A generic approach for detecting security anomalies in ISP infrastructures

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Jaap Mooij

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Summary

In this study we address an important challenge for Internet Service Providers: detecting cyber security anomalies in growing streams of heterogeneous data. Internet Service Providers (ISP's) play a pivotal role in managing the complexity behind "the Internet". In a world of ever changing threats to cyber security, they face the daunting responsibility to keep the Internet safe for themselves and for their customers. Early detection of security breaches is an important building block towards achieving this goal. During the past two decades ISP's have implemented virus- and vulnerability-scanning, intrusion- and DDoS-detection, log analysis and other measures: all different ways of looking at the infrastructure and its behaviour to detect intrusions. Each new tool adds more visibility, but also increases the burden on security staff to monitor, correlate, prioritize and follow up on alarms. This is the reason that ISP's, like other organizations, are embracing Security Information and Event Management (SIEM); solutions that process security logs from different sources in real time and generate correlated, prioritized alarms. Additional tooling is available to support manual data analysis and forensics. This typical set-up with automated real time detection and manual off-line analysis significantly improves overall security, but still has important limitations. Current SIEM products are optimized for reliable detection of pre-configured, known attack scenarios, but they are less effective for detecting new intrusion patterns. Manual analysis is effective for following up on specific alarms or suspicions, but the volume of available data is so large that only a small fraction of events can be examined.

This thesis demonstrates that applying statistical anomaly detection to complement existing solutions can significantly improve detection of anomalies for ISP's. This is achieved by systematically processing data coming from various sources in the infrastructure, and triggering alerts when an anomaly is suspected. In order to accomplish a functional system, our solution introduces a new anomaly detection mechanism that is able to handle the nature of the available data:

- Data comes from heterogeneous sources
- The volume of potentially relevant data is typically very large.
- The vast majority of events contain no evidence of security incidents
- Labelled data is scarce

Other requirements include scalability and the support of continuous, stream based processing. It should be possible to continuously optimize the solution based on expert knowledge, incident analysis, threat intelligence and user feedback.

A literature study has shown that existing approaches to security anomaly detection do not fully meet these requirements. The scientific community has developed advanced data mining algorithms, but has largely focused on labelled and/or small datasets. Existing commercial solutions are typically built for a limited number of known attack scenario's. More advanced solutions based on deep learning are at the peak of the hype cycle, but no clear solutions have emerged yet and little documentation is available. Fortunately, much can be learned from studying other disciplines. Financial fraud detection based on deviation from 'normal' behaviour has been studied intensely, as has the analysis of call detail records to detect phone related fraud.

To address the deficiencies in existing solutions, his thesis proposes a generic approach for unsupervised, stream based anomaly detection. This is achieved by aggregating data from heterogeneous sources into time/space points, where 'space' can be any relevant entity (e.g. a user or a computer) and time is a chosen time interval (e.g. an hour or a day). The behaviour of an entity during such an interval can be characterized by specific features, which can be collected in a 'feature vector'. By aggregating these feature vectors over multiple time/space points, the system can model

‘normal’ behaviour. The final step is to build a tuneable algorithm to detect anomalies in incoming data by matching its feature vectors to the stored profiles. Profiles can either be built along the spatial axis, where the behaviour of e.g. a computer is compared to that of other similar computers, or along the temporal axis, where the behaviour of an entity is compared to its own behaviour in the past. This study focuses on the second option.

A design approach is presented following a slightly adapted version of the CRISP-DM model to describe the data mining process. A five-step flow model is proposed for the implementation of historic profiling and anomaly detection system, and important design considerations are highlighted.

The proposed model is validated in two ways: Firstly, a round of interviews has been conducted with 10 security experts within the ISP for which the author works. These experts have expressed their belief in the validity of the basic approach, and have provided valuable feedback to improve the model. Secondly, the model has been applied to a realistic dataset of over 1.6 billion records. The Los Alamos comprehensive security data set captures 58 days of consecutive logging from different log sources in the network of the Los Alamos National Laboratory, and offers a good approximation of the data that will be encountered in ISPs. With the implemented model, several suspected security anomalies in the data were identified.

After discussing the proposed model with domain experts and applying it to the Los Alamos dataset, it can be concluded that it is a promising approach to complement existing tooling. The model proved straightforward to implement, intuitively links high level overviews to specific details and scales well. It is also flexible in the sense that there are many ways to gradually augment and improve it as experience with the tooling and the data grows.

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1 Introduction

In the span of three decades, “the Internet” has evolved from an obscure academic project into something that has permeated our daily lives up to the capillaries. Still, not many people realize that “the Internet” or “the Cloud” actually consists of thousands of individual infrastructures that have organically evolved over time into complex, interconnected structures. Internet Service Providers play a pivotal role in knitting everything together, since they supply much of the connectivity and run the access networks that connect their customers to the rest of the world. These customers use their connectivity for everything, from online flirting to running a business, and although the vast majority of transactions are benign, incidents and criminal activities do happen. Online Law enforcement is still very much in its infancy, and because much of the infrastructure is privately owned, private organizations play a much larger role in policing the Internet than they do in keeping our physical world safe.

