been explained in greater detail in the work of Andrew and Denis [22]. This work was extended by applying Bayesian neural network approach [2] for increasing the accuracy. Though these classification techniques proved to be efficient in differentiating network data they have a drawback that they can only distinguish the network data into known classes which is in contrast to our goal of identifying implicit behavior which is not known in advance.

Renata[3] looked at unsupervised techniques for traffic classification. In contrast to the existing approaches, he followed a principle of early detection. Accordingly, he looked

at the first few packets of TCP flow and classified them into different applications. The underlying logic behind this method is that during handshake process each application behaves in a specific way exchanging a particular sequence of messages. He used K-Means algorithm to form clusters. Initially, training data collected over a period is used to generate a model which gives a set of clusters. When new data arrives simple Euclidean distance is used to map this flow to a cluster. The flow belongs to the cluster which it is closest to. Though this approach had 80 percent accuracy it has few drawbacks, If we cannot capture initial few packets of a service it's effectiveness is compromised. If a flow doesn't fall under any cluster the behavior is undefined. Renata's [3] approach was similar to us as we also explored unsupervised techniques in our system but they differ in the point that they examine the packet data and map their clusters to only known classes of traffic.

Jeffrey and Mahanti et al. [12] explored hybrid techniques for traffic classification. The intuition behind this exploration is that not all data available will be labeled and when data from new services get appended to the existing dataset the supervised learning techniques are falling short in recognizing them and they map the new data set to one of the existing classes. To overcome this shortcoming they approached the problem in two steps. In the first step, the dataset containing labeled and unlabeled data is passed to a clustering algorithm. In the second step, the labeled data is used to classify clusters and this is done as follows: Within each cluster, all the labeled data is considered and the label with majority forms the label of this cluster. Clusters without any labeled data are classified as 'Unknown'. When new data arrives it will be assigned based on the Euclidean distance to the closest cluster similar to [3]. This has combined advantages of supervised and unsupervised learning. It also decreases the training time because of few labeled data. Its uniqueness comes from being able to map the data from new applications and services to 'Unknown' cluster or to their respective clusters if they are a simple variation of existing application's characteristics. A slight variation of this approach has been used by us during our experiments and the following issues have been noticed. First, there were cases in which we have seen a cluster mapping to multiple labels as both turned out to be major labels in the cluster differing by a small value. In this case, labeling a cluster just based on majority doesn't suggest the clusters behavior. Second, the amount of labeled data could be negligible compared to the size of the cluster. Third, two clusters could turn out to have

similar labels. Lastly, the time consumed for this two-step approach is high as we had to iterate through the data twice. Noticing that this technique isn't in-line with our goals we have embraced a totally unsupervised approach to our problem.

3.3 Usage of flow records for IDS/Classification

Traditionally network data inspection is done by inspecting the contents of every packet. But, the granularity at which this is happening is changing based on the requirements. Earlier packet inspection is used to be a norm but inspecting the contents of every packet is prohibitive in this data-centric age. In this section, we look at how flows (aggregated packet data) are being used as input for ML/DM algorithms in place of packets.

In our opinion, flow-based detection should not be seen as a replacement but should be treated as a complement to packet-based inspection. We envision that a network administrator should be able to understand the behavior of his network through an aggregated view of network data (in our case flows) and should dive into packet data only when suspicious about an activity. This two-step approach will ease the way the network administrators manage their network.

Work of Li et al. [13] and Gao et al. [14] are two examples of DOS detection using flows. In their approach, a process tracks the presence of a flow in a specified time frame and another process runs an anomaly-based engine that triggers if there is a sharp variation from the expected mean. A similar approach was proposed by Zhao et al.[31] to identify the IP addresses of the scanning hosts and DOS attackers using the flow data. Our system though uses flows captures a broader view apart from identifying these specific attacks. Network Flows are also used in building worm detectors [11] [10], botnet detectors [26] [21] [19]. Specifically, the botnet detector built by Livadas et al. [21] is of interest as they build a model using the aggregated flows similar to our work.

CHAPTER 4

DESIGN OVERVIEW

Detecting the behaviors implicit in the NetFlow data and using them in conjunction with existing tools to make network management easier is the overarching premise of this work. In this chapter we describe the design of our system, and how the different components fit into the architecture.

4.1 Components

Our design is comprised of the following essential components: NetFlow Collection, Feature Engineering, Pattern Detector, and Applications as shown in **Figure 4.1** on the following page.

4.1.1 NetFlow collection

While the term NetFlow has become a de-facto industry standard, many other network hardware manufacturers support alternative flow technologies namely JFlow, S-Flow, NetStream, etc.. The University routers from which we have collected the data for this experiment have been equipped with NetFlow on it which led to using NetFlow as our flow technology.

4.1.1.1 What is NetFlow?

NetFlow is a proprietary protocol for collecting IP flow packets information on networks. There are different variants to this protocol but across all these versions a flow is defined uniquely by its source and destination IP addresses, source and destination ports, transportation protocol. Whenever one of these values changes a new flow is created. For each flow the number of packets, bytes and other network related information are tallied and stored in the routers cache till it expires, then this information is exported to a collector.

The captured flows are exported to NetFlow collectors at frequent intervals. The flows

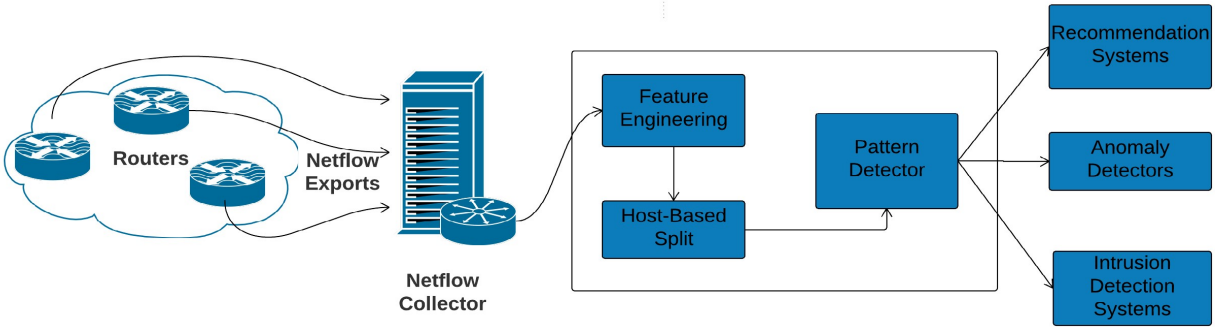

Figure 4.1. Architecture.

that are to be exported are determined based on the following rules: 1) When a flow is inactive for a certain time without receiving any new packets. 2) If the flow is active than max threshold time which is configurable. 3) If a TCP flag (FIN / RST) indicates the flow is terminated. NetFlow provides a powerful tool to keep track of what kind of traffic is going on the network and is widely used for network monitoring. Most vendors support different flavors of similar flow monitoring approaches and a common standardization is done within the IETF IPFIX working group.

There are different variants of NetFlow with each advanced version giving additional information about the flow. The fields that we used in our experiment and that are supported across the versions are in **Figure 4.2** on the next page.

4.1.2 Feature Engineering

Feature Engineering is the process of transforming raw data into features so as to better represent the underlying structure of the data. This helps in increasing the accuracy of the models we build using data mining techniques. This step comes before modeling and after seeing the data. Features extracted from the data directly influence the models generated and predictions made out of it. The better the features are the better the results will be. The results that we achieve when we are using DM approaches are a factor of the data set

NetFlow Data – Flow statistics	
Source IP address	IP address of the device that transmitted the packet.
Destination IP address	IP address of the device that received the packet.
Source Port	Port used on the transmitting side to send this packet.
Destination Port	Port that received this packet on the destination device.
TCP Flags	Result of bitwise OR of TCP flags from all packets in the flow.
Bytes	Number of bytes associated with an IP Flow
Packets	Number of packets associated with an IP Flow

Figure 4.2. NetFlow fields captured in a Flow

in hand, the features generated, the prediction model and the way the problem is framed. Most of the times even simpler models perform better if the features describe the structure inherent to the data. Below we describe different steps involved in the feature engineering with a sample set of data.

4.1.2.1 Missing Data

Table 4.1 on the following page is a sample of network data collected using NetFlow. In total there are 40 columns (only 9 columns are shown in the table) for each record with each column capturing different flow information. From the table, we can see that there are few missing values. Missing data is a common issue that every data science experiment has to deal with and there could be different reasons why NetFlow records could be missing some values such as, few filters could be turned on the router that doesn't let the NetFlow collector collect all the information, overloading of NetFlow collector and others. We handled Missing data using the following techniques

1) Replace missing values with the mean. For the features such as duration, total packets and bytes exchanged we assume that missing values are distributed similarly to the values that are present for each source IP. The rational approach here would be to substitute values using mean as it maintains the existing distribution.

Table 4.1. Netflow raw data.

Source IP	Destination IP	Source Port	Destination Port	Protocol	Duration	Flags	Packets	Bytes
59.2.154.56	155.98.47.116	11045	7547	TCP	318.0618	.....	10	64516.125
223.157.2.51	155.98.44.63	7828	80	TCP			22	19800
190.72.57.37	155.98.47.29	44539	2323	UDP	318.0618	..s..	1	
223.157.2.51	155.98.44.63	24342	23		50.023	.....	50	45838.708
113.23.73.77	155.98.36.146	6176	80	TCP	318.0618	.....	17	
223.157.2.51	155.98.46.35	52336	23	TCP	12.6705	.....	50	388.098
184.105.247.2	155.98.34.233	44969	3389	UDP		.....	50	19800
184.105.247.2	155.98.34.233	1318	21	TCP	40.230		121	19800
208.100.26.22	155.98.35.94	50861	53	ICMP	40.230		21	

2) Replace missing values with the median/ mode. This is another technique to handle missing data, It should be noted that using different statistical measures to replace missing values yield different solutions. Features that have categorical data cannot be handled using mean or median and hence we approach mode to fill in their missing values. The feature protocols were handled using the mode approach, filling the missing values with the most frequently occurring protocol value for that source IP.

