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Intrusion detection with the K nearest neighbour algorithm

A study of how well the K-nearest-neighbour algorithm performs to detect attacks

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Abstract

In machine learning there are many algorithms. This thesis will focus on the *K-nearest-neighbour* algorithm with focus on how different portions of training data and the value of *k* affects the predictions in three different datasets. The main focus is on discovering different types of attacks in the *KDD cup* dataset from 99, but the algorithm will also be tested on the built in *IRIS* dataset. The findings in the thesis were that the *KNN* algorithm proved to be quite accurate in predicting attacks.

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Preface

I would like to thank all my friends and family for their outstanding support when writing this thesis. Writing a thesis is not an easy task, so without their support this task would have been much more difficult. Also a big thanks to staff at UiO and HiOA for helping me out with many questions during this process.

Chapter 1

Introduction

Today Intrusion Detection Systems (IDS) are used to warn against suspicious activity against a system. *IDS* do have some issues though. In *IDS* there are alerts which send messages that something may be going on. False statements are alerts which send us a message which is not true. These represent a threat in all systems. So how can these be filtered out? System administrators use a lot of time to look into these statements. One technique is for instance to use machine learning. One can implement different machine learning algorithms to make sure that one can extract the right kind of attack data from a dataset.

Machine learning techniques are used widely today. We see this for instance in spam filters where the email provider or client filters out spam messages. Machine learning is also widely used in search engines for pattern recognition. *IDS* is also a domain for pattern recognition. However, machine learning is not widely used in IDS commercially, despite the the fact that area is heavily researched.

1.1 Problem statement

The main aim of this thesis is to look at the question: "How does the value of *K* and different training data affect the *KNN* algorithm in different training sets?" The thesis will also take a closer look at different concepts in intrusion detection and some other machine learning algorithms.

1.1.1 Scope

The scope of this thesis is to apply machine learning algorithms on the *KDD Cup* dataset from 99. To do this the programming language *R* will be used. The advantages of using this dataset are that the dataset is already sorted and labelled and therefore one does not need to spend much time generating a new dataset. In addition to the already widely known machine learning algorithms, this thesis will also research some algorithms not widely known in the area of machine learning. That may provide some new information about other algorithms which may be appropriate for machine learning in instrusion detection. This thesis will also take a closer look at *SNORT*, which is a widely used *IDS*, and also use another built in dataset to compare the performance relative to the *KDD* dataset.

Chapter 2

Background

In this chapter the situation regarding IDS now will be described and then introduce concepts when it comes to machine learning. Research already done in the area will also be covered.

2.1 IDS

Wikipedia defines *IDS* as "an intrusion detection system (IDS) is a device or software application that monitors network or system activities for malicious activities or policy violations and produces electronic reports to a management station" [6]. There are many types of IDS systems. I will now take a closer look at the different types and go into some of the advantages and disadvantages of them.

2.1.1 Types of IDS

The two main types of IDS systems are active and passive. [5]. The main difference between them is that an active system is configured to intervene when suspicious activity is detected, whereas a passive system only gives us alert messages and it is more up to the *sysadmin* to take action on the messages. The advantage of an active *IDS* is, of course, that a *sysadmin* can "relax" in the sense that he or she can, in most cases, rely on the *IDS* taking action on suspicious activity in the network. However, the biggest advantage of an active *IDS* may also be its biggest disadvantage. If a *sysadmin* does not check the*IDS* regularly (e.g. for updates) we can end up with an IDS which does not work as intended. Attackers always look for new ways to bypass the *IDS* and one can imagine the possibly disastrous consequences if your *IDS* does not work.

The main advantage of a passive IDS is that a *sysadmin* has to stay on the alert all the time all and has to take the proper action according to the alerts. You will always be sure that something will be done. The main disadvantage is that a *sysadmin* may not have enough knowledge to take the proper action. It may even result taking the *wrong* action with some some really serious consequences.

IDS can be subdivided into more types. There are host-based IDS and network-based IDS. A host-based *IDS* runs on each individual host (for instance our own laptop with a firewall software). Network based IDS, on the other hand, run in the boundary of the network (think of a server running). Most companies run a combination of both (since virtually all versions of Windows nowadays come with a security kit included). Network-based IDS clearly have an advantage over host-based IDS. With a host-based IDS we can't in an easy way discover attacks on multiple nodes. Network-based IDS, however, monitor traffic on the whole network and can easily discover attacks bound for multiple nodes.

One can also divide IDS into the methods they use to discover attacks. There are both signature-based IDS and behaviour-based IDS. Signature-based IDS discover attacks using data from a huge database of known attacks. These databases must of course be maintained by someone and they might be behind when there are new types of attacks which is not yet added to the database. *SNORT* is probably the most well known signature-based IDS available. Behaviour based IDS on the other hand have patterns they regconize in the network to distinguish normal traffic from suspicious traffic.

As an example of a behaviour-based IDS, let us say you one day deal with a huge amount of data to upgrade some sort of software on many clients. This may trigger a false alarm on the IDS. The IDS' learnt behaviour may be 100 megabytes of data pr day - but on the next day it is 5 gigabytes. This is of course a huge deviation and may trigger an alarm. In a smaller company the *sysadmin* more probably knows what is going on, but if the company is larger with many people working in the IT department, one *sysadmin* may not know. That person may then take some sort of action. Now this scenarios is pretty unrealistic but it illustrates an example of what may happen in these settings.

2.2 Machine learning

One can fnd the following defintion of machine learning on Wikipedia "Machine learning is a subfield of computer science that evolved from the study of pattern recognition and computational learning theory in artificial intelligence." [7] As mentioned in the introduction one of the most common uses of machine learning are spamfilters on your email. When you log into your Gmail account you will notice you have a folder called spam (or in Norwegian søppelpost). In the early days of email spamfilters were not there so you could end up spending a lot of time deleting all the spam.
Gmail is a particular interesting case to analyse. They even have folders for advertisements (e.g. campaigns for cheap airline tickets), social media (e.g. email notifications from Facebook, Twitter etc) and of course your primary folder where all important email (or what Gmail thinks is important to be

clear) are located. All these folders are in addition to the spam folder, where all the real junk go (e.g. letters from Nigeria).

So how does Gmail knows all this? One could imagine a situation where Gmail had to employ people to go through each individual email sent into the Gmail servers and place them in the right folder. If they had to do this there would be work for every single individual on the planet. The idea is good, but not practical. The way Gmail knows this is of course by different *machine learning algorithms*. By using these algorithms Gmail can look for patterns in each email and direct the email to the relevant folder.

2.2.1 Usage of machine learning

I have already provided an example of how machine learning is used in email. I will in this section take a closer look of usage of machine learning today. Machine Learning Mastery [2] has a list of 10 examples of machine learning problems. One interesting example which is in that list is medical diagnostics. Medical professionals can by inserting a list of different symptoms into a software, get a prediction on whether the patient is ill or not. However, if a patient obtains access to these systems we may have a lot of self diagnosis of illnesses. There are already many websites which do this with lists of symptoms.

Another usage according to Machine Learning Mastery is speech understanding. One example is the iPhone *Siri*. [8]. *Siri* can help you to find your way or just find the nearest restaurant from the location you are at. *Siri* was not, however, Apple's original idea. It was first released in the *appstore* of Apple by another company before it was bought by Apple. The funny thing though is that Google's own voice search for iPhone was found to work better than *Siri*. Speech understanding can pose some problems. *Siri* has been widely criticized for not understanding certain accents.

2.2.2 Machine learning usage in IDS

Machine learning is not widely used in IDS today, despite the fact that the area is heavily researched. According to Sabhani and Serphen [4], the algorithms were not that effective to discover user to root and remote to local attacks. A user to root attack is an attack where a user has some access to a system and then tries to gain root access (e.g. by exploiting flaws in an OS or by social engineering). A remote to local attack is of course when somebody outside the network tries to attack your system. These are two major flaws in the machine learning algorithms that were tested in the paper above. This reason alone may be one big reason for why machine learning is not widely used. The algorithms must be able to discover such basic attack types. A good example of a remote to local attack is when an attacker takes control of your system to use it in a botnet. Now we have to take in account that the paper mentioned is from 2003, so normally the algorithms should be improved by now. The dataset used

(*KDD CUP 1999*)) though is still heavily used in research, however, there are some criticism of it that it does not resemble real network traffic. I will use the *KDD Cup* dataset later on to the thesis.

Chapter 3

Approach

The experiments will be performed on the *Alto cloud* provided by HiOA and on my own computer. The main advantage of doing experiments on virtual machines in the cloud, is that we can test in different environments (e.g. we can check performance with different amount of memory). One can also do experiments without having to worry too much about destroying anything. For collection of statistics I will use the programming language *R* [3] . The advantage of using *R* is that we can easily read data from large files and analyse them. With these two tools one can easily compare the performance between different algorithms and the more traditional *IDS*.

3.0.1 Types of machine learning algorithms

According to Machine Learning mastery there are two main categories of machine learning algorithms. The two categories are *grouping by learning style* and *grouping by similarites* (e.g. grouping similar animals). Learning style algorithms typically have some "learnt" interaction with the data we would like to interact with. This can for instance be that the algorithm has learnt to distinguish spam from not spam. Algorithms grouped by similarity, however, are grouped by how they work. In this category we find tree based algorithms and bayesian based algorithms. I will now go through some types in the different categories.

I will start with the algorithms grouped by learning style. One algorithm in this category is supervised learning. In this algorithm we have a known label (e.g. spam or not spam), and the model is then "trained" to learn what kind of data the label contains. Another model in this category is unsupervised learning. In this model input data is not labelled and we do not have a known result. Mathematical rules are used to organize and recognize the data. A third algorithm in this category is semi supervised learning. In this algorithm we have a combination of the two already mentioned (e.g. both labelled and unlabelled data). This algorithm is more flexible in terms that it has to handle both.

In the algorithms grouped by similarity we have more algorithms than the ones grouped by learning style so I will only cover the most important ones. One example here are the *decision tree algorithms*. These algorithms are one of the most popular ones when it comes to machine learning. It is quite simple to understand. The decision tree has a set of decisions based on the data attributions. For instance a packet can arrive with a label (e.g. *ICMP*) and then the algorithm will take a decision of what kind of action to do. These actions can for instance be to drop the packet, to let the packet pass or investigate the packet closer. In a decision tree this *moves* the packet down the tree based on the instructions the algorithm have.