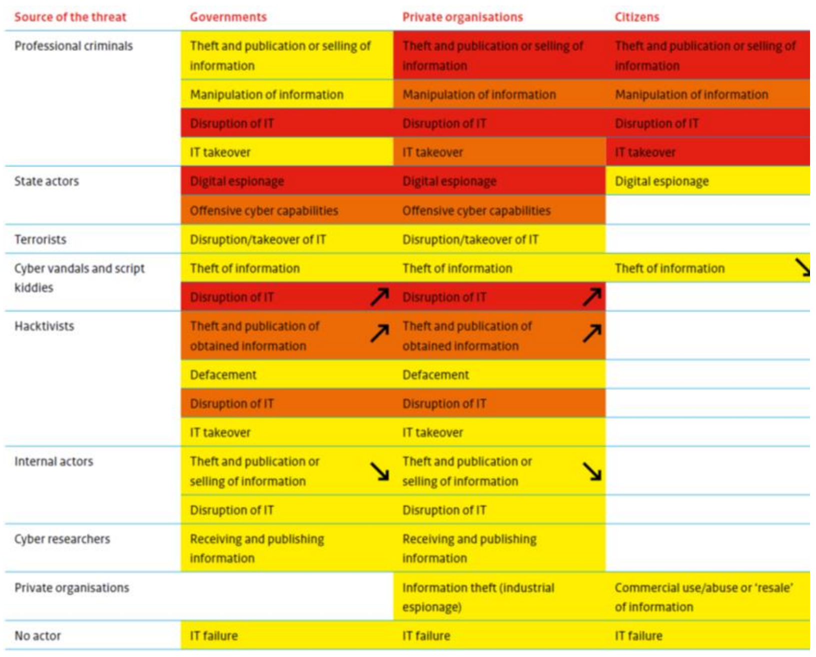
This thesis will take the point of view of an Internet Service Provider (ISP). Care for the customer, fear of reputation damage and legal obligations give ISP’s a strong incentive to protect their networks against intruders. However, the industry is struggling to keep up with the increasingly complex challenges it faces:

- Technological development cycles are accelerating. Even though security awareness has grown, pressure to go to market may tempt equipment vendors and software suppliers into taking security shortcuts. New developments such as network virtualization are largely uncharted territory as far as security is concerned.
- At the same time, phasing out legacy systems proves challenging, leaving ISP’s with large pieces of infrastructure that are virtually impossible to keep in line with the latest security requirements.
- Many ISP’s are outsourcing large parts of their operations to Managed Service Providers (MSP’s) across the world. Even though security is now a standard annex in MSP contracts, verifying that all security policies are adhered to by all subcontractors is virtually impossible.
- Intrusion attempts are becoming more frequent and more professional, as organized crime and state actors are scaling up their online operations. The Cyber Security Assessment Netherlands 2016 observes that “Professional criminals are an ever greater danger to digital security in the Netherlands” (National Cyber Security Center, 2016). Because ISP’s count citizens, private organizations and governmental agencies amongst their customers, all developments in the threat landscape ultimately affect them (see Figure 1).

Cyber security is a complex, multi-disciplinary subject ranging from law to psychology to economics. This thesis will focus on technical security measures, and the processes needed to enable them. Different models exist to structure these cyber security activities. One of the best known is the NIST Security Framework (National Institute of Standards and Technology, 2014), which recognizes 5 functions in security:

Identify	- Understand business context, identify key assets, threat- and risk-assessment etc.
Protect	- Develop safeguards in the infrastructure and implement processes to support them.
Detect	- Develop activities and tooling to detect cyber-security incidents.
Respond	- Organize activities to take appropriate actions when a security incident is detected.
Recover	- Prepare for quick recovery of normal operations after a cyber-security incident.

Each of these functions is a security discipline in itself, and a good security policy will need to address all five. However, this study will focus on the third aspect: the "Detect" function.



Source of the threat	Governments	Private organisations	Citizens
Professional criminals	Theft and publication or selling of information	Theft and publication or selling of information	Theft and publication or selling of information
	Manipulation of information	Manipulation of information	Manipulation of information
	Disruption of IT	Disruption of IT	Disruption of IT
	IT takeover	IT takeover	IT takeover
State actors	Digital espionage	Digital espionage	Digital espionage
	Offensive cyber capabilities	Offensive cyber capabilities	
Terrorists	Disruption/takeover of IT	Disruption/takeover of IT	
Cyber vandals and script kiddies	Theft of information	Theft of information	Theft of information ↘
	Disruption of IT ↗	Disruption of IT ↗	
Hacktivists	Theft and publication of obtained information ↗	Theft and publication of obtained information ↗	
	Defacement	Defacement	
	Disruption of IT	Disruption of IT	
	IT takeover	IT takeover	
Internal actors	Theft and publication or selling of information ↘	Theft and publication or selling of information ↘	
	Disruption of IT	Disruption of IT	
Cyber researchers	Receiving and publishing information	Receiving and publishing information	
Private organisations		Information theft (industrial espionage)	Commercial use/abuse or 'resale' of information
No actor	IT failure	IT failure	IT failure

Figure 1 Cyber Security Assessment Netherlands (National Cyber Security Center, 2016)