3) The question that arises when replacing missing values is what percentage of values can a feature miss atmost. For example, filling in half the values of a feature in this step with a statistical measure is not reasonable. Features of this kind are considered as noise and could affect the effectiveness of the data mining algorithm. The better option here would be to discard the column that has too may missing values. In our case, there were a handful of columns that fell under this category and are discarded. flags shown in **Table 4.1** on the current page is one among them. After handling missing values our data looks as in **Table 4.2** on the following page.

Table 4.2. NetFlow raw data after handling missing values

Source IP	Destination IP	Source Port	Destination Port	Protocol	Duration	Packets	Bytes
59.2.154.56	155.98.47.116	11045	7547	TCP	318.0618	10	64516.125
223.157.2.51	155.98.44.63	7828	80	TCP	**62.6935**	22	19800
190.72.57.37	155.98.47.29	44539	2323	UDP	318.0618	1	19800
223.157.2.51	155.98.44.63	24342	23	**TCP**	50.023	50	**20188.098**
113.23.73.77	155.98.36.146	6176	80	TCP	318.0618	17	388.098
223.157.2.51	155.98.46.35	52336	23	TCP	12.6705	50	388.098
184.105.247.2	155.98.34.233	44969	3389	UDP	**40.230**	50	**19800**
184.105.247.2	155.98.34.233	1318	21	TCP	40.230	121	19800
208.100.26.22	155.98.35.94	50861	53	ICMP	40.230	21	45838.708
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

4.1.2.2 Converting categorical to numerical variables

Features could be either numerical or categorical variables. When dealing with algorithms that work on numerical data we have to make sure that the categorical variables are handled. For example, in our case feature protocol, has values such as TCP, UDP, and others. One approach is to encode them as 0, 1, and 2 respectively converting them to numerical variables. This could pose a problem when using distance measuring algorithms as the distance between the encoded attributes, like 1 (UDP), 0 (TCP) is smaller than 0 (TCP), 2 (others) generating an unintended meaning to this feature and could lead to biasing of few values. Another approach would be to create a feature for each value of the categorical variable and mark it as 0 or 1 based on if the value is present or not. There are both pros and cons to this method. The pros are if we choose to aggregate the values on all features this conversion gives a numerical value to work with. The cons are scaling and standardization could be affected. **Table 4.3** on the next page represents data set after this step.

Above two steps fall under a family of techniques called data cleaning. After the data cleaning and removing the irrelevant columns of data using domain knowledge we aggregated NetFlow data based on source IP as our work focuses learning about hosts from their aggregate data. The **Table 4.4** on the following page shows a sample of aggregated

Table 4.3. After Converting categorical data to numerical

Source IP	Destination IP	Source Port	Destination Port	TCP	UDP	ICMP	Duration	Packets	Bytes
59.2.154.56	155.98.47.116	11045	7547	1	0	0	318.0618	10	64516.125
223.157.2.51	155.98.44.63	7828	80	1	0	0	62.6935	22	19800
190.72.57.37	155.98.47.29	44539	2323	0	1	0	318.0618	1	19800
223.157.2.51	155.98.44.63	24342	23	1	0	0	50.023	50	20188.098
113.23.73.77	155.98.36.146	6176	80	1	0	0	318.0618	17	388.098
223.157.2.51	155.98.46.35	52336	23	1	0	0	12.6705	50	388.098
184.105.247.2	155.98.34.233	44969	3389	0	1	0	40.230	50	19800
184.105.247.2	155.98.34.233	1318	21	1	0	0	40.230	121	19800
208.100.26.22	155.98.35.94	50861	53	0	0	1	40.230	21	45838.708
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

data with ten features. The first record in the **Table 4.4** on the current page conveys the information that in the given data set the host 59.2.154.56 (source IP) had appeared 450 times. Out of those 450 instances it had contacted 116 unique hosts. A total of 110 different source ports were used in the 450 flows and all the packets were sent to single destination port. The columns TCP, UDP, ICMP indicate how many of these flows fall under each category. So of the 450 flows there are 406 flows in which TCP protocol was used , 4 had UDP protocol used and the rest 40 had used ICMP protocol. And the columns Total Duration, Total Bytes, Total Packets indicate the respective information exchanged by this source IP on a whole. This aggregated data is what we use for learning host behaviors. But, before that, we have to apply few other feature engineering techniques as described below.

4.1.2.3 Feature scaling

Feature Scaling/Feature Normalization, a method used to standardize the range of independent features of data. Failure to standardize variables might result in algorithms placing undue significance to variables that are on a higher scale. For example from the **Table 4.4** on the preceding page it is evident that the total packets and total bytes have higher magnitude compared to total flows and destinations. This range difference

shouldn't bias our results. There are different ways to do feature scaling namely, Min-Max scaling, Variance scaling, L2 normalization etc.. The choice depends on the data and different statistics of it such as mean, variance, l2 norm. Scaling is not advisable in all instances we might lose valuable information if applied without proper thought. In our case, we have chosen simple Min-Max scaling as our goal was merely to change the range of the data and not the distribution and Min-Max scaling helps us in achieving this at a lower cost.

4.1.2.4 Feature transformation

Transforming non-normal distribution to normal, many ML/DM tools perform well on normalized data and having skewed data will give inaccurate results. Log transformations are generally used to normalize the skewed data which is the case with most network data. After transforming the data if it doesn't capture the essence of original data we could look at other options such as square root, cube root. BoxCox is also another technique that changes the distribution of variables from non-normal to normal or near normal. **Figure 4.3** on the next page shows the distribution of a feature 'Total Flows' from our aggregated data, as seen from the graph it is heavily skewed towards left and this can be directly attributed to the data set we have in hand. The graph indicates that in most instances number of flows in which a source IP appears is less than 100 and hence we employ transformation techniques to decrease the amount of skewness in the data. **Figure 4.4** on the following page shows the same data after applying log transformation.

Table 4.4. Aggregated data by Source IP

Source IP	Total Flows	Unique Destinations	Unique Source Ports	Unique Destination Ports	#TCP	#UDP	#ICMP	Total Duration	Total Packets	Total Bytes
59.2.154.56	450	116	110	1	406	4	40	318.0618	10	64516.125
223.157.2.51	3	2	78	80	3	0	0	62.6935	22	19800
190.72.57.37	84	10	10	2	70	14	0	318.0618	1	19800
113.23.73.77	18	18	1	23	18	0	0	50.023	50	20188.098

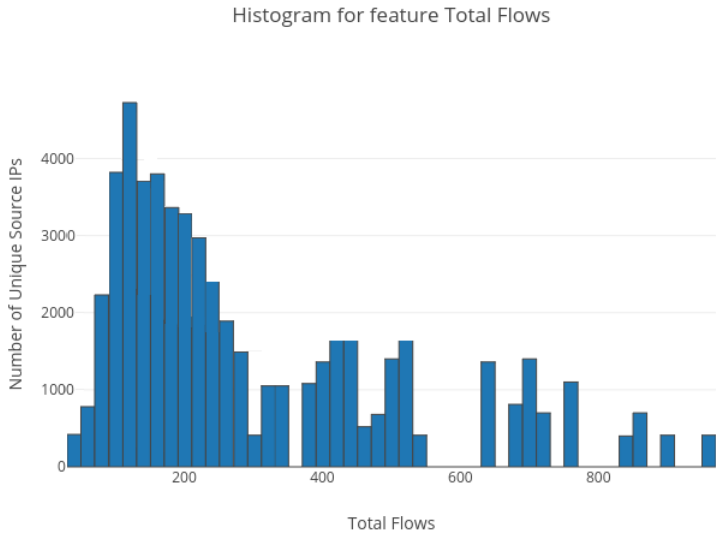

Figure 4.3. Skewed data before transformation

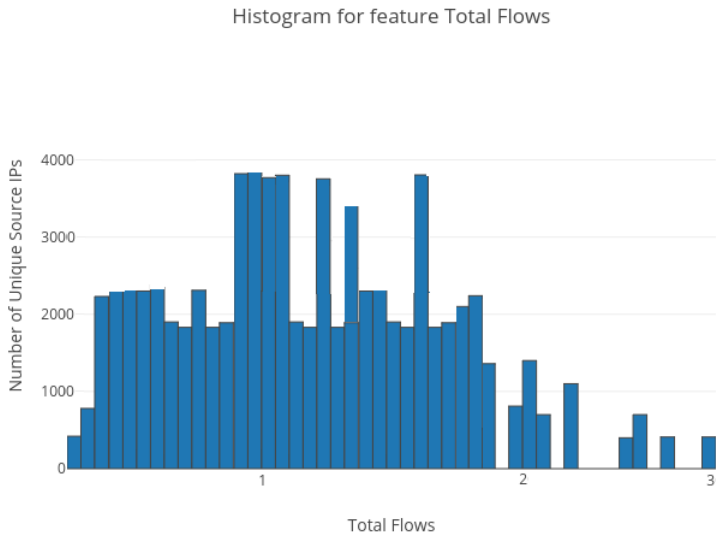

Figure 4.4. Normalized data

4.1.2.5 Feature selection

Feature selection refers to the process of selecting a subset of relevant features to model the data. It helps in shorter time periods of execution, overcoming the overfitting problem and making the solution more generic and avoid the curse of dimensionality. The

central premise of this process is to remove redundant or irrelevant features that don't make much sense to the problem we ought to solve. Feature selection and dimensionality reduction are two confusing terms. Though both methods seek to reduce the number of attributes in the dataset, but dimensionality reduction does it by creating new combinations of attributes, whereas feature selection methods include and exclude attributes present in the data without changing them. Principal Component Analysis, Singular Value Decomposition are examples of dimensionality reduction methods. The techniques used to do feature selection depend on text, numerical variables and they are three general classes of them Filter, Wrapper, Embedded methods. Feature selection is a much tougher problem in unsupervised setting as we don't have any labels that help us in determining the information gain with and without a feature. Problems of this kind have been rarely studied in the literature [5] [7].

The common strategy of most approaches is the use of filter methods, Filter model methods do not utilize any clustering algorithm to test the quality of the features. They evaluate the score of each feature according to criteria mentioned here [7]. It selects the features with the highest score. It is called filter since it filters out the irrelevant features using given criteria. Wrapper methods are another class of methods used for feature selection where we train the given model with different combinations of features and make inferences accordingly. Some common examples of wrapper methods are forward feature selection, backward feature elimination, and recursive feature elimination. Forward selection is similar to elbow method explained in the next section. It is an iterative technique where we start with zero features and in each step, we keep adding feature that has the most information gain or best expresses the underlying structure. This procedure is stopped when addition of an extra feature doesn't add any significant information to the model. The backward elimination technique is exactly opposite to the forward selection method. Here we start with all the features and remove the least significant feature at each iteration. This iterative procedure stops when no improvement is observed on removal of features.