There are also *instance based algorithms*. In this group we find for instance *K-nearest neighbour*. This is a distance based algorithm. The simplest way to describe this algorithm is to start of by describing a distance (e.g. k=5). This will now direct us to the five nearest neighbours. Since the nearest neighbour algorithm is determined by a "majority vote" we can say that if there are 2 apples and 3 pears (remember k=5) - the pears will be the outcome of our "search", simply because pears have more "votes" than apples in this example. Nearest neighbour algorithm is one of the most commonly used algorithms in machine learning. When using *R* ties are broken randomly (e.g. if apples and pears get the same amount of "votes"). This is of course a very simple description of this algorithm. There are of course different methods to measure the distance k. We can for instance give each neighbour a weight which counts more than a vote.

Another algorithm type which is more advanced than the *clustering* and the *classification* algorithms are the *artificial neural network* algorithms. This family of algorithms is in fact inspired by the *central nervous system* in humans. Real life applications of these algorithms include robotics, game-playing (for instance chess) and vehicle control. An artificial neural network has different nodes which are connected to each other.

3.0.2 Traditional IDS/IPS implementation

How is IDS/IPS implemented today? In most cases these are implemented on a server or in large corporations many servers to make sure every single part of the network is covered. As mentioned above SNORT is one of the most famous IDS. To set up SNORT one just needs a Linux host and then you can just start to look for intrusions if it set up properly with a set of rules. One can also set up your own rules in SNORT which is quite easy. Below is a sample rule in SNORT.

```
alert tcp any any <> 10.5.70.91 any (msg:"All traffic yoho"; sid:1; rev:3;)
```

This rule is very simple and actually not very useful as it does generate alerts for ALL TCP traffic in and out out of the IP address 10.5.70.91. The rule is, however, very useful for testing purposes to make sure SNORT works properly. One also has other options than alert. One can for instance replace *alert* with the *log* parameter. That means that we actually log the traffic specified. SNORT can of course run as a standalone installation (console mode), but one usually has some sort of web interface to make managing SNORT much easier (and also easier to read alerts and logs).

As mentioned earlier SNORT needs a set of rules or signatures to make sure we are aware of the newest attacks. SNORT rules come in different sets. The free of charge *community rules* and the paid *subscription rules*. The paid *subscription rules* are newer than the *community rules*, but usually the SNORT developers release the subscription rules to the community rules after a while. The subscription rules are also updated on a daily basis more or less, making these rules safer to use. For a business the cost of a subscription is 399 USD pr sensor/pr year. For personal use the price becomes much cheaper, but this is almost always the model in licensing costs.

SNORT ruleset

Luckily the *SNORT* developers have released information about what you get in the subscription rule set. There are quite many of them, but with the number of vulnerabilities in a network, this is of course essential. One interesting aspect with *SNORT* is that rules are not deleted permanently, just moved to the category called *deleted*. The reason for this may be that if there is an issue with a new rule, the old rule can easily replace the newer one if needed. As mentioned above there is a lot of rule sets ranging from rules about web browsers to rules about operating systems. The *SNORT* developers have sorted the rule set quite logically which makes it easy to know what to look for. All rules regarding a web browser begins with *browser-XXX* and for operating systems *os-XXX*. There are even rules regarding different protocols (for instance *IMAP* - which is an email protocol). The subscription rules do actually have the community rules included in them.

3.0.3 Technical part

As mentioned earlier on in this thesis, the technical part will be done on *ALTO cloud* and also my own computer. *R studio* runs easier on Windows computers than in the cloud where I only have a command line interface. My computer has an *Intel I7* processor, 8 gigabytes of ram and a 244 gigabytes of disk space. In the *ALTO cloud* we can choose from different configurations. In this thesis the experiments will run on the *large* configuration. This configuration has 4 virtual *CPUs*, 8 gigabytes of ram and 80 gigabytes of disk space. The producer of the virtual *CPUs*, however, is not mentioned, but the configuration should be more than enough for our use.

KDD cup dataset

The *KDD cup* dataset is a dataset which was used in a conference back in 1999. To generate this dataset they used a prgram called *TCPdump*. *TCP-dump* is a program which captures traffic on the network. This thesis will use the full dataset which is 743 megabytes uncompressed. The dataset has over 4 million entries which gives unlimited amount of opportunities to apply different machine learning algorithms and then analyse the results. As mentioned earlier the data is already labelled which means that we do not need to do much before we run different algorithms on the set. Since it is labelled we know if a packet is "normal" or if there is an attack going on.

One can now take a closer look at the attack types described in the *KDD cup* dataset. There are four main categories in the dataset. These are *DOS* (Denial of Service), *U2R* (User to Root), *R2L* (Remote to Local) and *PROBE*(probe attack). A *DOS* attack is when an attacker makes the machine too busy to handle *any* legitimate requests. This type of attack is very common, but it is also easy to prevent. Many attackers who perform this attack use several machines in a *botnet* to make the attack more powerful than it would otherwise be. The *KDD cup* dataset contains six different *DOS* attacks. These are *SMURF*, *NEPTUNE*, *POD*, *TEARDROP*, *LAND* and *BACK*. A *U2R* attack is when an attacker has a normal user account and then uses some exploits to gain root access to the system. The dataset contains four attacks of this type. These are buffer-overflow, *loadmodule*, *rootkit* and *perl*. A *R2L* attack is when an attacker tries to gain access via the network on a machine the attacker does not have an account on. The dataset contains 8 attacks of this type. These attacks are *warezclient*, *multihop*, *ftp-write*, *imap*, *guess-passwd*, *warezmaster*, *spy* and *phf*. A *PROBE* attack is when an attacker gathers information for the purpose of finding exploits. The dataset contains four attacks of this type. These are *nmap*, *satan*, *portsweep* and *ipsweep*. The attacks mentioned here are all subtypes of the main category, and it is probably enough to know the main categories. Of these categories *DOS* and *PROBE* attacks are the most common ones, the two others are in fact much rarer. *DOS* is, however, much more common than *PROBE* again. It is, however, not difficult to understand that *nmap* typically involves using the program *NMAP* to scan for information.

The *KDD cup* dataset also of course shows the protocols in the dataset. These are *TCP*, *UDP* and *ICMP*. The *TCP* protocol is probably the most important one. With *TCP* we do get reliable transfer, and hence this protocol is used in for instance *SMTP*(email) and *HTTP*.(websites) The *UDP* does not have reliable transfer and this protocol is then used for instance in transfer of *SKYPE* phone calls. The reason for this is that the *UDP* protocol is much faster. *TCP* will then require much more time to make sure the packet has arrived. The last protocol in the dataset *ICMP* is mostly used to send messages over a network.

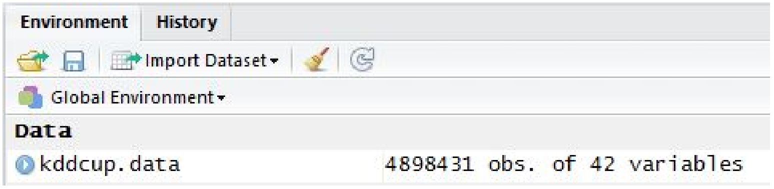
The contents of the *KDD cup* dataset is quite interesting. The training set (which is 10% extracted from the original dataset) has about 80% connections related to an attack and just about 20% normal connections. With these numbers in mind it should be quite easy to get an idea of how good different algorithms are to discover attacks. One can assume that the same numbers roughly correspond to the full set of data.

Performance of algorithms

Before one can perform the technical part one needs to have a process so that a plan can be laid out for all the experiments. In this way it will be easier to perform the experiments. So now to the very basic question - how good are the machine learning algorithms to discover attacks in the *KDD CUP* dataset? There are numerous papers on this. One paper is the Sabhani and Serpen. [4] That paper is from 2003 with less powerful hardware that is available today. The hardware they tested on was 400 mhz on the processor and 512 megabytes of RAM. The conclusion of this paper is that actually none of the algorithms they tested could discover *U2R* or *R2L* attacks in a significant way. Actually they were not able with any algorithms to discover any more than 30 % of the *U2R* attacks and any more than 10 % of *L2R* attacks. Also there were some algorithms that were better than discovering some types of attacks than others. This makes it of course more challenging to determine if there is *one* algorithm which is the best algorithm.

Now while algorithms themselves do not change over time, the power of hardware does. This might be something to consider when doing tests. Are the algorithms more powerful with more power than the original coding of the algorithms? Or do you only use less *time* to analyse something? As a *CPU* only provides power to perform tasks *faster*, the algorithm itself is still programmed the same way. A plausible answer to the question should be no. As a conclusion, a fast *CPU* does not affect the way an algorithm is programmed, but rather gives us better performance. In my case I may not need to wait several days to obtain a result from the 4 million entries of data. This is of course an huge advantage of *CPU* power.

There are of course many algorithms out there to test. *R* has built in many machine learning algorithms in a way so one does not need to program them in another programming language. With this the results are generated quickly and there is no need of programming these algorithms. Importing a dataset in *R* is also quite straightforward. In the screenshot below the interface of *R-studio* is seen.



```
Data
kddcup.data                    4898431 obs. of 42 variables
```

In this screenshot one can see how large the dataset actually is.
So how does one perform a *K-nearest neighbour* algorithm in *R*? In fact *R* has

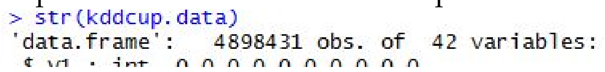
this implemented if you download some packages. Here is a closer look at the code required for this.

```
knn(train , test , cl , k = 1, l = 0, prob = FALSE, use.all = TRUE)
```

This is the syntax *R* uses to apply the *KNN* algorithm. Now a little bit about the parameters. The parameter *train* is a matrix or data frames of training set cases. The *test* parameter is a matrix or frame of testing set cases. The *cl* is a factor of true classifications of the training set. The *k=1* parameter is the value of *k*, which is how many neighbours which will be considered. The *l* parameter defines the minimum number of votes for a definite decision which in this case is 0. The *probe* is a parameter which returns the proportion of the votes required as the winning vote if it is set to true. In this example the parameter is false. The *use.all* parameter controls the handling of ties.