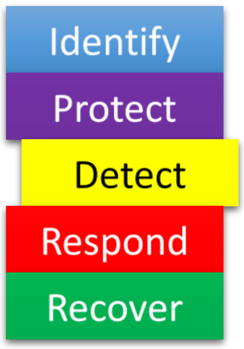


Figure 2. The NIST Security Framework

1.1 Detecting Security Intrusions in ISP infrastructures

ISP infrastructures are large, complex and constantly changing. A medium sized ISP will have hundreds of thousands of active elements in their data centres, plus millions of modems and set-top boxes at their customers' premises. All these elements are connected through fibres, routers, switches and firewalls, with thousands of mutations every day. Even though security policies, architecture guidelines and awareness programs are in place to keep intruders out (the 'prevent' function from the NIST model), successful attacks will still take place. ISPs have established Security Operation Centres (SOCs) and Cyber Emergency Response Teams (CERTs) to coordinate response and recovery.

To be effective, security breaches must be detected as early in the kill chain (Hutchins, Cloppert, & Amin, 2011) as possible. Over the past decades, the industry has developed different technologies to gather and analyse operational data to accomplish this, often supported by frequent intelligence updates to keep systems aware of the latest attack patterns. A typical ISP will have several of these solutions in place:

	Description	Point of detection	Intelligence feed
Virus scanning	Traditional virus scanning consisted of detecting known malware patterns in system files. Because virus makers have learned to evade this kind of signature matching, the industry is moving towards heuristics.	Files in storage, system memory, system behaviour	Signatures, heuristics
Vulnerability scanning	Systematically scanning system ports for known vulnerabilities.	Communication ports.	CVE databases
Intrusion Detection/ Prevention	Detecting intrusion patterns in network communications. Can be either network based or host-based.	Network, host communication.	Intrusion patterns
Anti DDoS	Detecting Denial of Service Attacks	Netflow Information, SNMP	Attack patterns
Abuse	Detecting the presence of malware on user systems by monitoring spam and C&C activities.	Sinkhole data, SPAM filters	E.g. Shadowserver
Honeypots	"Fake" systems in an infrastructure with no other purpose than detecting malicious traffic. Because honeypots have no function in the regular network, the assumption is that any attempt to interact with them is suspicious.	Communication (OSI layer 2-7 depending on the type of honeypot)	
Logfile analysis	Collecting and analysing system logging to detect suspicious activity	System logfiles	Malicious use cases

This list is not complete; solutions are added and improved as technology on both sides of the cyber arms race advances. As the list grows, security personnel are faced with the challenge of monitoring increasing number of security applications at once, each with its own interface, documentation and helpdesk. Alarm- correlation and -prioritizing has to be done manually, and respond- and recover-activities are often different for different kinds of security events. For the innovation and operation teams the diversity becomes hard to manage as well, since each solution has its own infrastructure requirements, its own technology, its own intelligence feed, its own vendor relations etcetera.

1.2 Moving towards automated alarm correlation and data lakes

To counter some of the challenges described in the previous paragraph ISP's, like other organizations, are embracing Security Information and Event Management (SIEM); commercial solutions that process security logs from different sources in real time and generate correlated, prioritized alarms. A parallel development is the storage of large volumes of security related data in data lakes, where it can be accessed via smart search tools to support manual data analysis and forensics. This typical set-up, with automated real time detection combined with manual off-line analysis, significantly improves overall security but still has important limitations:

- Current SIEM products are optimized for reliable detection of pre-configured, known attack scenarios, but they are less effective for detecting new intrusion patterns.
- Despite recent SIEM developments, correlation between events detected in different domains remains hard to determine. In all but the most straightforward cases, the expertise of security experts is still required.

- Much of the detection is still based on signatures or known attack vectors. Detection of behavioural anomalies in the infrastructure, which could in theory help to detect both known and unknown attacks, is still in its infancy.
- The sheer volume of data brings its own challenges. To keep the Security Operations Centre workload at an acceptable level the number of false positives has to be minimized and the information provided to the response process should be as specific as possible. In practice SIEMs only analyse a small subset of the available data.
- Manual analysis is effective for following up on specific alarms or suspicions, but the volume of available data is so large that only a small fraction of events can be examined.