We have chosen wrapper methods backward elimination technique for feature selection as it measures the usefulness of a subset of features by actually training a model on it. Though, it is computationally expensive compared to filter based approaches in our

context it was reasonable as we had only 10 features to look into. The result of feature selection is we have detected two features that have very less information gain namely the ICMP ports and duration and hence we removed these two from our feature list making our final feature count to 8. Feature Selection has helped us in enabling the machine learning algorithm to train faster. It reduced the complexity of the model and made it easier to interpret. We were also able to address the overfitting problem.

4.2 Pattern detector

Pattern detector consists of the core logic of our system. After cleaning the data and applying feature engineering we send the data through a pattern detector. Pattern detector sends the data through a clustering algorithm. It then maps the generated clusters to the host behaviors which is explained later.

As mentioned in the background section we choose to address our problem using unsupervised learning approaches. The most common unsupervised learning method is cluster analysis, which is used for exploratory data analysis to find hidden patterns or grouping in data.

4.2.1 Why K-Means ??

In section 2.1 we have discussed the different type of clustering techniques in detail. Here we provide a reasoning for choosing K-Means.

Connectivity models like hierarchical clustering don't have a provision for relocating objects that may have been incorrectly grouped at an early stage. Also, use of different distance metrics for measuring distances between clusters may generate different results. Performing multiple experiments and comparing the results is recommended to support the veracity of the original results. Lastly, a time complexity of at least O($n^2 logn$) is required, where n is the number of data points thus lacking scalability for handling big datasets.

Distribution Models assume a distribution for data but for many real data sets, there maybe no concisely defined mathematical model (e.g. assuming Gaussian distributions is a rather strong assumption on the data). Also, though distribution models have an excellent theoretical foundation but they suffer from one key problem known as overfitting.

We have experimented our data set with the density model DBSCAN and we have found the data being grouped at most into only two clusters. The reason for this is that density based models expect some kind of density drop to detect cluster borders. Recall from the above section that our dataset has many source IPs that appear in less than 100 flows and hence there wasn't any drop in density observed resulting in bad clustering.

Experimenting with centroid models especially K-Means gave us the advantage to play with the variable K and view into how hosts are being grouped with different values of K. It is scalable for heavier datasets and doesn't suffer from the overfitting problem. Also, there isn't any inherent assumption on which distribution the dataset should follow. Thus, making it a clear choice for building our system.

4.2.2 How to choose K ??

In many situations, parameters and variables chosen by the algorithm or by users affects the performance of the algorithm differently and results in different outputs. Similarly, an essential problem of the K-means clustering method is to define an appropriate number of clusters K. In the literature, there are different approaches proposed to determine an accurate value of K. These methods include direct methods and statistical testing methods. Direct methods consist of optimizing a criterion, such as the within-cluster sums of squares or the average silhouette. The corresponding methods are named elbow and silhouette methods, respectively. Statistical testing methods consist of comparing evidence against the null hypothesis. An example is the gap statistic. We have used the direct methods as they optimize a criterion, The elbow method was used to determine K and then cross-verified the values with the Silhouette Index obtained for this same data set.

Recall that, the basic idea behind partitioning methods, such as K-Means clustering, is to define clusters such that the total intra-cluster variation [or a total within-cluster sum of square (WSS)] is minimized. The total WSS measures the compactness of the clustering and we want it to be as small as possible. The elbow method looks at the total WSS as a function of the number of clusters: One should choose a number of clusters so that adding another cluster doesn't improve much better the total WSS. The optimal number of clusters can be defined as follow:

- Compute k-means clustering for different values of k. For instance, by varying k

from 1 to 50 clusters.

- For each k, calculate the total within-cluster sum of square (W_k).

$$D_k = \sum_{x_i \in C_k} \sum_{x_j \in C_k} ||x_i - x_j||^2$$
$$W_k = \sum_{1}^{K} \frac{1}{n_k} D_k$$

  Where K is the number of clusters, n_k is the number of points in cluster k and D_k is the sum of distances between all points in the cluster.

- Plot the curve of wss according to the number of clusters k.

- The location of a bend (knee) in the plot is generally considered as an indicator of the appropriate number of clusters.

The graph depicts the amount of information we are gaining with addition of each cluster. the first clusters will add much information, but at some point the marginal gain will drop, giving an angle in the graph. The number of clusters are chosen at this point, hence the elbow criterion. **Figure 4.5** on the current page shows the elbow curve obtained for our data set on a chosen day. This method gave us a value of 7 for K.

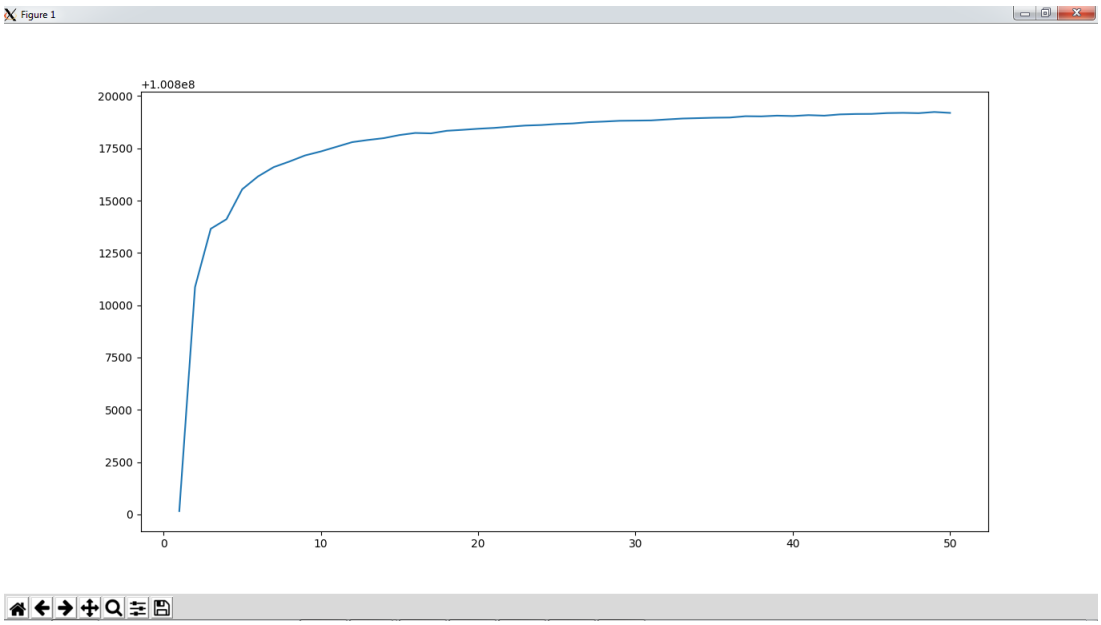

Figure 4.5. Elbow Method

However, the elbow method is not unambiguous. especially if the data is not very clustered we will notice that the elbow chart will not have a clear elbow. Instead, we see a fairly smooth curve, and it's unclear what is the best value of K to choose. In cases like this, we might try a different method for determining the optimal K. Hence, to corroborate the claim of elbow method for K we also ran our dataset through another technique called Silhouette.

The average silhouette approach measures the quality of a clustering. That is, it determines how well each object lies within its cluster. A high average silhouette width indicates a good clustering. Average silhouette method computes the average silhouette of observations for different values of K. The optimal number of clusters K is the one that maximizes the average silhouette over a range of possible values for K. The algorithm is similar to the elbow method and can be computed as follow:

- Compute k-means clustering for different values of k. For instance, by varying k from 1 to 50 clusters.
- For each k, calculate the average silhouette of observations (avg.sil).

$$s(i) = \frac{b(i)-a(i)}{max(a(i),b(i))}$$

  Here s(i) is the silhouette index of a cluster point i. Where a(i) is the average distance of point i to all the objects in the same cluster while b(i) is the minimum average distance from the point i to all the points of a different cluster. avg.sil is calculated by finding the mean of all the s(i) for each point in a cluster.

- Plot the curve of avg.sil according to the number of clusters k.
- The location of the maximum is considered as the appropriate number of clusters.

The intuition behind this approach is for a point as $a(i)$ is a measure of how dissimilar i is to its own cluster, a small value means it is well matched. Furthermore, a large $b(i)$ implies that i is badly matched to its neighboring cluster. Thus an $s(i)$ close to one means that the data is appropriately clustered. if $s(i)$ is close to negative one, then by the same logic we see that i would be more appropriate if it was clustered in its neighboring cluster.

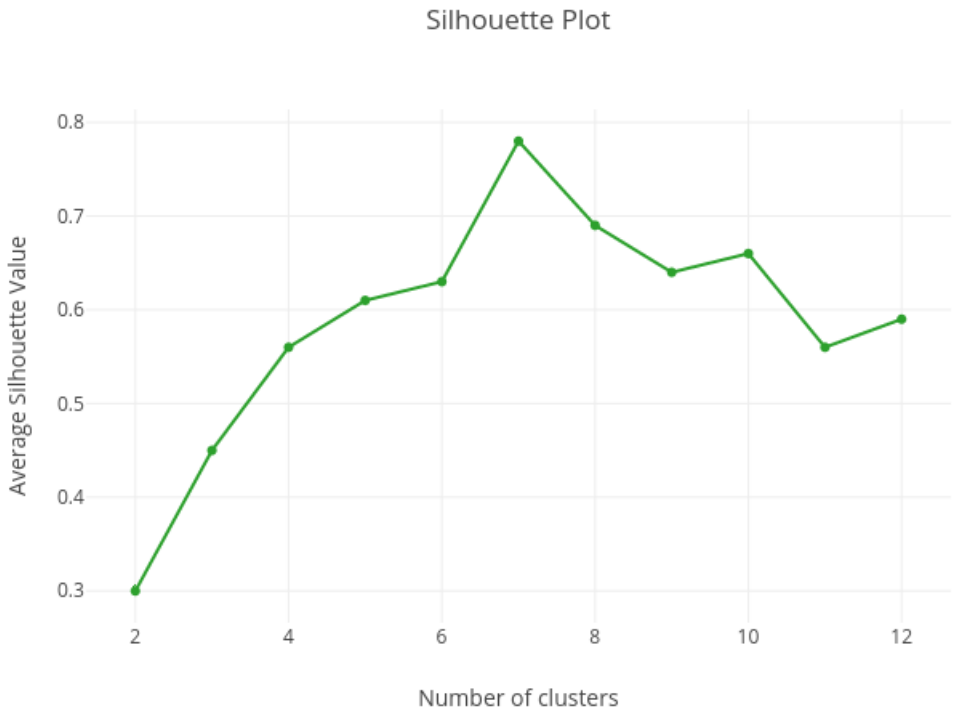

Figure 4.6. Silhouette Method

The average $s(i)$ overall data of a cluster is a measure of how tightly grouped all the data in the cluster are. Thus the average $s(i)$ overall data of the entire dataset is a measure of how appropriately the data have been clustered. **Figure 4.6** on the following page shows the plot obtained using silhouette technique.