R studio

Now a little bit closer look on *R studio* with the *KDD* dataset actually imported. Here we can see the imported dataset.



```
> str(kddcup.data)
'data.frame':   4898431 obs. of  42 variables:
```

As one can see here the dataset has nearly 5 million entries. The dataset has 42 variables, which in machine learning can translate into *features*. However, it has to be said that most of the variables are integers and may therefore be of less interest to analyse. Now one can take a look at how many packages there are of each type in the dataset.

```
 table (kddcup.data$V2)

   icmp      tcp      udp
2833545  1870598   194288
```

By using the *table* function in *R* makes this easy. The *$V2* parameter is the second variable of the dataset. Some examples are here:

```
 $ V1 : int  0 0 0 0 0 0 0 0 0 0 ...
 $ V2 : Factor w/ 3 levels "icmp","tcp","udp": 2 2 2 2 2 2 2 2 2 2 ...
 $ V3 : Factor w/ 70 levels "aol","auth","bgp",..: 22 22 22 22 22 22 22 22 22 22
 $ V4 : Factor w/ 11 levels "OTH","REJ","RSTO",..: 10 10 10 10 10 10 10 10 10 10
```

The reason for why we use the *table* function on the *$V2* variable is that this variable contains *icmp*, *TCP* and *UDP*. So what does this observation tell us? As one can see the protocol with most entries in the dataset is *ICMP*. A wild guess may imply that most attacks in the dataset are of the type *DOS*. One can also take a look at the *V3* variable. From the code above this may imply that the types of connections are stored in this variable. One can take a closer look at some of the connection types.

```
  http
  623091

    private
    1100831
```

From this one can see there are 623091 *http* connections in the dataset and 1100831 *private* connections. There are of course many more connection types in the document, but due to space constraints in the document, it is impossible to view all of them. There is absolutely no suprise that there are many *http* connections in the dataset. Every time a website is loaded many *http* packets are sent back and forth. There were even some *http* packets on port 443, which is the port used for *https* traffic.

There is also one more important variable here. The *$V42* variable contains the name of the attacks.

```
 table(kddcup.data$V42)
(..)
  smurf  2807886
```

Again due to space constraints it is not possible to view the whole output, but *smurf* is the one attack with more numbers than anything else. This is no suprise at all. As mentioned earlier *smurf* is a *DOS* attack and there were clearly most *ICMP* connections in the dataset. On the other hand there were quite few *normal* connections compared to the number of attacks. There were just 972781 *normal* entries in the dataset. With knowledge of these numbers we know what to look for when applying machine learning algorithms to the dataset. *R* has of course many more features than this, this is just a brief introduction of *R* with an imported dataset.

Algorithms to be tested

The *KNN* algorithm has been mentioned several times, and is of course a central algorithm in machine learning. There are, however, many more algorithms to test. A good starting point is to test *at least* three algorithms, with *KNN* to be one of them. Serpen and Sabhnani [4] tested 9 algorithms. However, the *KNN* algorithm was not one of them. Instead they focused more on *clustering* algorithms. It is very important to know that the *KNN* algorithm uses a completely different method than the *K-means* algorithm and that the letter *k* in both algorithms is just a coincidence, *Clustering* algorithms organize the data into clusters of where the data has the most in common where as *KNN* is more of a *classification* algorithm. In learning style - the *KNN* is supervised where as *K-means* is unsupervised. So to begin with it makes sense to test them both on this dataset. This will clearly give some results that may be quite different to each other.

Chapter 4

Experiments

In this chapter all the experiments will be presented. As mentioned in chapter 3 at least three algorithms will be tested on the *KDD* cup dataset. Then an experiment with one of the algorithms using *SNORT* will be presented. An analysis and a detailed discussion of the experiments will follow in chapter 5.

4.0.1 Experiment 1

Task: To analyse the *KDD cup* dataset using the *KNN* algorithm. Tools to be used are the dataset and *R-studio*. The goal is to see how well the *KNN* algorithm can discover attacks in the *KDD cup* dataset. The background information of the dataset is given in chapter 3.

Steps

To perform this experiment we need to follow some steps. The first step is of course to load the data into *R-studio*. Training of the algorithm is also needed so one has to define labels so the algorithm can be properly trained to recognize the attack. Then after the training part one can use the algorithm on the whole dataset.

Preparing R

To make the *KNN* algorithm to work we need a package called *class*. To use this package we need to type [1]

```
library(class)
Warning message:
package ‘class’ was built under R version 3.2.4
```

This function tells us that the package is installed, but that the package may be a bit old. Note - this package is not installed by default in *R*, but it was installed before performing this experiment. So the next step is to prepare

[1]Note: The source code in this experiment is taken from https://www.datacamp.com/community/tutorials/machine-learning-in-r

the data. If this data was not labelled there This means that one feature will not be overemphazised compared to another and the projections will be more accurate. To normalize a custom function has to be created. The source code for this can be seen below

```
normalize <- function(x) {
+       num <- x - min(x)
+       denom <- max(x) - min(x)
+       return (num/denom)
```

However, since our dataset is already labelled there is no need to normalize the dataset. The algorithm can then be applied to the dataset, but before that can be done a sample from the dataset needs to be randomly chosen (2/3 of the dataset will act as the training dataset).

```
set.seed(1234)
nd <- sample(2, nrow(kddcup.data), replace=TRUE, prob=c(0.67,
    0.33))
```

The *set.seed()* function is the random number generator in *R*. The *sample()* function in *R* gives us a sample of the data. In this case the number 2 is to assign either 1 or 2 to all elements in our dataset, *replace=true* means that that after assigning 1 or 2 to a vector, the next vector will be reset Now after preparing this, it is very important that the data is categorized between the test data and the training data. However, since the *KDD cup* data fails this experiment will instead use the *IRIS* dataset which is built into *R*. The reason for this failure is that somewhere in the dataset something is divided by zero. The steps are about the same as demonstrated above, but with fewer entries. The results, however, should be about the same. The *IRIS* dataset covers the *SEPAL* species of flowers. This dataset has only 150 entries, so the predictions may of course be more accurate than predictions on the *KDD* dataset. Now a closer look at how the *IRIS* dataset looks like.

```
 iris
    Sepal.Length Sepal.Width Petal.Length Petal.Width    Species
1            5.1         3.5          1.4         0.2     setosa
2            4.9         3.0          1.4         0.2     setosa
3            4.7         3.2          1.3         0.2     setosa
4            4.6         3.1          1.5         0.2     setosa
5            5.0         3.6          1.4         0.2     setosa
6            5.4         3.9          1.7         0.4     setosa
```

These are the 6 first entries in the dataset, the dataset is sorted so the other species do not come before well into the dataset, so here is a sample from the other species.

```
51           7.0         3.2          4.7         1.4 versicolor
52           6.4         3.2          4.5         1.5 versicolor
53           6.9         3.1          4.9         1.5 versicolor
54           5.5         2.3          4.0         1.3 versicolor
```

```
108         7.3       2.9       6.3       1.8  virginica
109         6.7       2.5       5.8       1.8  virginica
110         7.2       3.6       6.1       2.5  virginica
111         6.5       3.2       5.1       2.0  virginica
```

To make this dataset suitable to run the *KNN* algorithm on, the entries have to be sorted randomly. There are 50 of each type of species, so the predictions of the species may be less accurate that what have would have been the case of the whole *KDD* cup dataset. All source code for the experiments are in the appendix chapter except for the results. Then the trainingset, testset and labels are defined

```
> iris.training <- iris[iris_sample==1,1:4]
> iris.test <- iris[iris_sample==2,1:4]
> iris.trainlabel<-iris[iris_sample==1,5]
> iris.testlabel<-iris[iris_sample==2,5]
>
```

The task in this experiment is to predict the species in the dataset so the training labels and the test labels are set from row 5 in the dataset. The data is now prepared and the algorithm can be run with *k*=3 for the first part.

```
> iris_knn
 [1] setosa     setosa     setosa     setosa     setosa     setosa
          setosa     setosa     setosa     setosa     setosa
     versicolor
[13] versicolor versicolor versicolor versicolor versicolor
    virginica  versicolor versicolor versicolor versicolor
    versicolor virginica
[25] versicolor versicolor versicolor versicolor versicolor
    versicolor versicolor versicolor virginica  virginica
    versicolor virginica
[37] virginica  virginica  virginica  virginica  virginica
    virginica  virginica  virginica  virginica  virginica
    virginica  virginica
```

These are all the predictions of each species in each row in the *IRIS* dataset. So how well did the algorithm perform in this case?

```
> table (iris_knn)
iris_knn
    setosa versicolor  virginica
        11         20         17

        > table (iris.testlabel)
iris.testlabel
    setosa versicolor  virginica
        11         21         16
```

The two tables displayed compare the predictions versus the actual dataset. The predictions clearly show that there is one error by predicting one *virginica* too much. The algorithm should if it was perfect predict the species in the *iris.testlabel* variable.

Short analysis

As mentioned above there was one error in this prediction, so the model is actually quite accurate when it comes to predicting. The sample size, however, of this dataset is quite small compared to for instance the *KDD* dataset. Still it was one error. A guess could be that the error margin when running this algorithm on *KDD* dataset is very huge. Even if predicting 70% of the attacks and the normal traffic correctly in numbers that is still 1,2 million errors. One interesting thing with this algorithm is to see if there are more or less errors with a different size of the training and test set. That is covered in the next experiment.

4.0.2 Experiment 2

So what happens if the training data is reduced to 50% of the data? Will the *KNN* model be more accurate or less? A hypothesis of this may be that the model becomes *less* accurate, simply due to less data. The source code for this experiment is shown in the appendix chapter.

One can now look at the results:

```
> table(knn50)
knn50
    setosa  versicolor   virginica
        25          27          28
> table (iris.testlabel50)
iris.testlabel50
    setosa  versicolor   virginica
        25          30          25
```

This clearly has some of the same results from experiment number 1 were $\frac{2}{3}$ of the data was used as the training data.

Short analysis

The algorithm's performance of predicting the species is actually quite ok. The prediction of the *Setosa* species was 100% correct, but the predictions of *Versicolor* and *Virginica* species were both slightly incorrect. Compared to experiment 1, the deviations from the original data set is bigger, but still not significant enough to tell much about the algorithm's performance when you reduce the training dataset. A further reduction is required, and will be done in experiment number 3.