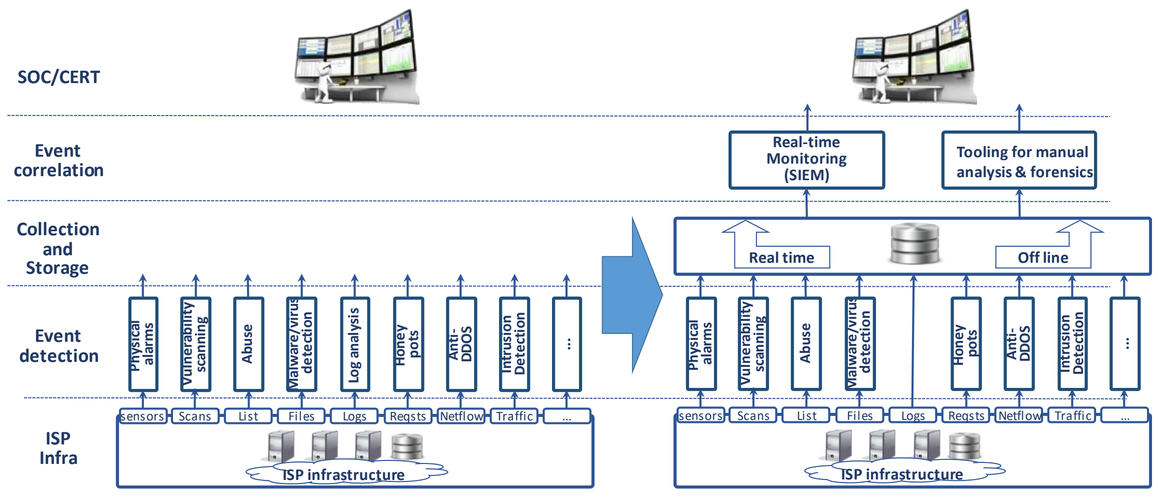


Figure 3 Towards automated alarm correlation and data lakes

1.3 Ambition of this study

To help overcome the deficiencies in current solutions, we propose a new approach. This thesis will demonstrate that applying statistical anomaly detection to complement existing solutions can significantly improve the detection of questionable events for ISP's. This is achieved by systematically processing data coming from various sources in the infrastructure, and triggering alerts when an anomaly is suspected. Such alerts can serve as starting points for manual analysis, directing the focus of security experts. This manual step will result in much slower response times than the near real time alarms from commercial SIEMs. However, value is still added when anomalies are discovered that would otherwise remain undetected, especially given that

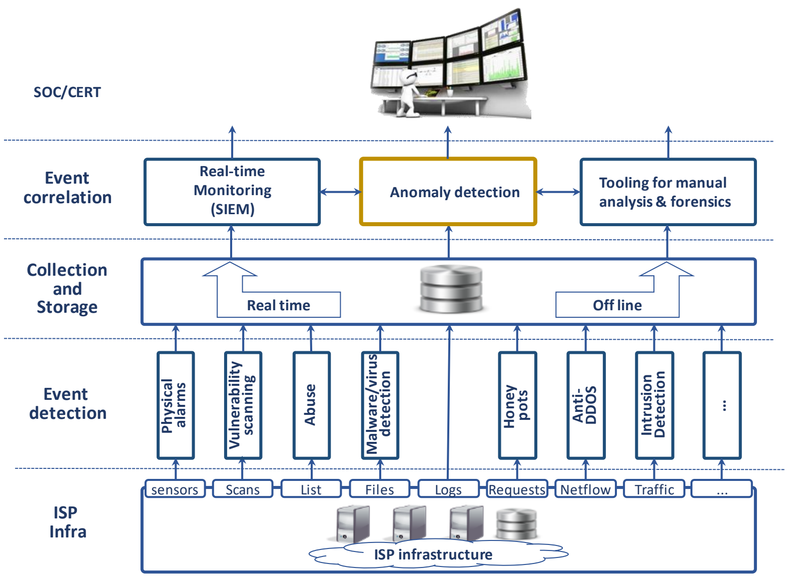


Figure 4. The role of anomaly detection

commercial security firms report that the average time between a security breach and its discovery is several months (Mandiant Consulting, 2016). By feeding the results from manual analysis back into the system, its detection reliability can be improved continuously. Moreover, once specific alarms become sufficiently reliable to warrant automatic response, they can be migrated to the real-time monitoring environment.

In order to accomplish a functional system, our solution introduces a new anomaly detection mechanism that is able to handle the nature of the available data:

- Data comes from heterogeneous sources
- The volume of potentially relevant data is typically very large.
- The vast majority of events contain no evidence of security incidents (assumption)
- Labelled data is scarce; if labels are available they are usually positive (e.g. when an alarm is triggered)

Other requirements include scalability and the support of continuous, stream based processing. It should be possible to continuously optimize the solution based on expert knowledge, incident analysis, threat intelligence and user feedback.

1.4 Design approach and structure of this document

The remainder of this thesis will describe how a solution was designed and prototyped that meets the requirements listed in the previous paragraph. The design process roughly followed the structure as described by Hevner et all and depicted in Figure 5 (Hevner, March, Park, & Ram, 2004). In the previous paragraphs the ISP environment and its business needs have been introduced. In chapter 2 we will evaluate the existing knowledge base and identify relevant knowledge gaps. Based on the business needs and the applicable knowledge, we will propose a model for detecting anomalies in heterogeneous data sources in chapter 3. In order to evaluate this model, it has been applied on a real-life dataset. This is the subject of chapter 5. A special role is played by domain experts. Their knowledge has contributed to all elements in the design process. A summary of their input has been place between chapters 3 and 5, because much of their feedback concerned the proposed model and its application to the dataset. Finally, in chapter 6 we will present our conclusions and give recommendations for further study.