An important point that has to be noted here is that, though we have a method to evaluate K, we don't invoke this method daily to determine the K value. We chose a reference day and determine the K value for that day and that K value is used for the remaining days till the network admin chooses to change this reference day. A reference day is selected generally to reflect all the behaviors that are seen in our network in day-to-day basis. The choice of changing this reference day also vests with the network admin as he knows how the usage of the network has been changed and whenever a reference day is changed we need to calculate the K value again.

4.2.2.1 Cluster labeling and comparison

The output of the pattern detection step is a set of clusters. We explored these clusters to better understand the grouping of hosts. We observed that each cluster exhibits a unique behavior. That is all the hosts in a cluster exhibit similar behavior. These clusters were labeled accordingly. Recall the overarching premise of our work is to analyze the behavior of hosts looking at the aggregated host data. In order to analyze the behavior of hosts over a time period, we should be able to compare hosts behavior across days. We dealt with this by initially comparing the host's behavior for any two days and then extended it to any given time period. To achieve this we chose a reference day and label the clusters on that day through manual inspection. On any other day, we label the clusters by comparing it with this reference day. Cluster comparison is an active research area but in our case, it is slightly easier to solve because the number of clusters that are formed on each day is constant (i.e, as we choose the same K value as on reference day.) and each cluster maps to a unique behavior. So, all that we need to do is to find a one-to-one mapping with the reference day clusters. Now, this turns out to be an assignment problem which is well studied [20]. Assignment problem is a special type of linear programming problem which deals with the allocation of the various resources to the various activities on one to one basis. It does it in such a way that the cost or time involved in the process is minimum and profit or sale is maximum.

In our case both the resources and activities are nothing but clusters formed on two different days and this has to be done in such a way that the total effort is least. Assignment problem is a well-studied problem and has polynomial time solutions. One such algorithm is the Hungarian algorithm[20].

4.3 Applications

Our system can be used to build different applications that help in network management as listed below.

- *Anomaly Detectors*, applications that expose the hosts that are behaving as outliers and don't conform to an expected pattern. We can use our system to build such applications. For example, we found a cluster of hosts that are exhibiting anomalous behavior during our exploration of emulab data. We can observe the change of this

cluster size and center over days and thereby notifying the network admin if there is a shift in anomaly behavior that network admin has to be aware of. Here we can take the help of work done by [9] to determine when should a network admin be notified.

- *Dynamic Security Rules Generator*, Looking at the historic user behavior we can generate dynamic rules for security of the network. Few of them could be, to block certain IPs that are exhibiting inconsistent behavior etc. Authentication rules can also adapt dynamically by observing the changes of different clusters and their cluster centers. Such as, number of unsuccessful attempts a client can make to a server can also be limited based on the different ports client is using.

- *Recommendation Systems*, We can capture the different behaviors exhibited by network users over time and use this to predict a behavior on a certain day of a week or month using the historical data. This helps network admin to prepare well ahead and plan the bandwidth or other network resources accordingly.

  In this direction of building applications through the results obtained from our system we have created a web tool that analyzes data in different dimensions and is explained in detail in evaluation chapter.

CHAPTER 5

IMPLEMENTATION

In this chapter, we will discuss the implementation details of our system. Let us look at tools/techniques used at each step.

NetFlow Collection, The raw data collected at the routers is exported to NetFlow collectors as described in chapter 3. NFDUMP [17] tools are used to process the NetFlow data. They support NetFlow version v5, v7 and v9. The two tools of primary importance are nfcapd(netflow capture daemon) that reads the netflow data from the network and stores the data into files. nfdump (netflow dump) reads the NetFlow data from the files stored by nfcapd. Using nfdump we import the data on to our local machines from the NetFlow collectors. This imported data forms the primary source for our experiments. But this data is not in a usable format for applying data mining algorithms and hence we convert it into text format and save it in a CSV file.

Feature Engineering, We used different python libraries such as NumPy, Spacy and Pandas to clean and manipulate data. Specifically, the mean and median calculating methods from Pandas for missing data and min-max scaler respectively, log transformer for transformation from NumPy. For aggregating all the feature values by a host we used MongoDB contrary to keeping counters in the code. This has reduced the time taken for aggregation to under 2 minutes from 20 minutes for a day's worth data. In this context, we also wanted to try the approach of streaming algorithms such as bloom filters or count-min sketch which gives the aggregate information with little memory footprint which we have explored a little, but left for future work at this point.

Pattern Detection, As mentioned we have chosen K-Means for our pattern detector and to determine K we used elbow and silhouette approaches. Here we used scikit-learn package implementations of K-Means. To label the behaviors on a given day, we have selected a reference day and manually labeled its clusters mapping each cluster to a particular

behavior as shown in **Figure 5.1** on the current page.

Now for every other day, we compare the clusters formed on that given day with the reference day. Cluster comparison is an active research area and there are very few techniques to do this and hence we solved it by converting our cluster comparison problem into an assignment problem. An assignment problem generally deals with assigning machines to tasks, workers to jobs etc.. The goal is to determine the optimum assignment that, for example, minimizes the total cost. The assignment problem is a fundamental problem in the area of combinatorial optimization. It has many polynomial time implementations and one of them is Hungarian Algorithm [20]. So, in our case, the assignment problem is assigning the clusters on a given day to the clusters on the reference day. We use Hungarian algorithm to solve this cluster assignment. As per this algorithm, a cluster on a given day gets mapped to the cluster on a reference day based on the amount of effort it takes to move all the data points from this cluster to any of the reference day clusters

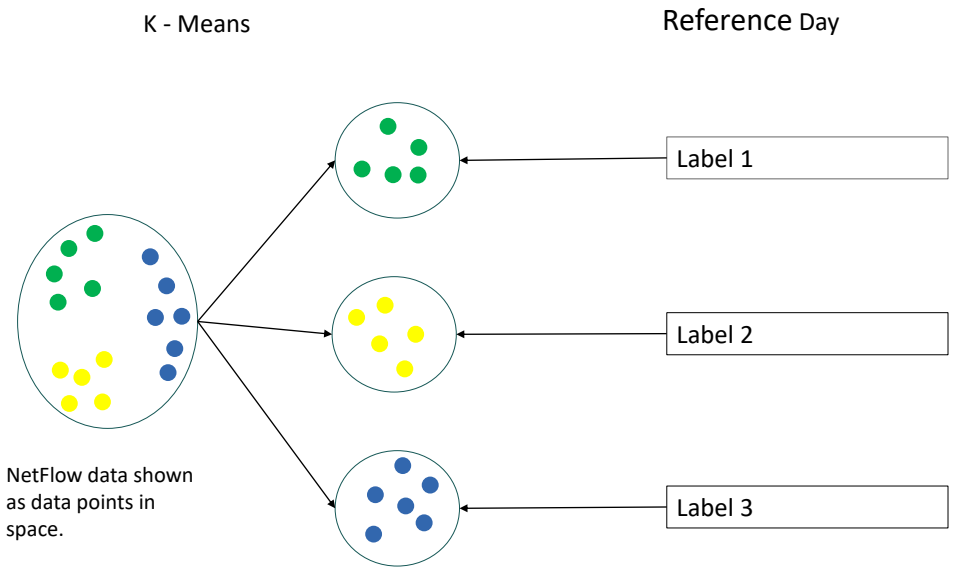

Figure 5.1. Process diagram on a reference day, with netflow eight-dimensional data aggregated based on host shown as a 2D data point which when passed through our pattern detector split into three clusters. These clusters are manually inspected and labeled accordingly.

centers. Overall the goal is to make the assignments in such a way that the total effort is least. The least effort assignment for dec 12th is shown in the **Figure 5.2** on this page. From the **Figure 5.2** on the current page one can see that the initial process of grouping data points into clusters on a non-reference day is similar to reference day as shown in **Figure 5.1** on the preceding page. Now, we make a one-to-one mapping of the clusters formed on a non-reference day with the clusters formed on a reference day from **Figure 5.1** on the previous page. Thus, the non-reference day clusters get mapped to reference day clusters and respectively get their labels.

A point to be noted here is that we might need to change the reference day with time. This could be because of change in the usage of applications over time. Our recommendation is to choose a reference day that suggests the changed behavior and keep visiting this periodically.