4.0.3 Experiment 3

In this experiment an even further reduction of the training set will be done. A slight worsening of the correct predictions were found in experiment 2 so the guess here is that the predictions will be much worse. A test with only 20 % of the original dataset should show some clearer indications. The source code is in the appendix chapter, but it is of course just some adjustments of some parameters. Now a closer look at the results.

```
> table(knn_20)
knn_20
    setosa versicolor  virginica
        38         40         47
> table(iris.testLabel20)
iris.testLabel20
    setosa versicolor  virginica
        38         42         45
```

The results are about the same as in the two other experiments performed here.

Short analysis

Three experiments have now been done with different training sets, and the results here clearly show that there is no evidence of a weaker prediction from the *KNN* algorithm when the training sample is reduced from 2/3 of the dataset, then to 50 % and then finally to 20%. This makes the algorithm quite robust in terms of predicting the correct results no matter the sample of the training data. One could of course have run one last experiment with by reducing the training data to 10%, but since the algorithm has proved to be quite robust, this is not needed. Instead it would have been more interesting to see if you adjust the value of *k* in the algorithm.

4.0.4 Experiment 4

The purpose of this experiment is to see how the value of *k* affects the results of the *KNN* algorithm. A valid hypothesis here is that the algorithm's performance in a significant way will be affected. The reason for this hypothesis is that different values of *k* will affect the neighbours the algorithm picks and this may yield completely different results than just adjusting the training data. If the value *k=1* is selected that means that only the closest neighbour will be considered. The value of *K* is usually an odd number so that the chance of having the same amount of votes when running the algorithm is eliminated.

```

> table(knn_k)
knn_k
    setosa versicolor  virginica
        38         40         47
> table(iris.testLabel20)
```

```
iris.testLabel20
    setosa versicolor  virginica
        38         42         45
```

Here the value of k is set to 5.

Short analysis

The result is exactly the same as in experiment 3. By increasing k more neighbours are covered in the testing scope. The predictions may then become more accurate. The result is as mentioned above the same as in experiment 3 and hence *increasing* k may until a certain point have more accurate predictions.This experiment can be tweaked. In this experiment only 20% of the data was used as the training set, but what happens if you increase k and use 2/3 set as the training set?

4.0.5 Experiment 5

This experiment will be mostly the same as in experiment 4, but with a different training sample (2/3) of the dataset. This will give a better idea how much the value of k matters to predict the right species. First the results from experiment 4.

```
> table(knn_k)
knn_k
    setosa versicolor  virginica
        38         40         47
> table(iris.testLabel20)
iris.testLabel20
    setosa versicolor  virginica
        38         42         45
>
```

The prediction here was two too many of the *virginica* species.

```

> table (knn_k_2_3)
knn_k_2_3
    setosa versicolor  virginica
        11         21         16
> table(iris.testlabel)
iris.testlabel
    setosa versicolor  virginica
        11         21         16
>
```

As one can see the prediction was 100% correct.

Short analysis

The prediction in this case was 100% correct. Now this is interesting. It seems that increasing the value of *k* actually increases this algorithm's accuracy. Still it must be a point where the value of *k* becomes too large (or too small) to make any sense when it comes to accurate predictions.

4.0.6 Experiment 6

From experiment 5 the conclusion was that the larger the number of *k* the more accurate the *KNN* algorithm's prediction was. The value of *k* was 5. What happens if the value of *k* is set to 20? The results from experiment 4 is in the appendix section so it is easy to compare. A hypothesis here is that the results should be exactly the same as in experiment 4.

```

> table (knn_k_20)
knn_k_20
    setosa  versicolor   virginica
        11          24          13
1
> table(iris.testlabel)
iris.testlabel
    setosa  versicolor   virginica
        11          21          16
```

The prediction here had more errors than experiment 5 which predicted everything 100% correct.

Short analysis

With *k=20* the prediction was wrong. The hypothesis was wrong and the result of this experiment has a significant error in it. One can therefore conclude that a unusually large value of *k* does not make the algorithm better to predict the correct results. Now, 20 is a much larger integer than 5 so taking an integer in between these two numbers should give a better idea.

4.0.7 KNN with KDD cup

6 experiments using the *IRIS* dataset have now been done and this gives an idea how the *KNN* algorithm works. However, the most important part of this thesis is to measure the performance of some machine learning algorithms to detect attacks As mentioned earlier the data set which is going to be used is the *KDD cup* dataset. The dataset used is a little bit modified from the original dataset. The main difference between this modified version and the original version is that some rows of the dataset are converted into integers rather than the original text. The reason for this is that non numeric values yields some errors in *R studio*. This should, however, not have any effects on the results. As there are quite many

entries (nearly 5 million), a random sample of 100.000 will be used in the experiments. A sample of 100.000 should be large enough to give an idea of how good the *KNN algorithm* is to detect attacks.

Preparing KDD cup

The source code to extract a random sample of a dataset in *R* is shown below.

```
kdd_sample<-kddcup.data[sample(nrow(kddcup.data), 100000), ]
```

The *sample* function in *R* is used to sample data from any dataset. This line takes 100.000 random lines from the number of rows in the dataset. It is very important to use the *sample* function correctly to receive the right sample as just small adjustments in the function gives a completely different sample. The experiments will be mostly the same as with the *Iris* set.

4.0.8 Experiment 7

First a recap on what to test. The tests are going to be on how well the *KNN* algorithm is to discover attacks. Different values of *k* will be used and also different samples of training data will be used as in experiment 1-6. In this experiment 2/3 of the data set will be used as training data, and 1/3 as the testing data.

Now as one can see here there are too many ties, which means the the *KNN* algorithm cannot choose between the ties. To get rid of this problem the dataset has to be normalized.

```
> kdd_norm <- as.data.frame(lapply(kdd_sample[1:41], normalize))
function(x) {
    num <- x - min(x)
    denom <- max(x) - min(x)
    return (num/denom)
}
```

The function *normalize* normalizes the data. With a normalized dataset the data should have less noise. However, after normalizing the data, there are still too many ties. The way to make this work properly is to have a sample small enough. Setting *k=1* should in theory eliminate the problem. However, another way to eliminate the problem is to just take a small sample of the data. With less data the risk of the *KNN* algorithm of yielding too many ties is greatly reduced. Since 100.000 is not a small enough number to eliminate this problem a much smaller sample with 10000 is used.

KDD with a smaller set

First a closer look at the sample being used. [2]

```
> table(small1$V42)

buffer_overflow.            normal.
               2               9998
```

This is not a representative sample of the whole *KDD* dataset, but this works in *R*..With an overweight of *normal* traffic and underweight of attacks it should be easy to have an idea of how well the *KNN* algorithm works to predict the correct results. This experiment is the same as in experiment 1, just with another dataset and much more data. Now a closer look at the results

```
> table (data_pred)
data_pred
buffer_overflow.            normal.
               0               3279
> table(data.testLabels)
data.testLabels
buffer_overflow.            normal.
               1               3278
```

The algorithm predicted 0 buffer-overflow attacks, but there was one of them in the testing set.

Short analysis

As predicted this algorithm was quite accurate in predicting attacks and the *normal* traffic. The error was in predicting no attacks, but at the same time there was just one attack in the test data. Actually as mentioned above there were few attacks in this sample from the *KDD* set, but predicting just one error in 3279 samples is quite good.

4.0.9 Experiment 8

The task here is to see what happens when the training set is reduced from 2/3 to 50%. In experiment 2 there were more errors which is of course no suprise since the training set is reduced. Now with a larger sample than the *IRIS* set, there should be more errors.

```

> table (data_pred)
data_pred
buffer_overflow.            normal.
               0               4990
> table (data.testLabels)
data.testLabels
```

[2]This is a highly modified sample made by Anis Yazidi

```
buffer_overflow.          normal.
              1              4989
```

Short analysis

The training data is here decreased to 50% of the original dataset. In experiment 1 and 7 the training data was 2/3 of the original dataset. This time the prediction yielded just 1 wrong prediction. 50% is probably a high enough portion of training data to yield few errors. This is about the same results that was in experiment 2.

4.0.10 Experiment 9

This experiment will be similar to experiment 3 with 20% of the dataset as training and 80% of the data as testing. In experiment 3 this did not yield many errors at all, even though in theory it should be more difficult to predict the correct data.

```

> table (data_pred)
data_pred
buffer_overflow.          normal.
              0              8014
> table (data.testLabels)
data.testLabels
buffer_overflow.          normal.
              2              8012
```

Short analysis

The algorithm predicted that everything was normal, but the fact showed that there were two attacks that the algorithm did not notice. The results, however, were quite similar to the results in experiment 3. The conclusion here is the need for more observations of attacks.

4.0.11 General observations

The results are quite similar with both the *IRIS* dataset and the reduced *KDD* cup dataset. Not all labels in the *KDD* dataset are used making the sample quite biased.There is a clear overweight of *normal* traffic whereas in the full dataset the *normal* traffic is just around 20%. A sample with all the labels should be used, but since the sample with 100.000 yields too many ties in *KNN* a smaller sample has to be used. In the following experiments a sample with 1000 will be used and it will be representative for the full dataset.

4.0.12 Experiment 10

Similar to experiment 1, just with 1000 samples from the full *KDD cup* dataset.

```
> table(data_pred)
data_pred
            back.  buffer_overflow.        ftp_write.    guess_passwd
               .            imap.         ipsweep.            land
               .        loadmodule.
               0                0                0
                   0                0                0
                                0                0
        multihop.         neptune.            nmap.          normal
           .              perl.            phf.            pod.
              portsweep.
               0               75                0
                  71                0                0
                                0                0
         rootkit.           satan.           smurf.             spy
            .          teardrop.      warezclient.    warezmaster.
               0                0              180
                   0                0                0
                                0
```

The results are not that clear, so an explanation is needed. The model predicted 180 *SMURF* attacks, 75 *Neptune* attacks, 71 *normal* traffic and no other attacks. Now a closer look at the facts.

```
> table(data.testLabels)
data.testLabels
            back.  buffer_overflow.        ftp_write.    guess_passwd
               .            imap.         ipsweep.            land
               .        loadmodule.
               2                0                0
                   0                0                0
                                0                0
        multihop.         neptune.            nmap.          normal
           .              perl.            phf.            pod.
              portsweep.
               0               72                0
                  68                0                0
                                0                3
         rootkit.           satan.           smurf.             spy
            .          teardrop.      warezclient.    warezmaster.
               0                0              181
                   0                0                0
                                0
```

Again it is difficult to see, but in *R studio* it is quite easy to see. Anyway an explanation is of course needed here too. The correct facts are 181 *SMURF* attacks, 68 *normal* traffic, 72 *neptune* attacks, 2 *loadmodule* attacks and 3 *portsweep* attacks.