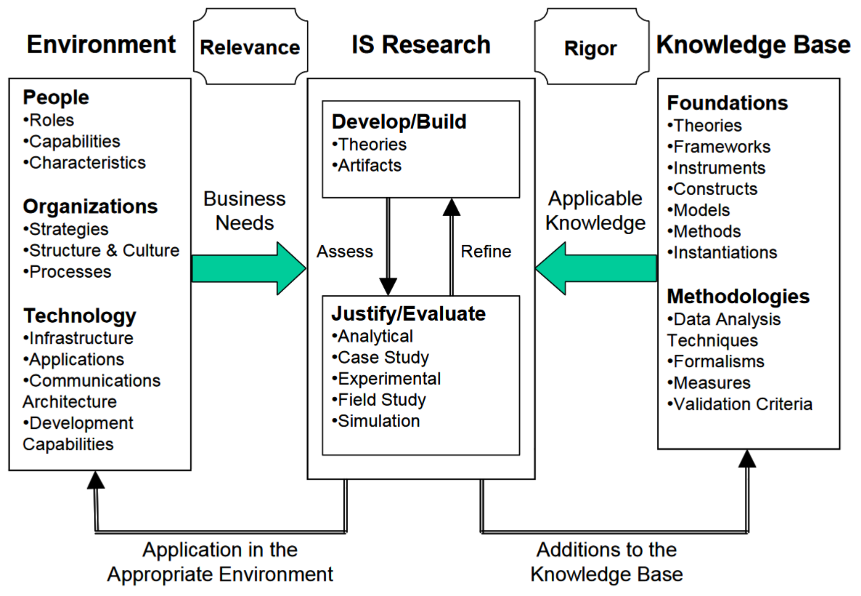


Figure 5. Information Systems Research Framework (from Hevner et al.)

2 Related research

The detection of security incidents using data mining- or machine learning-techniques has been a fruitful research area since the 1990's. Excellent overviews exist of the progress that has been made, in articles (e.g. (Buczak & Guven, 2016)), books (e.g. (Dua & Du, 2016), (Bhattacharyya & Kalita, 2014), (Barbará & Jajodia, 2002)) and university courses (e.g. (Stanford, 2014)).

A review, however, shows that most authors have focused on very specific types of attacks and/or have used limited datasets, e.g. from a single source, or containing fully labelled data. This allowed them to achieve accurate algorithms (e.g. UHAD (Hajamydeen, Udzir, Mahmod, & Abdul Ghania, 2016)), but makes their findings less relevant when addressing the ambition of this thesis: to find anomalies in high volumes of unlabelled data from heterogeneous sources.

The rest of section will focus on specific topics that are key to the challenge at hand: anomaly detection, logfile analysis and profiling. Also, a brief look will be taken at developments outside the academic world.

2.1 Anomaly detection

Anomaly detection is an area of data mining that has received academic interests since the 1990's, and has been applied to a wide range of problems including fraud detection, system health monitoring, image- and text processing and intrusion detection. Techniques can be grouped into several categories: ***Classification*** based approaches define "normal" based on available training data and label new points that do not fit this description as anomalous. ***Nearest neighbour*** algorithms calculate the multi-dimensional distance between data points, and assume that points that lie far from other points are anomalies. ***Clustering*** based techniques identify clusters in the data. Data points outside clusters are considered anomalies. Finally, ***statistical analyses*** identify anomalies by determining low probability regions in a stochastic model. Overviews of anomaly detection techniques can be found in (Chandola, Banerjee, & Kumar, September 2009), from which these categories were taken and (Goldstein & Seiichi, A Comparative Evaluation of Unsupervised Anomaly Detection Algorithms for Multivariate Data, 2016).

Portnoy et al. (Portnoy, Eskin, & Stolfo, 2001) recognize the fact that labelled data is expensive to obtain, and that methods relying on it are likely to miss new forms of attack. Based on metrics selected by domain experts, they use a clustering algorithm to form groups of data-points that have a smaller Euclidian distance to each other than to other clusters. By assuming that 'normal' network behaviour accounts for the vast majority of data, they reason that small clusters are likely to indicate malicious activity. They used the KDD dataset to evaluate their algorithm. Interestingly, performance was poor when applied to the normal dataset. This was caused by the fact that the KDD dataset is specifically created for testing incident detection algorithms, and contains an unrealistically high percentage of attack data. Once additional 'normal' points were added to the data, the algorithm was able to detect a significant percentage of the attacks contained in the set. In 2016 a U.S. patent was granted for a method expanding on this approach (U.S. Patentnr. US9306966 B2, 2016)

Wenjie et al. (Hu, Liao, & Vemuri, 2003) compare the performance of Support Vector Machines (SVM), Robust SVM (RSVM) and k Nearest Neighbours (kNN) in detection of anomalies in noisy data. Using the DARPA 1998 dataset (to which they added noise), they demonstrated that RVSM gives the best over-all performance. Their method, however, requires labelled data for training.

It is instructive to draw parallels to financial fraud detection, which is another area for which anomaly detection in imbalanced data has been widely studied. Data mining techniques such as logistic regression, Support Vector Machines, Random Forest (Bhattacharyya, Jha, Tharakunnel, & Westland, 2011) and Neural Networks (Brause, Langsdorf, & Hepp, 1999) have been applied to detect anomalies in credit card data. Again, data volumes in these studies seem relatively limited. Extensive overviews of research into financial fraud detection can be found in (Phua, Lee, Smith, & Gayler, 2010) and (Ngai, Hu, Wong, Chen , & Sun, February 2011).