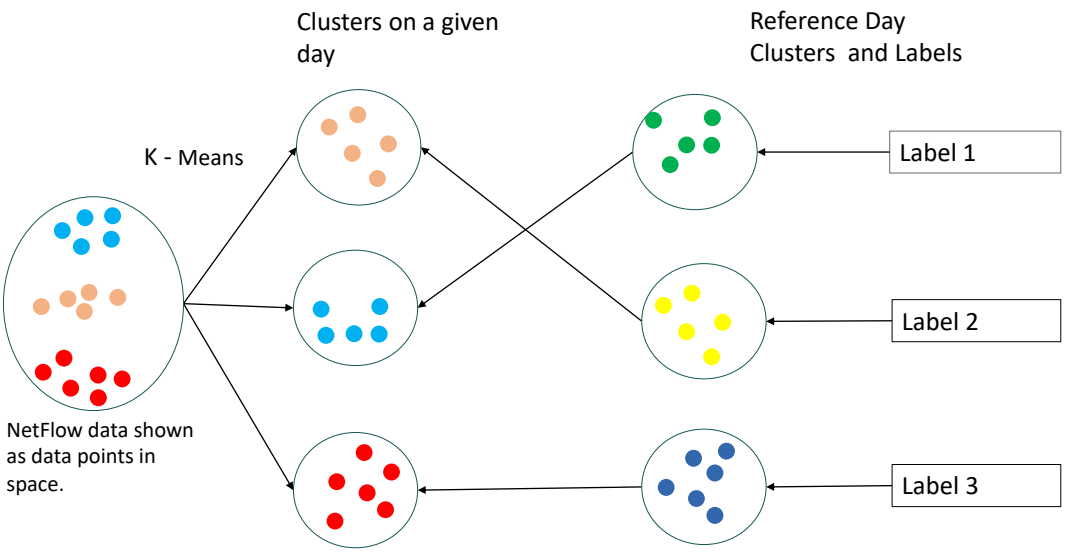

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Figure 5.2. Process diagram on a non-reference day.

CHAPTER 6

RESULTS

In this chapter, we evaluate our system using both labeled and unlabeled data. Our experiments in this section are conducted on a ubuntu16 virtual machine with 80 GB memory and 20 CPUs of computing power.

6.1 Dataset: description and clustering

The traffic analyzed here is collected at the University of Utah's emulab routers [28]. This is a private repository that contains traces of bidirectional traffic into the emulab network and no payload. Traffic is collected on full duplex links at a speed of 1Gbps.

We passed the NetFlow records collected over the last six months of 2017 through our system to determine the set of behaviors hosts exhibited over this time. We have handpicked 7 days of this data for analysis. The chosen days are October 15, October 16, November 14, November 23, December 5, December 12, December 16[1]. We made sure that there is a mix of both weekdays , weekends, normal and heavy traffic days. Each days traffic is treated independently as the same host that appeared on two different days could exhibit different behaviors. For different evaluations in this section, we used the data corresponding to these days.

As mentioned earlier in the section 4.2.2.1 we have chosen a reference day for labeling the clusters. We applied following techniques to label the clusters on the reference day. The first one is port-based analysis to identify applications such as web, mail, and DNS. The second one is the anomaly detection methods. Finally, a set of heuristic rules to label manually the behavior of the hosts. After the above steps, we found the following clusters. Clusters labeled as T consists of hosts which use few ports on both sides to exchange interactive traffic. Clusters labeled as S consists of hosts which serve clients requests and

[1]Days are picked without any prior knowledge of any metadata related to NetFlow records

conversely clusters labeled C consists of hosts which request servers for information. Let us list the differences in these behaviors in detail.

Clusters T1-T2 are mostly one-to-one connections, the dominant traffic in these clusters is http/https, ssh and peer to peer traffic. P2P traffic is defined as traffic where hosts use both TCP and UDP ports concurrently for communication, They also choose arbitrary ports for communication. Further analysis, reveals that clusters are split based on packet size and flow size. While T1 has long living flows with large average packet sizes. T2 has a large number of flows which are short-lived and an average packet size less than T1.

Clusters C1-C2 contains hosts which behave as clients making connections with different servers, The cluster C2 is dominated by DNS traffic which is in accordance with the heavy DNS requests that the hosts residing in the emulab network make with the external servers (machines outside the Emulab Firewall). Cluster C1 on the other hand comprises of hosts that request for web pages and that have outbound mail traffic.

Clusters S1-S2 as mentioned above comprises of hosts that behave as servers which respond to client requests. These hosts generally communicate with different ports of destination machines from a fixed port. S1 cluster contains of a majority of hosts which are within emulab network and are acting as servers accepting SSH requests. S2 cluster contains hosts that are both within and outside emulab network which are acting as servers for different sets of traffic such as SSH, Web and DNS which is further explained in section 6.2.

Cluster A1 is the cluster that is of interest for network security as it contains hosts that exhibit anomalous behavior trying to scan different access points to enter into the system.

The above description clearly points out that host-based behavior extraction produces a richer and finer classification of host behaviors than a port based classifier. For example, Http traffic is split across different clusters T or S which represents how the same protocol can be used by hosts exhibiting different behaviors. Same is the case with SSH traffic. While most of these clusters contain hosts using different protocols. They are similar in the sense that each cluster exhibits different functional behavior such as Server, Client or One-to-One traffic.

Figure 6.1 on the following page represents our further examination of clusters to determine if there is any similarity in the way the clusters T1/T2 , C1/C2 and S1/S2 are

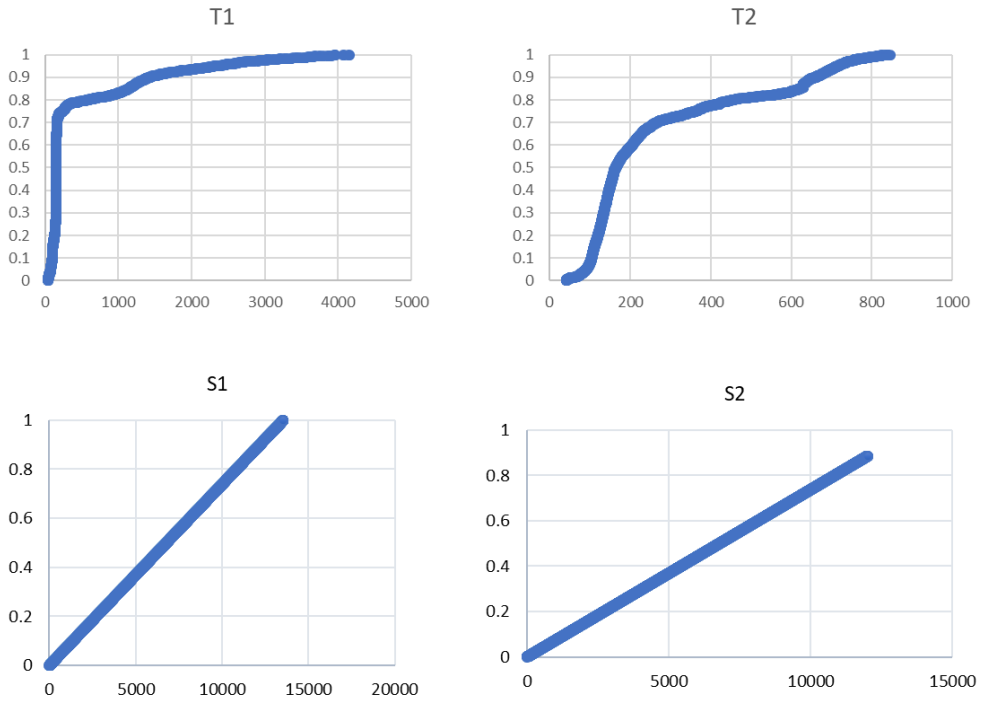
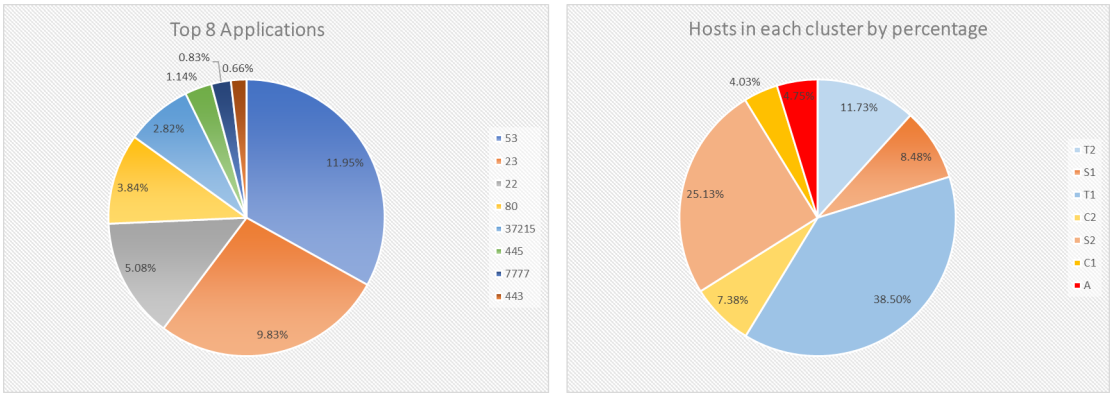


Figure 6.1. Average Bytes feature cdf for clusters T1,T2,S1,S2

formed. While we found that the clusters T1/T2 are distinguished by average byte size with hosts in T1 having an average byte size higher than hosts in the cluster T1, there were no such features that uniquely defined C1/C2 , S1/S2. This verifies our system is not biased by any single feature.

The **Figure 6.2** on the next page is a comparison between the classification made by a traditional port-based classifier 6.2(a) and our host-based classifier 6.2(b). The traditional port-based classifier identified the top 8 applications used by the hosts in the system. DNS(53) is the most used application with 11.95% of the whole traffic trying to query DNS servers. It is followed by Telnet(23), SSH(22) with a share of 9.83% and 5.08% traffic respectively. We can also see web traffic both secured and unsecured in the top 8 accounting to 3.84%, 0.66% traffic. While we can see the applications that accounted to majority of traffic by a traditional classifier, Our system, on the other hand, provided an alternate view for the same NetFlow data by extracting the behaviors these hosts are exhibiting. From the **Figure 6.2** on the following page we can see that, hosts that are behaving as



6.2 (a) 6.2 (b)

Figure 6.2. Comparison of hosts using port based classifier (left) and host behavior extractor (right) on December 12, 2017.

clients account to 11.41% (both C1 and C2 combined) of traffic and hosts that are behaving as servers account to 33.61% (both S1 and S2 combined). The majority of the traffic(50.23%) comprises of interactive communication between hosts while the anomalous hosts trying to invade into the network form the minority(4.75%).

6.2 Cross Validation

We compared the results obtained from our system with other classification techniques to better understand the significance of our approach.