Short analysis

With 180 predicted *SMURF* attacks, 75 predicted *neptune* attacks and 71 predicted *normal* traffic compared to 181 *SMURF* attacks, 68 *normal* traffic, 72 *neptune* attacks, 2 *loadmodule* and 3 *portsweep* attacks one can see that the algorithm clearly considered some of the attacks as *normal* traffic. The algorithm even classified some attacks as wrong attacks. The critical part here is not that the algorithm classified some attacks as another type of attack, but that the algorithm considered some attacks as *normal* traffic. The error percentage is, however, not very high so the threat should not be significant.

4.0.13 Experiment 11

As 1000 entries of the *KDD* gives a representative idea one can now see what happens with 50% of the set acts as the training set and 50 % as the testing set. This experiment is similar to experiment 2 and 8.

The results:

```
> table(data_pred)
data_pred
           back.  buffer_overflow.        ftp_write.     guess_passwd
              .              imap.          ipsweep.             land
              .        loadmodule.
              0                 0                 0
                  0                 0                 0
                                  0                 0
       multihop.           neptune.            nmap.           normal
          .              perl.            phf.              pod.
                portsweep.
              0               101                 0
                  94                  0                 0
                                  0                 0
        rootkit.             satan.           smurf.              spy
            .          teardrop.      warezclient.      warezmaster.
              0                 1               279
                  0                 0                 0
                                  0
```

Again the predictions are difficult to see due to space constraints so they will be explained. The number of predicted *SMURF* attacks were 279, the number of predicted *neptune* attacks were 101, the number of predicted *normal* were 94, the number of predicted *warezmaster* attacks were 1. Now a closer look at the actual case.

```
> table(data.testLabels)
data.testLabels
           back.  buffer_overflow.        ftp_write.     guess_passwd
              .              imap.          ipsweep.             land
              .        loadmodule.
              0                 0                 0
                  0                 0                 2
                                  0                 0
```

```
        multihop.             neptune.              nmap.            normal
    .                 perl.                 phf.                pod.
            portsweep.
                0                99                 0
                    92               0                 0
                                 0                 2
         rootkit.              satan.              smurf.               spy
    .              teardrop.          warezclient.        warezmaster.
                0                 1                279
                    0                 0                 0
                                 0
>
```

The number of *SMURF* attacks is 279, the number of *neptune* attacks is 99, the number of *normal* traffic is 92, the number of *portsweep* attacks is 2, the number of *satan* attacks is 1.

Short analysis

Once more the *KNN* algorithm predicted just a little bit too much *normal* traffic. This is actually not something a company wants. The question here after these two experiments are what kind of attacks the *KNN* algorithm predicts as *normal* traffic. A table function in *R* actually shows this.

```
> CrossTable(x = data.testLabels, y = data_pred, prop.chisq=FALSE)


   Cell Contents
|-------------------------|
|                       N |
|           N / Row Total |
|           N / Col Total |
|         N / Table Total |
|-------------------------|


Total Observations in Table:  475


                | data_pred
data.testLabels |   neptune. |    normal. |     satan. |     smurf. |
    Row Total |
----------------|------------|------------|------------|------------|------------|

       ipsweep. |          0 |          2 |          0 |          0 |
          2 |
                |      0.000 |      1.000 |      0.000 |      0.000 |
              0.004 |
                |      0.000 |      0.021 |      0.000 |      0.000 |
                    |
                |      0.000 |      0.004 |      0.000 |      0.000 |
                    |
----------------|------------|------------|------------|------------|------------|

       neptune. |         99 |          0 |          0 |          0 |
         99 |
                          |      1.000 |      0.000 |      0.000 |      0.000 |
                                  0.208 |
                          |      0.980 |      0.000 |      0.000 |      0.000 |
                                        |
                          |      0.208 |      0.000 |      0.000 |      0.000 |
                                        |
-------------------------|-------------|-------------|-------------|-------------|-------------|

                  normal. |          0 |         92 |          0 |          0 |
                     92 |
                          |      0.000 |      1.000 |      0.000 |      0.000 |
                                  0.194 |
                          |      0.000 |      0.979 |      0.000 |      0.000 |
                                        |
                          |      0.000 |      0.194 |      0.000 |      0.000 |
                                        |
-------------------------|-------------|-------------|-------------|-------------|-------------|

               portsweep. |          2 |          0 |          0 |          0 |
                      2 |
                          |      1.000 |      0.000 |      0.000 |      0.000 |
                                  0.004 |
                          |      0.020 |      0.000 |      0.000 |      0.000 |
                                        |
                          |      0.004 |      0.000 |      0.000 |      0.000 |
                                        |
-------------------------|-------------|-------------|-------------|-------------|-------------|

                   satan. |          0 |          0 |          1 |          0 |
                       1 |
                          |      0.000 |      0.000 |      1.000 |      0.000 |
                                  0.002 |
                          |      0.000 |      0.000 |      1.000 |      0.000 |
                                        |
                          |      0.000 |      0.000 |      0.002 |      0.000 |
                                        |
-------------------------|-------------|-------------|-------------|-------------|-------------|

                   smurf. |          0 |          0 |          0 |        279 |
                    279 |
                          |      0.000 |      0.000 |      0.000 |      1.000 |
                                  0.587 |
                          |      0.000 |      0.000 |      0.000 |      1.000 |
                                        |
                          |      0.000 |      0.000 |      0.000 |      0.587 |
                                        |
-------------------------|-------------|-------------|-------------|-------------|-------------|

             Column Total |        101 |         94 |          1 |        279 |
                   475 |
                          |      0.213 |      0.198 |      0.002 |      0.587 |
                                        |
-------------------------|-------------|-------------|-------------|-------------|-------------|
```

Now this table is quite huge, but it tells something interesting. It tells that there are two packets of predicted *normal* traffic instead of the *ipsweep* attack. An *ipsweep* attack is where a host sends *icmp* packets to various hosts just hoping for a reply. Not a serious mistake as an *icmp* packet isolated is something anybody can send to check for instance internet connectivity. The most important result is that the error rate for *actual* attacks is low, for instance the prediction of *smurf* was 100% correct which is a *ddos* attack.

4.0.14 Experiment 12

Now one can reduce the training data down to 20% and take a closer look at the errors in the predictions.

The results:

```
> table(data_pred)
data_pred
                back.  buffer_overflow.         ftp_write.     guess_passwd
                   .              imap.           ipsweep.             land
                   .        loadmodule.
                   0                  0                  0
                   0                  0                  0
                                      0                  0
            multihop.          neptune.              nmap.           normal
             .                perl.               phf.             pod.
                   portsweep.
                   0                198                  0
                 155                  0                  0
                                      0                  0
             rootkit.             satan.             smurf.              spy
              .             teardrop.       warezclient.      warezmaster.
                   0                  0                456
                   0                  0                  0
                                      0
```

The predictions here are 456 *SMURF* attacks, 198 *NEPTUNE* attacks and 155 *normal* traffic. How good was this prediction?

```
> table (data.testLabels)
data.testLabels
                back.  buffer_overflow.         ftp_write.     guess_passwd
                   .              imap.           ipsweep.             land
                   .        loadmodule.
                   2                  0                  0
                   0                  0                  1
                                      0                  0
            multihop.          neptune.              nmap.           normal
             .                perl.               phf.             pod.
                   portsweep.
                   0                182                  0
                 163                  0                  0
                                      0                  2
             rootkit.             satan.             smurf.              spy
              .             teardrop.       warezclient.      warezmaster.
                   0                  3                456
                   0                  0                  0
                                      0
```

The prediction was correct in regards to the number of *SMURF* attacks with 456. Other than it was 182 *Neptune* attacks, 163 *normal* traffic, 3 *SATAN* attacks, 2 *loadmodule* attacks, 2 *portsweep* attacks and 1 *ipsweep* attack.

Short analysis

The prediction here was correctly predicting the *SMURF* attacks, but failed on the others. In fact the prediction actually predicted too few *normal* traffic which is in this case would lead to false positives. It also predicted too many *Neptune* attacks. One can take a closer look at the table to see where the predictions were wrong.

```
data.testLabels |   neptune. |     normal. |      smurf. |  Row Total |
----------------|------------|-------------|-------------|------------|
          back. |          0 |           2 |           0 |          2 |
                |      0.000 |       1.000 |       0.000 |      0.002 |
                |      0.000 |       0.013 |       0.000 |            |
                |      0.000 |       0.002 |       0.000 |            |
----------------|------------|-------------|-------------|------------|
       ipsweep. |          0 |           1 |           0 |          1 |
                |      0.000 |       1.000 |       0.000 |      0.001 |
                |      0.000 |       0.006 |       0.000 |            |
                |      0.000 |       0.001 |       0.000 |            |
----------------|------------|-------------|-------------|------------|
       neptune. |        182 |           0 |           0 |        182 |
                |      1.000 |       0.000 |       0.000 |      0.225 |
                |      0.919 |       0.000 |       0.000 |            |
                |      0.225 |       0.000 |       0.000 |            |
----------------|------------|-------------|-------------|------------|
        normal. |         11 |         152 |           0 |        163 |
                |      0.067 |       0.933 |       0.000 |      0.201 |
                |      0.056 |       0.981 |       0.000 |            |
                |      0.014 |       0.188 |       0.000 |            |
----------------|------------|-------------|-------------|------------|
     portsweep. |          2 |           0 |           0 |          2 |
                |      1.000 |       0.000 |       0.000 |      0.002 |
                |      0.010 |       0.000 |       0.000 |            |
                |      0.002 |       0.000 |       0.000 |            |
----------------|------------|-------------|-------------|------------|
         satan. |          3 |           0 |           0 |          3 |
                |      1.000 |       0.000 |       0.000 |      0.004 |
                |      0.015 |       0.000 |       0.000 |            |
                |      0.004 |       0.000 |       0.000 |            |
----------------|------------|-------------|-------------|------------|
         smurf. |          0 |           0 |         456 |        456 |
                |      0.000 |       0.000 |       1.000 |      0.564 |
                |      0.000 |       0.000 |       1.000 |            |
                |      0.000 |       0.000 |       0.564 |            |
----------------|------------|-------------|-------------|------------|
   Column Total |        198 |         155 |         456 |        809 |
                |      0.245 |       0.192 |       0.564 |            |
----------------|------------|-------------|-------------|------------
```

11 *normal* traffic packets were incorrectly defined as *Neptune* attacks, and also 2 *portsweep* and 3 *satan* were also incorrectly defined as the same. Also

1 *ipsweep* and 1 *back* attack were incorrectly defined as *normal* traffic. How serious is this? A *NEPTUNE* attack is the same as *SYN-Flood attack* which in turn is a type of *DoS* attack. [1] This attack leaves many connections half-open so no valid connections can be established. As the predictions were that some *normal* were incorrectly defined as a kind of *DoS* attack this clearly gives the *sysadmin* wrong alerts.