2.2 Logfile analysis

Logfiles are increasingly recognized as an important source of network- and security- incident detection. Makanju et al cluster logs generated by specific nodes over time into “nodehours”. They generate signatures of anomalies by asking experts to indicate when and where anomalous events have occurred in historic data, and then mining the indicated nodehours for patterns that characterize them. They show that they can detect similar anomalies by matching these signatures to historic or real time (unlabelled) data (Makanju, Zincir-Heywood, & Milios, 2013).

In order to address the problem that very little labelled training data is available in real-life situations, Wurzenberger et al. propose to actively create different kinds of security incidents in an infrastructure and analyse how these incidents are reflected in the loggings of the systems involved. Because such tests cannot be performed on live networks, they suggest how a realistic test environment can be realized that sufficiently reflects the behaviour of the production networks (Wurzenberger, Skopik, Settanni, & Scherrer, 2016).

2.3 Profiling

User profiling has been used in different disciplines to detect unwanted behaviour. One such discipline is the telecommunication industry, where fraud relating to international telephony or premium numbers has long been a major source of revenue loss. Wiens et al (Wiens, Wiens, & Massoth, 2014) used unsupervised profiling of phone-usage based on VoIP Call Detail Records (CDR’s) to detect fraudulent customers. Using a sliding window approach, they compare current behaviour against historic evidence and calculate a ratio in order to measure change. Once this ratio passes a certain threshold, fraud is suspected. To adjust for normal fluctuations (weekends, holidays, business peaks) they use global parameters to scale the corresponding user parameters. In a similar use case, Hilas et al. (Hilas, Mastorocostas, & Rekanos, 2015) apply K-means and agglomerative clustering to a set of anonymized CDR’s using various measures of distance. Their data set is very small, but results suggest that using correlation as a distance measure yields the best results. Perhaps unsurprisingly, using more detailed user profiles also increases accuracy.

Of course, profiling has also been studied extensively in the context of cyber security. In most cases, the parameters used to define user profiles are a combination of available system logging and specifically calculated data (e.g. change over time) constructed by domain experts. Examples can be found in (Lee & Stolfo, 1998), (Lee, Stolfo, & Mok, 1999) and (Phua, Alahakoon, & Lee, 2004).

Shavlik & Shavlik present a model to build profiles of individual Windows users (Shavlik & Shavlik, 2004). They start by recording hundreds of parameters per second for each user during a training period (during which they assume no fraud takes place). Next, they derive which standard distribution best fits each parameter for each user (normal, uniform, exponential or Erlang), which enables them to estimate the likelihood that new measurements are in fact generated by that user. To determine which parameters best characterize a user, they create a training set by adding “abnormal” data taken from other users. Each parameter that helps to correctly detect this abnormal behaviour gets a higher weight factor, while the weight of parameters that do not attribute to detection is decreased. Despite this pruning, their model still ends up with long user vectors.

2.4 Commercial incident detection

Needless to say, the detection of security incidents is receiving significant interest outside the academic community as well. Many major vendors invest in Security Information and Event Management (SIEM) solutions that use large streams of different kinds of logging to generate security alarms. Figure 6 shows the often cited 2016 Magic Quadrant, in which the Gartner group assesses the merits of different vendors. Global market size is estimated at $1,73 billion in 2015 (Kavanagh, Rochford, & Bussa, 2016). More infrastructure specific solutions exist, e.g. Microsoft Advanced Threat Analytics and Cisco Stealthwatch. Little is known about the algorithms deployed in these commercial solutions, but a brief survey of patent filings gives snippets of insight: Nokia received a patent for building application profiles by monitoring the interaction of applications with their environment, but details on profile parameters and anomaly detection mechanism are not given (US Patent No. US20080022404 A1, 2008). A patent granted to Derek Lin (EMC Corporation) gives an interesting listing of meaningful metrics that can be monitored to detect security intrusions (U.S. Patentnr. US9112895 B1, 2015). The author goes on to describe a method to link security incidents likely to related into an attack chain by looking for shared attributes between events.

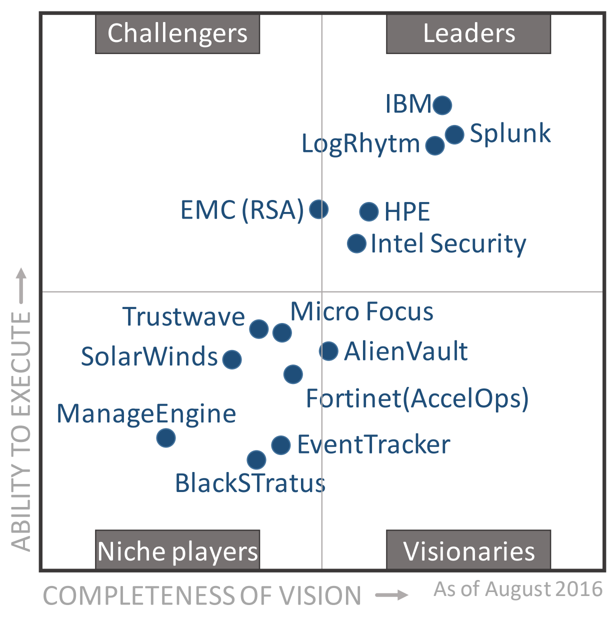


Figure 6. The Gartner Magic Quadrant for Security Information and Event Management (SIEM)

More recently, IBM reports that it is starting a pilot using its deep learning environment “Watson” to discover security incidents in the networks of several pilot customers (IBM, 2016). Unfortunately, few details are available at the time of writing.