Cross Validation with a port based classifier, We used a classic port based classifying technique to cross-validate our results. Though, it isn't a perfect measure and fails in many cases it is good enough to classify a host to a particular class in most of the cases. In the scenarios when this technique cannot classify a host to particular class we label it as a 'Mix' traffic. The heuristic that we used for labeling as 'Mix' traffic is when the dominant class accounts for less than 50 percent of the traffic by that host. Applying this procedure we observed 20 different classes of traffic, out of which the most frequently observed are discussed here: HTTP, DNS, SSH, MAIL, TELNET, FTP, CHAT, SCAN, SMTP, MIX. Most of these classes are self explanatory based on the ports they operate. SCAN is a class that is different from others while all the other classes deal with single port SCAN deals with

multiple ports. A host falls under SCAN category if majority of its traffic is trying to hit multiple ports on a system trying to find an open port to infiltrate. The cross-validation between the port based approach and our procedure on one of the chosen day December 12th is reported in **Table 6.1** on the current page.

The row headers in the table correspond to the labels of the clusters generated by our system while the column headers correspond to the different classes of traffic derived by a port based classifier as mentioned above. Each row in the table describes the percentage of hosts within each cluster that fall under different classes of traffic as classified by a port based classifier. For example, in the cluster T1 we have 60.88% of hosts that are using web applications, 0.86% of hosts are involved in DNS traffic, 15.03% of hosts exchange SSH, 0.72% exchange TELNET traffic and 22.04% of the hosts in this cluster are classified as MIX traffic. Some important observations from this table are:

- From the bolded parts in the table, we can safely conclude that we have a high match of host classification which reflects the competence of the proposed procedure.
- It is also clearly evident from here that the nature of clusters described earlier confirm

Table 6.1. Cross-valdation of the host behavior extraction with port based analysis.

Label	WEB	DNS	SSH	TELNET	SMTP	FTP	SCAN	MIX	# Hosts
T1	**60.88%**	0.86%	15.03%	0.72%	0.36%	0.02%	0	22.04%	14526
T2	8.29%	0.67%	27.27%	1.01%	0.60%	0	0	**62.10%**	3375
C1	**40.12%**	0.92%	0	0	**41.31%**	5.13%	0	12.52%	1159
C2	2.14%	**90.82%**	3.05%	0	2.74%	0.07%	0.10%	1.18%	2123
S1	1.64%	8.37%	**78.50%**	10.45%	1.03%	0	0	3.51%	2439
S2	15.45%	38.98%	1.40%	0	16.52%	0	0	27.65%	4927
A1	2.78%	12.12%	2.31%	6.98%	0.73%	0.91%	**64.91%**	9.26%	217

with the results obtained with cross-validation.

- This also suggests that all the hosts that fall into a particular class based on port-based analysis are not necessarily in the same cluster. They are dispersed across the clusters which shows the necessity of a host-based behavior extraction.

For example, cluster S1 clearly confirms the fact that the hosts in this cluster are dealing with SSH traffic and the same traffic is also present in T1 and T2 clusters. Similarly, hosts in the cluster S2 contains servers that provide responses for web, ssh and other requests. This cluster has a similar distribution as cluster C1 but they act exactly opposite like servers and clients respectively. Some other noticeable points from the table are, T1 has mostly requests and responses between hosts spread across different applications. hosts which are grouped as T2 have most of its hosts labeled as Mix, which on further investigation revealed that many of the hosts in this class don't pass the majority test to be distinguished into any particular class. Finally, Scanners distribution was minimal across all the clusters. The sparsity of this table also serves as a confident measure for our proposed approach.

6.3 Labeled data: description and clustering

In this section, we are evaluating our system to determine its accuracy and precision in identifying host behaviors using labeled data. The labeled data that we used in this section is provided by Center for Applied Internet Data Analysis (CAIDA). CAIDA is a research group based at the San Diego Supercomputer Center (SDSC) on the UC San Diego campus who conduct network research and build research infrastructure to support data collection, and data distribution to the scientific research community.

CAIDAs dataset consists of thirteen different scenarios. Each scenario is a capture of network data written into a pcap file. Each capture consists of both real network traffic and the synthetic traffic they have generated to emulate that scenario. For our evaluation purpose we are considering four of these scenarios.

- In the first scenario they have generated traffic to emulate the situation of scanners in the network and hence their capture consists of two classes of traffic namely, Normal and Scanning web proxies.

- In the second scenario they have generated traffic to emulate the situation of chinese attackers in the network and hence their capture consists of two classes of traffic namely, Normal and Chineses hosts.
- The third scenario consists of synthesized traffic to emulate DDOS attacks. Also, they have let the background traffic to mix with normal traffic. Hence, in total we have three classes of traffic namely, Normal, Background and UDP& ICMP DDOS attacks.
- Fourth scenario consists of synthesized traffic to emulate multiple classes of traffic which we are using to measure the scalability of system and its performance in face of multiple classes of traffic.

These scenarios are captured into pcap files which are further processed to obtain information about NetFlows. **Table 6.2** on this page represents the duration of each scenario and the contents of the pcap file such as the number of packets, the number of NetFlow records and the size of the file itself.

The distinctive character of this data set is that the data captured in each scenario is manually examined and labeled. The labeled dataset looks similar to the one which we

Table 6.2. Dataset description.

Id	Duration(hrs)	# Packets	#NetFlows	Size
1	11.63	4,481,167	129,833	37.6 GB
2	0.38	7,467,139	114,078	5.8 GB
3	4.21	62,089,135	1,121,077	53 GB
4	66.85	167,730,395	4,710,639	121 GB

capture at the emulab router except for the last column where the flow is labeled which can be seen in the **Figure 6.3** on the current page.

Using the different captures in **Table 6.2** on the preceding page we evaluated our systems basic functionality such as how effectively our system is able to extract the host behaviors, the detection rate of the different possible attacks and how will it respond with scale (when there are multiple hosts from multiple networks communicating simultaneously). Before looking into these results let us examine some basic terminology to understand the evaluations.

Let us consider a labeled dataset with two different labels A and B. The results produced when this dataset is sent through a classifier for classification can be tabulated as a confusion matrix as shown in **Table 6.3** on the next page. This table tells us that dataset consists of a total of N values both of label A and label B combined. TP_A indicates number of data points that are labeled as A and are classified as A. TP_B indicates the number of data points that are labeled as B and are classified as B. E_{AB} indicates the number of data points that are labeled as B by the classifier but actually belong to label A. E_{BA} indicates the number of data points that are labeled as A by the classifier but actually belong to label B. The key of this matrix is the number of correct and incorrect classifications are summarized with count values and broken down by each class. The confusion matrix shows the ways in which a classification model is confused when it is making classifications. It also gives

```
StartTime,Dur,Proto,SrcAddr,Sport,Dir,DstAddr,Dport,State,sTos,dTos,TotPkts,TotBytes,SrcBytes,Label
2011/08/15 10:42:52.613616,1065.731934,udp,188.114.23.248,14268,  <->,147.32.84.118,1150,CON,0,0,2,252,145,flow=Background-UDP-Established
2011/08/15 10:42:52.676517,1471.787109,udp,2.224.28.134,48279,  <->,147.32.84.118,1150,CON,0,0,2,252,145,flow=Background-UDP-Established
2011/08/15 10:43:34.544316,1095.947266,udp,41.145.83.148,40812,  <->,147.32.84.118,1150,CON,0,0,2,288,145,flow=Background-UDP-Established
2011/08/15 10:58:26.370803,2896.377197,udp,217.42.33.104,55066,  <->,147.32.84.118,1150,CON,0,0,3,433,290,flow=Background-UDP-Established
2011/08/15 10:58:27.208147,1384.708008,udp,41.107.0.220,11066,  <->,147.32.84.118,1150,CON,0,0,2,288,145,flow=Background-UDP-Established
2011/08/15 10:59:02.040572,1071.322388,udp,213.44.235.37,9200,  <->,147.32.84.118,1150,CON,0,0,2,288,145,flow=Background-UDP-Established
2011/08/15 11:00:05.704408,3582.270264,tcp,147.32.84.134,45266,  <?>,205.188.10.203,443,PA_PA,0,0,662,70674,25955,flow=From-Normal-V45-Jist
2011/08/15 11:00:05.704760,44.728664,tcp,62.44.1.18,80,  <?>,147.32.84.118,51463,PA_FRA,0,0,768,756975,741555,flow=Background
2011/08/15 11:00:05.707670,0.000000,udp,147.32.80.9,53,   ->,147.32.85.103,18006,INT,0,,1,175,175,flow=From-Normal-V45-UDP-CVUT-DNS-Server
2011/08/15 11:00:05.709591,0.003098,udp,147.32.85.103,41094,  <->,147.32.80.9,53,CON,0,0,2,223,71,flow=To-Background-UDP-CVUT-DNS-Server
2011/08/15 11:00:05.715153,0.080609,udp,147.32.85.103,27423,  <->,147.32.80.9,53,CON,0,0,2,212,73,flow=To-Background-UDP-CVUT-DNS-Server
2011/08/15 11:00:05.716016,35.265488,tcp,212.194.183.145,49584,  <?>,147.32.85.56,44076,FPA_FPA,0,0,43,3147,2061,flow=Background
2011/08/15 11:00:05.718808,136.336746,tcp,74.63.47.82,80,  <?>,147.32.84.59,60106,PA_RA,0,0,2451,2319965,2272325,flow=Background-Established-cmpgw-CVUT
2011/08/15 11:00:05.721037,0.000273,udp,147.32.86.20,62510,  <->,147.32.80.9,53,CON,0,0,2,284,76,flow=To-Background-UDP-CVUT-DNS-Server
2011/08/15 11:00:05.721591,0.888468,tcp,147.32.86.20,1962,   ->,193.93.174.21,80,FSPA_FSPA,0,0,99,92657,1946,flow=Background-TCP-Established
2011/08/15 11:00:05.722349,3599.194336,tcp,109.80.225.83,49708,  <?>,147.32.84.171,57116,PA_A,0,0,79509,59759658,57384858,flow=Background
2011/08/15 11:00:05.724203,0.000256,udp,147.32.84.222,55073,  <->,147.32.80.9,53,CON,0,0,2,210,80,flow=To-Background-UDP-CVUT-DNS-Server
2011/08/15 11:00:05.724587,0.000241,udp,147.32.84.222,39714,  <->,147.32.80.9,53,CON,0,0,2,236,93,flow=To-Background-UDP-CVUT-DNS-Server
2011/08/15 11:00:05.724940,0.000302,udp,147.32.84.222,51315,  <->,147.32.80.9,53,CON,0,0,2,282,80,flow=To-Background-UDP-CVUT-DNS-Server
2011/08/15 11:00:05.727892,0.000000,udp,129.6.15.28,123,   ->,147.32.87.135,4927,INT,0,,1,90,90,flow=Background-UDP-Attempt
2011/08/15 11:00:05.728471,0.121183,tcp,147.32.84.59,36828,  <?>,75.101.227.132,80,FA_A,0,0,2,120,60,flow=Background-Established-cmpgw-CVUT
2011/08/15 11:00:05.729558,0.000313,udp,147.32.84.36,43561,  <->,147.32.80.9,53,CON,0,0,2,313,85,flow=To-Background-UDP-CVUT-DNS-Server
2011/08/15 11:00:05.730093,0.000264,udp,147.32.84.36,39498,  <->,147.32.80.9,53,CON,0,0,2,288,83,flow=To-Background-UDP-CVUT-DNS-Server
```

Figure 6.3. Manually labeled dataset by CAIDA.