4.0.15 Experiment 13

The last few experiments have focused on reducing the *training data*. What happens if one *increases* the training data instead? A hypothesis here is that the algorithm's accuracy is increased, due to more data to train on. In this experiment the training data is increased to 80 % of the original data set.

Until now the results have been listed with both the *table* function in *R* and the *crosstable* function.

```
Total Observations in Table:  208


               | data_pred
data.testLabels |   neptune. |    normal. | portsweep. |      smurf
    . |  Row Total |
---------------|------------|------------|------------|------------|------------|
          back. |          0 |          2 |          0 |
          0 |          2 |
               |      0.000 |      1.000 |      0.000 |
      0.000 |      0.010 |
               |      0.000 |      0.043 |      0.000 |
      0.000 |            |
               |      0.000 |      0.010 |      0.000 |
      0.000 |            |
---------------|------------|------------|------------|------------|------------|
       neptune. |         47 |          0 |          0 |
          0 |         47 |
               |      1.000 |      0.000 |      0.000 |
      0.000 |      0.226 |
               |      1.000 |      0.000 |      0.000 |
      0.000 |            |
               |      0.226 |      0.000 |      0.000 |
      0.000 |            |
---------------|------------|------------|------------|------------|------------|
        normal. |          0 |         43 |          0 |
          0 |         43 |
               |      0.000 |      1.000 |      0.000 |
      0.000 |      0.207 |
               |      0.000 |      0.935 |      0.000 |
      0.000 |            |
               |      0.000 |      0.207 |      0.000 |
      0.000 |            |
---------------|------------|------------|------------|------------|------------|
     portsweep. |          0 |          0 |          1 |
          0 |          1 |
                              |         0.000  |         0.000  |         1.000  |
      0.000  |         0.005  |
                              |         0.000  |         0.000  |         1.000  |
      0.000  |                |
                              |         0.000  |         0.000  |         0.005  |
      0.000  |                |
------------------------------|----------------|----------------|----------------|----------------|----------------|

                       smurf. |             0  |             1  |             0  |
          114  |           115  |
                              |         0.000  |         0.009  |         0.000  |
      0.991  |         0.553  |
                              |         0.000  |         0.022  |         0.000  |
      1.000  |                |
                              |         0.000  |         0.005  |         0.000  |
      0.548  |                |
------------------------------|----------------|----------------|----------------|----------------|----------------|

                 Column Total |            47  |            46  |             1  |
          114  |           208  |
                              |         0.226  |         0.221  |         0.005  |
      0.548  |                |
------------------------------|----------------|----------------|----------------|----------------|----------------
```

Short analysis

The prediction here was a bit too much *normal* traffic than actually was the case. One *SMURF* attack was falsely predicted as *normal* traffic. Also one *back* attack was also falsely predicted as *normal* traffic. False negatives are something one does not want when dealing with *IDS*.

4.0.16 Experiment 14

The previous experiments focused on reducing and increasing the training data to different levels of the original dataset. Now what happens if one increases the value of *k*? The optimal value of *k* is discussed in the next chapter, but this experiment may give a hint. It will be performed with 2/3 of the dataset as the training data as was the case in the first experiment. Increasing *k* just a number or two should not have any impact, so in this experiment the *k* will be 13. There is a possibility that *R* might crash, due to the algorithm becoming more expensive when increasing *k*

Then the results.

```
> CrossTable(x = data.testLabels, y = data_pred, prop.chisq=FALSE)


   Cell Contents
|-------------------------|
|                       N |
|           N / Row Total |
|           N / Col Total |
|         N / Table Total |
|-------------------------------|


Total Observations in Table:  326


                 | data_pred
data.testLabels  |  neptune. |   normal. |    smurf. | Row Total |
-----------------|-----------|-----------|-----------|-----------|
           back. |         0 |         0 |         2 |         2 |
                 |     0.000 |     0.000 |     1.000 |     0.006 |
                 |     0.000 |     0.000 |     0.011 |           |
                 |     0.000 |     0.000 |     0.006 |           |
-----------------|-----------|-----------|-----------|-----------|
        neptune. |        72 |         0 |         0 |        72 |
                 |     1.000 |     0.000 |     0.000 |     0.221 |
                 |     0.878 |     0.000 |     0.000 |           |
                 |     0.221 |     0.000 |     0.000 |           |
-----------------|-----------|-----------|-----------|-----------|
         normal. |         7 |        61 |         0 |        68 |
                 |     0.103 |     0.897 |     0.000 |     0.209 |
                 |     0.085 |     1.000 |     0.000 |           |
                 |     0.021 |     0.187 |     0.000 |           |
-----------------|-----------|-----------|-----------|-----------|
      portsweep. |         3 |         0 |         0 |         3 |
                 |     1.000 |     0.000 |     0.000 |     0.009 |
                 |     0.037 |     0.000 |     0.000 |           |
                 |     0.009 |     0.000 |     0.000 |           |
-----------------|-----------|-----------|-----------|-----------|
          smurf. |         0 |         0 |       181 |       181 |
                 |     0.000 |     0.000 |     1.000 |     0.555 |
                 |     0.000 |     0.000 |     0.989 |           |
                 |     0.000 |     0.000 |     0.555 |           |
-----------------|-----------|-----------|-----------|-----------|
    Column Total |        82 |        61 |       183 |       326 |
                 |     0.252 |     0.187 |     0.561 |           |
-----------------|-----------|-----------|-----------|-----------|
```

Short analysis

As one can see the most significant errors in this prediction are too many *neptune* attacks and too few *normal* traffic.

Chapter 5

Discussion

In this chapter a more in depth discussion of the experiments in chapter 4 will be done. Also some mathematical predictions of how the *IRIS* dataset can be used to make a prediction of how well the algorithms tested on the *IRIS* dataset will perform on the *KDD* dataset.

5.0.1 KNN algorithm

So what does the *KNN* algorithm really do? Mathematically implemented in *R* the algorithm uses *Euclidan* distance to determine the nearest neighbour.

$$d(p,q) = \sqrt{(q1 - p1)^2 + (q2 - p2)^2} \tag{5.1}$$

The formula above describes the *Euclidan* distance between two points in a two dimensional plane. The equation is based on the *Pytaghorian* theorem. The equation above be rewritten into:

$$d(p,q) = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \tag{5.2}$$

The value of k is of particular importance. The less the value of k the less neighbours are used. It is therefore very important to find the optimal value of k in the algorithm. So what is the optimal value of k in the *KNN* algorithm? The larger the value of k makes the algorithm costly to run. With a smaller value there will be more noise in the results. Running *KNN* with a k value of 100 made *R studio* crash. The predictions would have been quite accurate though, but at a huge cost. A rule of thumb seems to be $k = \sqrt{n}$ is the best value of k. N is here the number of features in the dataset. A *feature* in machine learning is a property or a value that is being observed. An example of a *feature* in the datasets used are the species in the *IRIS* dataset and attack type in the *KDD* dataset. In the *IRIS* dataset there were three species. $\sqrt{3} = 1{,}73$ so a value of either 1 or 2 should be optimal. However, the value of 2 is an even value and 1 may not give the optimal result. So the value in most of the experiments involving the *IRIS* dataset was 3. The number 3 is small enough to predict nearly correct result, but it is not high enough to make the cost of the algorithm so high that running the algorithm takes a lot of resources in terms of hardware. The number of features in the modified *KDD* dataset is 2. $\sqrt{2} = 1$, so according to the formula *1* would have been the optimal value of k in this case. However, again due to the reasons mentioned above the value of k in most of the experiments were 3. In the full *KDD* dataset there are 23 features so the optimal value of k would have been $\sqrt{23} = 4,79$ or rounded up to 5 to avoid ties.

5.0.2 Discussions of the experiments

Many experiments have been done with more or less three different datasets. The first experiments were with the built in *IRIS* dataset and the other ones were with a modified *KDD-cup* 99 and a sample of 1000 lines from the full *KDD-cup* 99 dataset. To know the exact accuracy and performance it is important to calculate the error rate in each scenario. The *KNN* algorithm does not make any assumptions of the data beforehand, hence making the algorithm quite powerful in terms of predictions.

Experiment 1

A quick recap of the results from experiment 1

```
> table (iris_knn)
iris_knn
    setosa  versicolor   virginica
        11          20          17

        > table (iris.testlabel)
iris.testlabel
    setosa  versicolor   virginica
        11          21          16
```

The prediction was correct in predicting *setosa*, but not the two others. The total number of observations was 48. The prediction was 17 on the *virginica* species, but the actual number was 16. Likewise the prediction was 20 of *versicolor*, but the actual number was 21. This makes the prediction wrong in 2/48 of the observations in this experiment or in 4,2% of the cases. In other terms the algorithm predicted correctly in about 96% of the cases. In this case 2/3 of the dataset was used as a training data and it was also a very small dataset. The question here if this margin of error scales to a larger dataset. This requires to take a closer look at the similar experiment with the 1000 samples from the *KDD* dataset.

Experiment 10

So what happens when the dataset is bigger? Experiment 1 proved that the predictions were right in about 96% of the cases. If this scales to bigger datasets, the *KNN* algorithm is a viable option when choosing a machine-learning algorithm to work with intrusion-detection-systems. As the table of experiment 10 is too large to fit into for formatting reasons, the results will be just be written out in plain text. The prediction was 180 *SMURF* attacks, 75 *Neptune* attacks, 71 *normal* traffic and no other attacks. This is a total of 326 observations. The correct observations were 181 *SMURF* attacks, 68 *normal* traffic, 72 *neptune* attacks, 2 *loadmodule* attacks and 3 *portsweep* attacks. This means there was an error in 7 of the 326 packets in the prediction. In other terms this means that the algorithm predicted only 2,14% wrong or around 98% correctly. If this is the case in the other experiments as well using the *KNN* algorithm in regards to *IDS* will be quite powerful.