3 Building a model for detecting anomalies in heterogeneous data

Starting point for developing our model is the realization that the behaviour of almost any entity in a network can be described by extracting metrics from available logfiles. As an example: the behaviour of a user on a given day could be described by features such as the time he/she first logs on, the programs she/he runs, the protocols that are used, the number of other users that are contacted etcetera. These features can be described by numerical ***parameters*** that each describe an aspect of the user's behaviour. In this thesis, the set all parameters for a specific user and time interval is called a ***feature vector***.

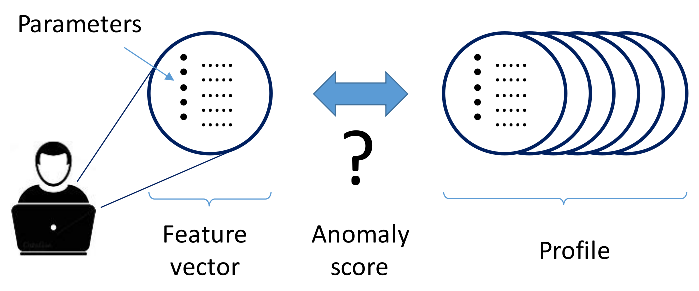


Figure 7. A simple illustration of the terminology used in this thesis

Of course, there will be natural fluctuations in behaviour, and therefore in the values of the parameters describing it. To model the range of "normal" behaviour, a series of feature vectors can be combined to form a ***profile*** for a specific user. Now, if we want to determine whether any observed behaviour is "normal", we can compare the parameters describing it with the user's profile. This results in an ***anomaly score***. The more a new measurement deviates from what is seen in the profile, the higher the score.

The remainder of this chapter describes how this basic concept was developed into a practical model.

3.1 The data mining process model

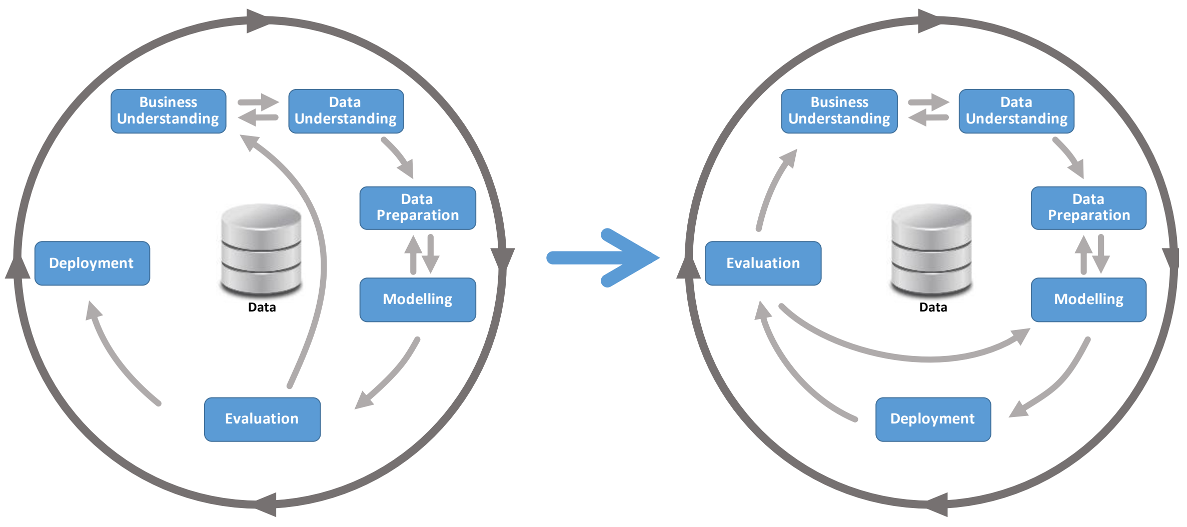


Figure 8. The original CRISP - DM model (left) and the adapted version used in this thesis (right)

To develop and build a data mining solution that meets the requirements described in chapter 1.3, the CRISP Data Mining process model (Wirth & Hipp, 2000) was used as a starting point. The Cross Industry Standard Process for Data Mining was developed in the late 90's by a consortium of developers and users, with support from the European Committee, and is the most widely used data mining framework today (kdnuggets, 2014). However, the CRISP model is primarily aimed at one-off data mining studies, with clear preparation-, development- and deployment-phases and an evaluation at the end. Since the goal of this study is to develop a system that will run indefinitely, with continuous improvement, a small adaptation is made to the original model: The "Deployment" and "Evaluation" steps are interchanged This closes the circle (see Figure 8) and in the view of the author makes it better suitable to serve as a framework for this study. Also, an arrow is added between "Evaluation" and "Modelling" to indicate that there exists a second, shorter feedback loop for day to day optimization. The following paragraphs will expand on each of the steps in the model.