Table 6.3. Confusion Matrix

Total = N		Classified	
		A	**B**
Actual	**A**	TP_A	E_{AB}
	B	E_{BA}	TP_B

insights into the errors classifier is making and more importantly the type of errors that are being made. From this matrix we can calculate accuracy and prediction of a system which are defined as follows:

- **Accuracy:** is calculated as the sum of correct classifications divided by the total number of classifications.

$$\text{accuracy (A)} = \frac{TP_A + TP_B}{N}$$

- **Precision:** of a class is calculated as correct classifications divided by total number of classifications for the class in consideration.

$$\text{precision (P) for class A} = \frac{TP_A}{TP_A + E_{BA}}$$
$$\text{precision (P) for class B} = \frac{TP_B}{TP_B + E_{AB}}$$

- **Misclassification Rate:** is calculated as the sum of incorrect classifications divided by the total number of classifications.

$$\text{Misclassification (M)} = \frac{E_{AB} + E_{BA}}{N}$$

On similar lines, the confusion matrix can be extended to any number of classes and can be useful in calculating different performance numbers of this system. One important point to note here is when we pass this labeled dataset through our system we get clusters contrary to a classifier which gives a label for each data point. In order to circumvent this issue we look at the clusters and label them. If a cluster is dominated by any particular label we retain the label for that cluster and the other clusters are named according to the manual inspection. After this process, the results obtained are as below.

6.3.1 Scenario 1:

The scenario 1 is of duration 11.63 hours with 37.6 GB of data. This dataset contains hosts exhibiting two unique behaviors namely normal traffic and scanners. Through this experiment, we would like to check our systems basic functionality of identifying different behaviors. When we passed this data through our system we found the formation of two major clusters each dominated by a label and hence we retained the labels for these clusters as mentioned above. The results are as shown in **Table 6.4** on the following page.

- **Accuracy:** (42503+80252)/129833 = 94.54%
- **Misclassification Rate:** (3987+3091)/129833 = 5.45%
- **Precision:**
  - (42503)/46490 = 91.4% precise in finding scanners.
  - (80252)/83343 = 96.2% precise in finding normal hosts.

From this, we learn that our system can identify unique behaviors with high accuracy and precision.

6.3.2 Scenario 2:

The scenario 2 is of duration 0.38 hours with 5.8 GB of data. This dataset contains hosts exhibiting two unique behaviors namely normal traffic and chinese hosts. This experiment is aimed to determine the basic functionality of our system as scenario 1 and to determine the rate of detection of chinese hosts which are prevalent in our real data set collected at Emulab routers. When we passed this data through our system we found the formation

Table 6.4. Scenario 1.

N= 129833		Classified	
		Scanning Web Flows	Normal Flows
Actual	Scanning Web Flows	42,503	3,091
	Normal Flows	3,987	80,252
		46,490	83343

of two major clusters each dominated by a label and hence we retained the labels for these clusters and the results are as shown in **Table 6.5** on the next page.

- **Accuracy:** (22456+76713)/107978 = 89.18%
- **Misclassification Rate:** (5912+2897)/107978 = 11.7%
- **Precision:**
  - (22456)/28368 = 76.1% precise in finding chinese hosts.
  - (76713)/79610 = 96.3% precise in finding normal hosts.

This experiment confirms that our system does well in distinguishing normal hosts but fairs poorly in identifying chinese hosts.

6.3.3 Scenario 3:

The scenario 3 is of duration 4.21 hours with 53 GB of data. This dataset contains hosts exhibiting three unique behaviors namely normal, background, UDP & ICMP DDOS traffic. This experiment is aimed to determine the functionality of our system in face of adversary attacks and multiple types of traffic. When we passed this data through our

Table 6.5. Scenario 2.

N= 107,978		Predicted	
		Chinese Hosts Flows	Normal Flows
Actual	Chinese Hosts Flows	22,456	2,897
	Normal Flows	5,912	76,713
		28,368	79,610

system we found formation of three major clusters each dominated by a label and hence we retained the labels for these clusters and the results are as shown in **Table 6.6** on the following page.

- **Accuracy:** (681167+66377+320011)/1111836 = 96.01%
- **Misclassification Rate:** (3123+27169+139+1757+7943+4150+2897)/1111836 = 3.98%
- **Precision:**
  - (681167)/689249 = 98.8% precise in finding hosts pertaining to normal traffic.
  - (66377)/73650 = 91.17% precise in finding background hosts.
  - (320011)/348937 = 90.23% precise in finding UDP & ICMP DDOS hosts.

6.3.4 Scenario 4:

The scenario 4 is of duration 66.85 hours with 121 GB of data. This dataset contains hosts exhibiting multiple behaviors namely normal, background, UDP & ICMP DDOS, HTTP, Port Scan, DNS and Fast Flux traffic. This experiment is aimed to determine the

Table 6.6. Scenario 3.

N = 1,111,836		Predicted		
		Normal Flows	UDP & ICMP DDOS Flows	Background Flows
Actual	Normal Flows	681,167	3,123	27,169
	UDP & ICMP DDOS Flows	139	66,377	1,757
	Background Flows	7,943	4,150	320,011
		689,249	73,650	348,937

functionality of our system in a complex network scenario where we see multiple behaviors. When we passed this data through our system we found formation of seven major clusters, interestingly the labeled dataset also exhibits seven different behaviors. When we looked at these clusters six of them are dominated by a label and hence we retained the labels for these clusters where as the last cluster didn't have any majority label and hence we labeled it by inspection as Heavy Hitters. cluster results are as shown in **Table 6.7** on the next page.

- **Accuracy:** (930944+621778+401622+1299861+337343+599899)/4710639 = 89.78%
- **Misclassification Rate:** (518170)/4710639 = 10.22%
- **Precision:**
  - (930944)/991297 = 93.9% precise in finding hosts pertaining to normal traffic.
  - (621788)/673650 = 92.3% precise in finding background hosts.
  - (401622)/418659 = 91.23% precise in finding UDP & ICMP DDOS traffic.
  - (1299861)/1367855 = 95.23% precise in finding HTTP traffic.
  - (337343)/368911 = 91.4% precise in finding UDP & ICMP DDOS hosts.

– (599899)/696994 = 86.06% precise in finding DNS traffic.

Our system was unable to detect the hosts exhibitng Fast Flux behavior on the other hand it grouped hosts which are transferring heavy payload across all the different labeled behaviors. We believe there are certain areas that our system has to focus on when it comes to grouping hosts in multiple networks.

6.3.5 Hosts behavior with time:

To determine the change in hosts behaviors over time we passed six months worth of data through our system similar to the experimental set up mentioned at the start of evaluation section. But this time we also invoked the method to calculate K value on every day. The K value determines the different behaviors the hosts are exhibiting on that day as mentioned in section 4.2.2.1. So, we have K unique behaviors on every day. We wanted to verify how this K value is changing with time. i.e, how are the behaviors changing with time? Hence, we plotted the K values for the last six months and it looks as follows **Figure 6.4** on the following page. The value of K on X-axis and the day on which we found this value on Y-axis. Except for few points, it is a straight line indicating the constant behaviors that hosts are exhibiting in our system. This needn't be the case with all the

Table 6.7. Scenario 4.

N = 4,710,639		Predicted						
		Normal Flows	Background Flows	UDP & ICMP DDOS Flows	HTTP	Port Scan	DNS	Heavy Hitters
Actual	Normal Flows	930,944	40,351	4,500	35,993	12,675	40,148	55,001
	Background Flows	38,002	621,778	2,959	16,120	9,023	9,898	6,436
	UDP & ICMP DDOS Flows	984	872	401,622	1,770	732	37,197	38,401
	HTTP	11,014	610	1,541	1,299,861	2970	2199	75,285
	Port Scan	0	49	716	231	337,343	1801	101
	DNS	5,567	9900	7,321	13,880	6,168	599,899	8,027
	Fast Flux	4,786	90	0	12	0	5,852	22
		991,297	673,650	418,659	1,367,855	368,911	696,994	193,273

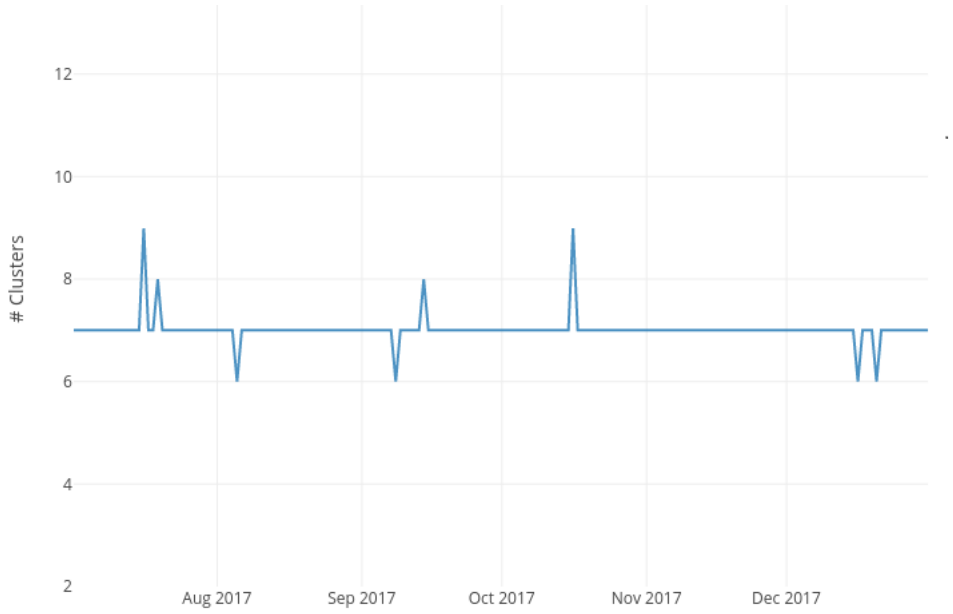


Figure 6.4. Plot of number of clusters formed over a time period.

networks. In an environment with multiple networks, the K value could be different and we might see it changing frequently. It depends on the environment in which our system is going to be used.