Experiment 2

In this experiment the training data of the *IRIS* dataset was reduced from 2/3 of the original dataset to 50%. The results were as following.

```
> table(knn50)
knn50
    setosa  versicolor   virginica
        25          27          28
> table (iris.testlabel50)
iris.testlabel50
    setosa  versicolor   virginica
        25          30          25
```

The total number of observations in total was 80. The number of wrong predictions was 6. The algorithm predicted incorrectly in 7,5% of the cases. This is probably due to the reduced amount of training data. Does the margin of error scale to a larger dataset? A closer look at experiment 11 should tell that.

Experiment 11

Experiment 11 narrowed the training data of the *KDD* dataset down to 50% of the original dataset. The number of predicted *SMURF* attacks were 279, the number of predicted *neptune* attacks were 101, the number of predicted *normal* were 94, the number of predicted *satan* attacks were 1. In total the number of observations were 475. The facts here were the number of *SMURF* attacks were 279, the number of *neptune* attacks were 99, the number of *normal* traffic were 92, the number of *portsweep* attacks were 2, the number of *satan* attacks were 1 and the number of *ipsweep* were 2. This means that there were 4 wrong predictions in total or 0,84%. This is interesting. In experiment 2 the error rate was 7,5%. What is the explanation of this? With reduced amount of training data the logical hypothesis should be that the error rate should be *larger* not *smaller*. To be certain that this is the case, the experiment should be rerun. The full source code is shown, just to document every step in case it was some errors in experiment 11.

```
> data_normalized=data
> set.seed(1234)
> ind <- sample(2, nrow(data_normalized), replace=TRUE, prob=c
    (0.50, 0.50))
> data.training <- data_normalized[ind==1, 1:41]
> data.test <- data_normalized[ind==2, 1:41]
> data.trainLabels <- data[ind==1, 42]
> data.testLabels <- data[ind==2, 42]
> data_pred <- knn(train = data.training, test = data.test, cl =
    data.trainLabels, k=3)
```

The predictions:

```
> table(data_pred)
data_pred
                 back.  buffer_overflow.        ftp_write.      guess_passwd
                    .             imap.          ipsweep.              land
                    .       loadmodule.
                    0                 0                 0
                        0                 0                 0
                                  0                 0
             multihop.          neptune.             nmap.            normal
               .                perl.             phf.              pod.
                  portsweep.
                    0               118                 0
                        95                0                 0
                                  0                 0
              rootkit.            satan.            smurf.               spy
                .           teardrop.      warezclient.      warezmaster.
                    0                 1               301
                        0                 0                 0
                                  0
```

The facts:

```
> table(data.testLabels)
data.testLabels
                 back.  buffer_overflow.        ftp_write.      guess_passwd
                    .             imap.          ipsweep.              land
                    .       loadmodule.
                    2                 0                 0
                        0                 0                 1
                                  0                 0
             multihop.          neptune.             nmap.            normal
               .                perl.             phf.              pod.
                  portsweep.
                    0               116                 0
                        91                0                 0
                                  0                 2
              rootkit.            satan.            smurf.               spy
                .           teardrop.      warezclient.      warezmaster.
                    0                 1               302
                        0                 0                 0
                                  0
```

Now as one can see here there were 7 wrong predictions out of 515 observations making the error rate 1,3%. Now this is interesting. Why was the error rate much *less* here than in the similar experiment using the *IRIS* dataset? A theory is that the features of the *IRIS* dataset is evenly distributed (50 of each species), whereas in the *KDD* has much more of the *SMURF* attack than anything else. One can in a way say that the features in the *KDD* dataset is somehow*skewed*. The *SMURF* attack is represented in 2.807.886 observations in a dataset of 4.8 million. Discovering most of the *SMURF* attacks will be much easier. However, it is more likely that since the *IRIS* dataset is much smaller, three or four errors will of course have much more impact on the results than in a larger dataset. If there are 10 observations and 2 of them are wrong, then the error is 20%. A further discussion of some experiments are needed to draw this conclusion, but if this small error margin proves to be the case throughout, there is no doubt that the *KNN* algorithm is powerful on even bigger datasets.

Experiment 7, 8 and 9

These experiments were just done with two features of the *KDD* dataset, so the error margin is very small. Here are the predictions and the results of experiment 7, 8 and 9.

```
> table (data_pred)
data_pred
buffer_overflow.           normal.
               0              3279
> table(data.testLabels)
data.testLabels
buffer_overflow.           normal.
               1              3278

               > table (data_pred)
data_pred
buffer_overflow.           normal.
               0              4990
> table (data.testLabels)
data.testLabels
buffer_overflow.           normal.
               1              4989
               > table (data_pred)
data_pred
buffer_overflow.           normal.
               0              8014
> table (data.testLabels)
data.testLabels
buffer_overflow.           normal.
               2              8012
```

The margin of error here is less than 1% in all cases, but as the sample of that dataset contains only two of the features these three experiments can be disregarded. The other reason for disregarding these three experiments is that one feature is very overrepresented compared to the other feature in the whole dataset. The margin of error then becomes very small. It is, however, important to mention from these three experiments that skewing the data may not give any idea how well the predictions are. 1

Experiment 3

In this experiment the training data in the *IRIS* dataset was further reduced to 20%. The results are below.

```
> table(knn_20)
knn_20
    setosa  versicolor   virginica
        38          40          47
> table(iris.testLabel20)
iris.testLabel20
    setosa  versicolor   virginica
        38          42          45
```

The total number of observations here was 125 and with 4 wrong predictions gives a margin of error of 3,2%. Now this is interesting. In the experiment 2 the margin of error was 7,5%. This does not need to mean anything special. In theory the margin of error should have been larger with less training data to train the algorithm on. Does this margin of error scale with the *KDD* dataset? Now in the other experiments the margin of error were less than in the *IRIS* dataset. This is due to the number of entries in the dataset which is 150 in the *IRIS* set and a sample of 1000 in the *KDD* dataset. A further look at the similar experiment with the *KDD* dataset is needed. If the margin of error is less than in the experiment with 50%, the hypothesis that the accuracy of the algorithm becomes *less* with less training data to work on might be invalid.

Experiment 12

In the *IRIS* the margin of error was less with 20% of the dataset as training data than with 50% of the training data. It is interesting to see if this is the case with the *KDD* dataset as well. If this is the case these experiments might have to be done again. The predictions in experiment 12 were 456 *SMURF* attacks, 198 *NEPTUNE* attacks and 155 *normal* traffic. The facts were 456 *SMURF* attacks, 182 *Neptune* attacks, 163 *normal* traffic, 3 *SATAN* attacks, 2 *loadmodule* attacks, 2 *portsweep* attacks and 1 *ipsweep* attack. In total there were 809 observations. In total the number of wrong predictions here are 24. That gives a margin of error of 2,97%. Compared to experiment 11 which had a margin of error of under 1%, this means that the hypothesis is more or less correct in this case. In the experiment with the *IRIS* dataset the error margin was much less with 20% training data than with the 50%. The reason for that might just be a "noisy" experiment, but there may also be other reasons for that. Now it is time to take a closer look at the value of *K*.

Experiment 4, 5 and 6

These are the tree experiments which focused on the value of *k* when using the *IRIS* dataset. The results of these are listed below. Experiment 4:

```
> knn_k<-knn(train=iris_train_20,test=iris_test_20,cl=iris.
    trainLabel20,k=5)
> table(knn_k)
knn_k
     setosa versicolor  virginica
         38         40         47
> table(iris.testLabel20)
iris.testLabel20
     setosa versicolor  virginica
         38         42         45
```

Experiment 5:

```
 knn_k_2_3<-knn(train=iris.training,test=iris.test,cl=iris.
     trainlabel,k=5)
> table (knn_k_2_3)
knn_k_2_3
     setosa versicolor  virginica
         11         21         16
> table(iris.testlabel)
iris.testlabel
     setosa versicolor  virginica
         11         21         16
>
```

Experiment 6:

```
> knn_k_20<-knn(train=iris.training,test=iris.test,cl=iris.
    trainlabel,k=20)
> table (knn_k_20)
knn_k_20
     setosa versicolor  virginica
         11         24         13
1
> table(iris.testlabel)
iris.testlabel
     setosa versicolor  virginica
         11         21         16
```

In experiment 4 there were 4 errors, in experiment 5 there predictions were 100% correct while in experiment 6 there were 6 errors. This means that in experiment 4 the error margin was 3,2% and in experiment 6 was 12,5% which is the highest in the experiment encountered. In experiment 4, the training data used was 20% of the original dataset, in experiment 5 the training data was 2/3 of the original dataset, whereas in experiment 6, the training data was back to 20% of the original dataset. With 2/3 of the original dataset used for training and the value of *k*=5, the predictions were 100% accurate. It is a quite interesting observation that with a value of

$k = 20$ the predictions were the most inaccurate in all of the experiments. The predictions should in theory at least become more accurate when increasing the value of k. This may have something to do with the way the *KNN* algorithm determines the nearest neighbour. The *KNN* determines a classification by a majority vote. With a k value of 20, there are many neighbours to classify and this may give noise in the predictions. As mentioned earlier in this chapter it is very important to find the optimal value of k to make the algorithm both cost efficient and to make as good predictions as possible.

Experiment 14

In this experiment k was increased to 13 on the *KDD* dataset, but with 2/3 used as training data. The predictions here ended up with 82 *Neptune* attacks, 61 *normal* traffic and 183 *SMURF* attacks, in total 326 observations. However, the facts were 72 *Neptune* attacks, 68 *Normal* traffic, 181 *SMURF* attacks, 2 *back* attacks and 3 *portsweep* attacks. This gives us a margin of error 12/326 or around 3,68%. This is close to the margin of error encountered in the other experiments with the *KDD* dataset.

General observations

The *KNN* algorithm applied on the *KDD* dataset generally had a low number of errors whereas on the *IRIS* dataset the margin of error greatly varied. This is of course due to the number of entries in each dataset. The *IRIS* dataset had 150 observations whereas the two modified datasets from *KDD* had 10000 and 1000 observations. The reason for why only 1000 entries from the entire *KDD* dataset was that having too many entries resulted the algorithm yielding too many ties when predicting. Without drawing any final conclusion on this, this may make the *KNN* algorithm unusable on very large datasets. Still there are many examples out there that researches have used machine-learning algorithms on this particular dataset without any problem, so the problems encountered here may be solved if the dataset was tuned correctly to fit into the *R* function.

5.0.3 Other algorithms

There are other algorithms which could have been used on the datasets. The *KNN* algorithm is quite simple. What other algorithms could have been used on the three datasets used? All data in the three datasets are *labelled* meaning that the datasets have certain properties to apply the algorithm on. The case in the *IRIS* dataset was the flowers and the case in the *KDD* dataset was the attack types. If the data was unllabeled, the *KNN* algorithm would be unsuitable. In this case a *unsupervised* learning algorithm would be more suitable instead. The main difference between *supervised* and *unsupervised* learning is that in *supervised* learning the input labels are known, whereas in *unsupervised* learning they are not. In these cases other *supervised* learning algorithms are the most suitable ones. However, the *KDD* dataset can be downloaded as a completely unlabeled dataset, so it is possible to use *unsupervised* algorithms as well. *R* has support for the *K-means* algorithm for instance which is a *unsupervised* learning algorithm. However, since the details are discussed in chapter 3 there is not much need to go into too much detail here. It is difficult to tell how good a prediction from one of the algorithms will be without actually performing experiments with them. Sabhanhi and Serpen [4] did apply more algorithms to the *KDD* dataset with both *supervised* and *unsupervised* learning. As shown in the paper there is not much difference between the types of algorithms when it comes to the margin of error.

5.0.4 Training data

So far in this thesis the phrase *training data* has been mentioned many times, but has not been discussed properly. It is important to understand what the *training data* means when using the *KNN* algorithm and what impact the *training data* has on the results. The *training data* in *machine learning* is used to train the algorithm and to build a model. In the experiments done, the amount of training data was 66%, 50% and 20%. It is very important that the *training data* used contains all features in the dataset, otherwise the algorithm will predict something completely else. The *R* code for choosing the training and test samples does this and is even resembled in experiments 7, 8 and 9 where the sample was completely different than in the original dataset.

Chapter 6

Conclusion and future work

This thesis has focused on using the *KNN* algorithm on three different datasets with emphasis on discovering attacks in a dataset extracted from *Tcpdump*. A background of how *IDS* are used today was also provided. From the experiments the *KNN* algorithm has proved to be a quite powerful algorithm for predicting observations in a dataset. In this thesis three different datasets have been used. These were *IRIS* and two versions of the *KDD cup* dataset. A total number of 14 experiments were performed with the *KNN* algorithm. The *KNN* algorithm proved to be quite powerful on both small and larger datasets with a low average margin of error. Even with reducing the training data to 20%, the margin of error proved to stay quite low. Also the value of k did not have significant impact other than in experiment 6, which had a margin of error of over 12%. Overall one can quite safely assume that the *KNN* algorithm can be applied to detect attacks without much of a concern. As mentioned in the introduction, machine learning is not widely used in *IDS* today, but as the results showed, the algorithms used in both research papers in the area and in this thesis proved to be quite powerful. It is, however, unlikely that machine learning will replace the tradition *IDS* implementation any time soon.

6.0.1 Future work

This thesis applied one of the simplest machine learning algorithms to three different datasets with the primary focus on the *KDD* dataset. To cover more algorithms it is essential to get a complete overview in the field of machine learning and *IDS*. Further work in this field could be actual implementation of machine learning algorithms in the traditional *IDS*. This can for instance be *SNORT* or some other system. This does require a considerable effort, even though machine learning algorithms are widely used in nearly similar scenarios, for instance email SPAM filtering.

Appendix

Experiment 1

```
set.seed(1234)
iris_sample <- sample(2, nrow(iris), replace=TRUE, prob=c(0.67,
    0.33))
```

Experiment 2

```
> set.seed(1234)
> iris_sample_50<-sample(2, nrow(iris), replace=TRUE, prob=c(0.50,
    0.50))
> iris.train50<-iris[iris_sample_50==1, 1:4]
> iris.test50<-iris[iris_sample_50==2, 1:4]
> iris.trainlabel50<-iris[iris_sample_50==1,5]
> iris.testlabel50<-iris[iris_sample_50==2,5]
>knn50<-knn(train=iris.train50,test=iris.test50,cl=iris.
    trainlabel50,k=3)
```

Experiment 3

```
> set.seed(1234)
> iris_20 <- sample(2, nrow(iris), replace=TRUE, prob=c(0.20,
    0.80))
> iris_train_20<- iris[iris_20==1, 1:4]
> iris_test_20<- iris[iris_20==2, 1:4]
> iris.trainLabel20 <- iris[iris_20==1, 5]
> iris.testLabel20 <- iris[iris_20==2, 5]
> knn_20<-knn(train=iris_train_20,test=iris_test_20,cl=iris.
    trainLabel20,k=3)
```

Experiment 4

```
> knn_k<-knn(train=iris_train_20,test=iris_test_20,cl=iris.
    trainLabel20,k=5)
```

Experiment 5

```
knn_k_2_3<-knn(train=iris.training,test=iris.test,cl=iris.
    trainlabel,k=5)
```

Experiment 6

```
knn_k_2_3<-knn(train=iris.training,test=iris.test,cl=iris.
    trainlabel,k=5)
> table (knn_k_2_3)
knn_k_2_3
    setosa versicolor  virginica
        11         21         16
> table(iris.testlabel)
iris.testlabel
    setosa versicolor  virginica
        11         21         16
>
```

```
> knn_k_20<-knn(train=iris.training,test=iris.test,cl=iris.
    trainlabel,k=20)
```

Experiment 7

```
> ind <- sample(2, nrow(kdd_sample), replace=TRUE, prob=c(0.67,
    0.33))
> kdd.training <- kdd_sample[ind==1, 1:41]
> kdd.testing <- kdd_sample[ind==2, 1:41]
> kdd.trainlabels <- kdd_sample[ind==1, 42]
> kdd.testlabels <- kdd_sample[ind==2, 42]
> kdd_knn <- knn(train = kdd.training, test = kdd.testing, cl =
    kdd.trainlabels, k=3)
Error in knn(train = kdd.training, test = kdd.testing, cl = kdd.
    trainlabels,  :
  too many ties in knn
```

```
> data = small1
> data_normalized=data
> set.seed(1234)
> ind <- sample(2, nrow(data_normalized), replace=TRUE, prob=c
    (0.67, 0.33))
> data.training <- data_normalized[ind==1, 1:41]
> data.training <- data_normalized[ind==1, 1:41]
> data.trainLabels <- data[ind==1, 42]
> data.testLabels <- data[ind==2, 42]
> data_pred <- knn(train = data.training, test = data.test, cl =
    data.trainLabels, k=3)
```

Experiment 8

```
> set.seed(1234)
> ind <- sample(2, nrow(data_normalized), replace=TRUE, prob=c
    (0.50, 0.50))
> data.training <- data_normalized[ind==1, 1:41]
> data.test <- data_normalized[ind==2, 1:41]
> data.trainLabels <- data[ind==1, 42]
> data.testLabels <- data[ind==2, 42]
> data_pred <- knn(train = data.training, test = data.test, cl =
    data.trainLabels, k=3)
> data_pred <- knn(train = data.training, test = data.test, cl =
    data.trainLabels, k=3)
```

Experiment 9

```
> ind <- sample(2, nrow(data_normalized), replace=TRUE, prob=c
    (0.20, 0.80))
> data.training <- data_normalized[ind==1, 1:41]
> data.test <- data_normalized[ind==2, 1:41]
> data.trainLabels <- data[ind==1, 42]
> data.testLabels <- data[ind==2, 42]
> data_pred <- knn(train = data.training, test = data.test, cl =
    data.trainLabels, k=3)
```

Experiment 10

```
>data = kddcup.data[sample(nrow(kddcup.data), 1000), ]
> set.seed(1234)
> data_normalized=data
> ind <- sample(2, nrow(data_normalized), replace=TRUE, prob=c
    (0.67, 0.33))
> data.training <- data_normalized[ind==1, 1:41]
> data.test <- data_normalized[ind==2, 1:41]
> data.trainLabels <- data[ind==1, 42]
> data.testLabels <- data[ind==2, 42]
> data_pred <- knn(train = data.training, test = data.test, cl =
    data.trainLabels, k=3)
```

Experiment 11

```
> ind <- sample(2, nrow(data_normalized), replace=TRUE, prob=c
    (0.50, 0.50))
>
> data.training <- data_normalized[ind==1, 1:41]
> set.seed(1234)
> data.training <- data_normalized[ind==1, 1:41]
> data.test <- data_normalized[ind==2, 1:41]
>
> data.trainLabels <- data[ind==1, 42]
> data.testLabels <- data[ind==2, 42]
> data_pred <- knn(train = data.training, test = data.test, cl =
    data.trainLabels, k=3)
```

Experiment 12

```
> ind <- sample(2, nrow(data_normalized), replace=TRUE, prob=c
    (0.20, 0.80))
> data.training <- data_normalized[ind==1, 1:41]
> data.test <- data_normalized[ind==2, 1:41]
> data.trainLabels <- data[ind==1, 42]
> data.testLabels <- data[ind==2, 42]
> data_pred <- knn(train = data.training, test = data.test,1 cl =
    data.trainLabels, k=3)
```

Experiment 13

```
> set.seed(1234)
> ind <- sample(2, nrow(data_normalized), replace=TRUE, prob=c
    (0.80, 0.20))
> data.training <- data_normalized[ind==1, 1:41]
> data.test <- data_normalized[ind==2, 1:41]
> data.trainLabels <- data[ind==1, 42]
> data.testLabels <- data[ind==2, 42]
```

Experiment 14

```
> set.seed(1234)
> ind <- sample(2, nrow(data_normalized), replace=TRUE, prob=c
    (0.67, 0.33))
> data.training <- data_normalized[ind==1, 1:41]
> data.test <- data_normalized[ind==2, 1:41]
> data.trainLabels <- data[ind==1, 42]
> data.testLabels <- data[ind==2, 42]
> data_pred <- knn(train = data.training, test = data.test, cl =
    data.trainLabels, k=13)
```

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