6.3.6 Applications:

As mentioned in section 4.3 our system can be used to build different applications that are helpful in network management. In that direction, we have built a web tool to analyze these host behaviors. Our web tool collects the information from the pattern detection process such as cluster centers, labels etc.. and renders different visualizations.

- **Figure 6.5** on the next page is a screenshot of the web tool. Left nav bar provides different options to explore the output produced by our system. In **Figure 6.5** on the following page we can see a comparison of host behaviors on two different days. The second line can be read as follows, There are 1221 hosts which are exhibiting anomalous behavior on March 1st were as it drops to 199 on June 8th which acoounts to a decrease of 84%.

- The figure **Figure 6.6** on the next page gives an insight of how hosts behavior is changing over a month. In the graph, each line represents different host behaviors.

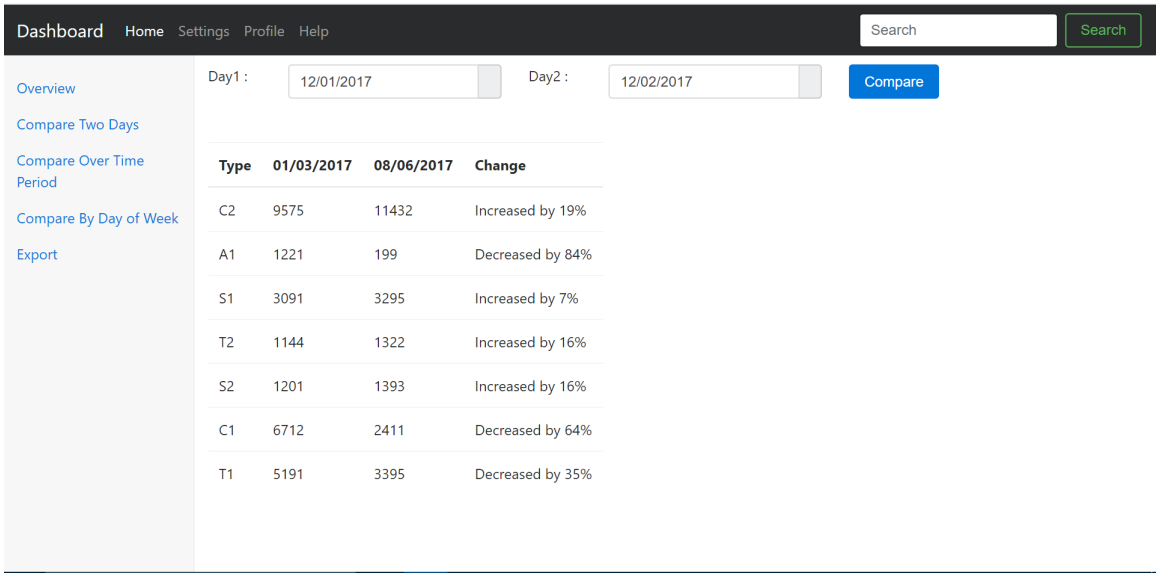


Figure 6.5. Compare Host Behaviors on two days.

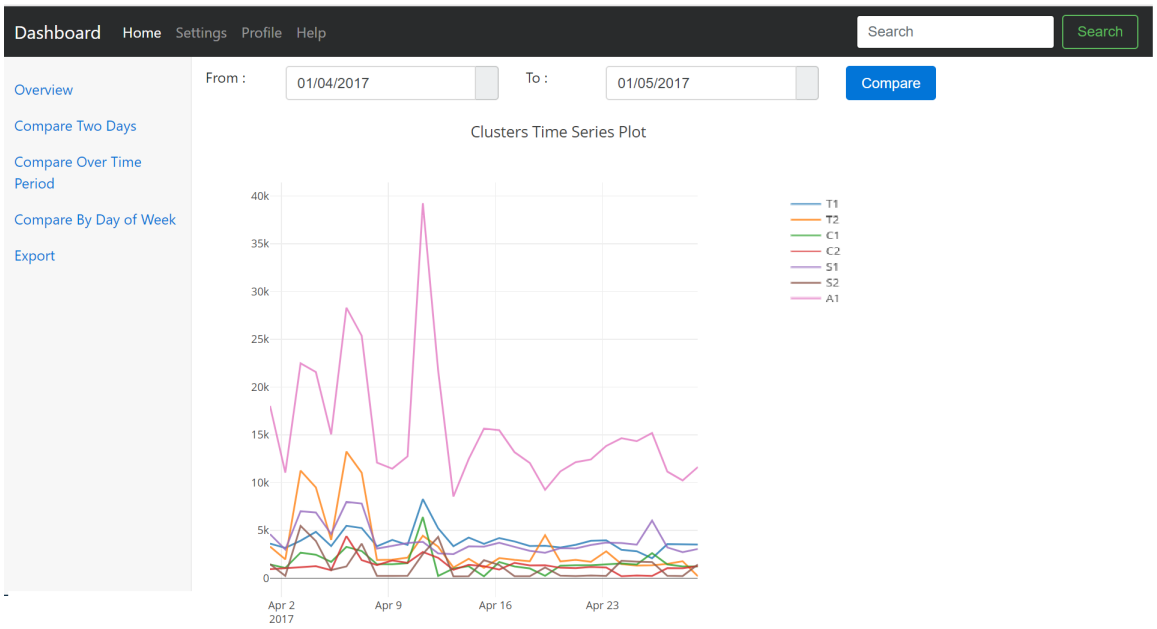


Figure 6.6. Compare Host Behaviors over a time period.

The X-axis and Y-axis represent the date on which this host behavior is observed and the number of hosts which exhibited this behavior respectively.

CHAPTER 7

CONCLUSION

Section 1.1 remarked the following thesis statement:

"By combining clustering and other data mining techniques we can produce a view of host behaviors that help network administrators to understand the behavior of the networks. This system complements existing network analysis tools to ease network management."

We have found conclusive evidence for this statement by evaluating the university network data and the labeled data obtained from Center for Applied Internet Data Analysis (CAIDA). We analyzed hosts and studied the behavior of groups of hosts. This research of grouping hosts based on their behaviors is one of a kind and was conducive in comprehending the behavior of networks. The cross-validation of university data and the high accuracy obtained in classifying labeled data confirm this fact. This system with the help of existing tools helped us in making recommendations to the network administrators about different management activities. While evaluating the university network data, we found hosts exhibiting seven unique behaviors. We had hosts behaving as clients, servers, exchanging normal traffic and scanners. Few of these behaviors extracted by our system were in-line with the expected behaviors by the network admins and others helped them better understand the network. We also presented a web-based assisting tool that helps in visualizing these behaviors over time periods and look into historic behaviors that this network exhibited.

The primary contributions of this work are threefold. First, an 8D feature vector has been defined and shown to characterize the host behavior accurately. Our feature set supports high volumes of traffic and doesn't consider payload. Also, the feature vector is of low dimension (8D) signifying the richer information each feature contains. Second, the grouping is based on the K-means approach: this is an unsupervised technique which

doesn't require ground truth knowledge about the data set. It doesn't start with any initial assumptions with respect to the number of clusters and is adaptive in nature by adjusting itself to new classes of traffic previously unobserved. Third, the systems performance and functionality are tested on a real dataset collected at the University routers and the labeled dataset obtained from CAIDA. Cross-validation with port-based approaches and accuracy on characterizing and classifying the labeled data respectively reflect the potentiality of our approach and the relevance of our procedure. Hence, our contribution shows that the 8D feature vector, that captures the behavior of a host, with K-means clustering technique yields an unsupervised classification of host behaviors.

7.1 Future Directions

1. Investigate and build applications using the results of our system. Our system groups hosts exhibiting similar behaviors and defines each group by certain characteristics such as the cluster sizes, cluster centers etc.. Using this information about each group we can build various applications such as anomaly detectors, dynamic firewall rule generators or bandwidth predictors which can become further handy to network administrators in their day-to-day activities.

2. In our work, we define host as any unique IP address that has in-bound or outbound traffic. But, network users needn't always have a unique IP address. Each user can be communicating in a network with multiple IP addresses. This could happen because of a malicious user trying to hide his identity by using different IP addresses or because of dynamic allotment by ISP provider. In that direction, it would be useful to group hosts at a user level instead of using IP address as a basis. Even in this approach most of our techniques should work well.

3. When analyzed with labeled data our system had higher accuracy in scenario1 and scenario3 but when it comes to detecting chinese hosts or multi-network scenarios our rate of detection is a bit low. We could further improve the accuracy by tuning our system. Few pointers to explore here are to evaluate different normalizing techniques.

4. When multiple networks are fused together we see a high traffic in such setting.

Exploring streaming algorithms [16] which leave a lesser memory footprint while capturing various characteristics of the data or concurrent programming to speed up the individual components of our proposed procedure to improve performance is advised.

7.2 Parting Thoughts

Today's system administrator has to navigate through a set of tools to manage networks. It is a complex job to do and is critical for maintaining network performance. In our work we have built a tool that complements the existing tools to ease the network admins burden and our observation is that further research efforts should be invested in trying to provide a holistic view of the network through a single tool to the administrator thus requiring less effort. It would be interesting to also embed intelligence into these tools that can capture network admins experiences and decisions. These efforts should also take into consideration the changing characteristics of the network and provide solutions that adapt with time. We believe there is a lot of potential for ML/DM algorithms in doing so.

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