3.2 Business- and data-understanding

The first step in any applied data mining development is understanding the business and its requirements. These have already been discussed extensively in the introduction to this thesis. Closely related to business understanding is understanding the data that is available to meet the project objectives. Many different data sources are available in ISP infrastructures. This study will focus on a source that is especially important for anomaly detection: Log messages.

Logs are short, generally text based, messages that can be generated by virtually all active elements in an ISP infrastructure to record events or report on their status. As such, they form an invaluable source of information for many ISP processes, including fault-, performance- and capacity-management, audits, and also security monitoring. The size of the log-stream that is generated by an ISP infrastructure depends on factors such as the number of active elements, their log configuration and the completeness of the log collection infrastructure, but will easily reach many thousands of messages per second. Some logs will be collected continuously, others will arrive in batches of varying time intervals. The content and format of messages is highly system specific, and fields with the same meaning may have different notations in different log formats.

It is important to realize that logging isn't free: generating log messages consumes system resources, as does collecting, storing and processing them. For most systems, logging can be set to different levels. Configuration should be handled with caution: Setting a system to full debugging mode may lower its performance to a point that its operational readiness is impacted. Designing a system for log analysis therefore has to be approached end-to-end, in close cooperation between security analysts, network operators and capacity planning. For security developers, it is good practice to first make an inventory of the logging that is already in use for other business processes before requesting additional data.

3.3 Data preparation: log collection

The availability of sufficiently relevant, accurate and complete data is an important pre-condition for effective anomaly detection. For solutions based on log processing this begins by ensuring that all systems are configured to generate the right logging. The gathering of the resulting log messages from throughout the infrastructure requires a network of (typically local) log collectors. Additional connectivity and tooling is needed if logs are to be stored and analysed centrally. Tools and procedures have to be implemented to constantly monitor and manage the log collection process once it is in production.

Log collection is a challenging topic in itself; one that has recently seen revived interest in both industry- and research-communities with the rise of "Big data". For this thesis log collection is out of scope; it is simply assumed that a log collection infrastructure is in place and that the required data is available.

3.4 Modelling

Processing all individual log messages to detect security anomalies has a high computational cost. Most SIEM implementations therefore only process a fraction of the total volume of logging available, with the risk of missing important indicators. As described in the introduction to this chapter, this thesis proposes a method that enables ISP to process a much broader scope of logging at a reasonable computational cost. This is achieved by clustering all messages that are collected during a time interval around the entities they provide information on (see Figure 9). These entities can be anything in the infrastructure whose behaviour (or change of behaviour) is relevant from a security perspective. Obvious choices for the entity dimension are:

- ***Users*** (which can be both human beings or processes using user credentials). Deviant user behaviour could indicate for instance stolen credentials or an insider attack.
- ***Systems*** (e.g. servers, pcs, routers), whose behaviour will change when they are compromised by malware.
- ***Processes or applications***, which may behave different when they are used in attacks.

By processing all the log messages that contain information about an entity, a set of parameters can be derived that describes its behaviour during a specific time interval (for instance of user A on day B). Such a set is called a "feature vector". By collecting a set of such feature vectors, a profile can be built that describes "normal" behaviour. When behaviour deviates too much from this norm, an anomaly is suspected and an alarm can be triggered.

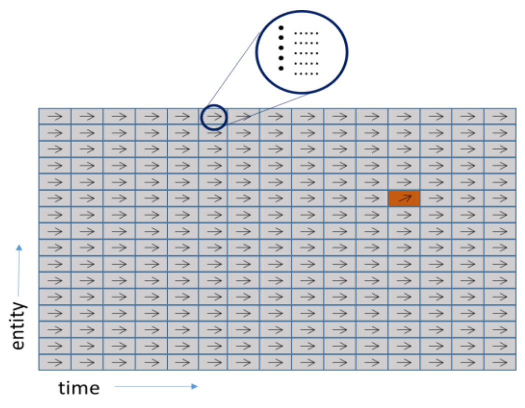
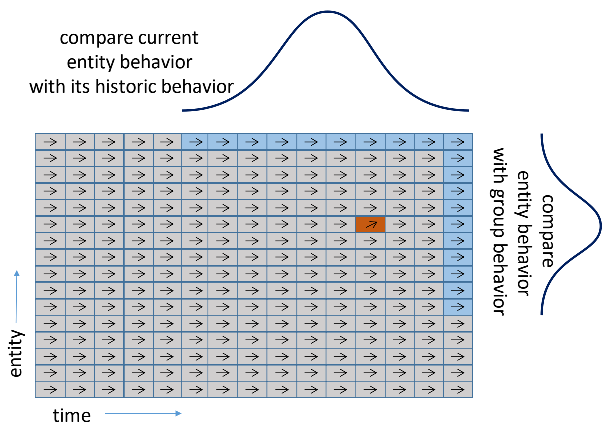


Figure 9. Discretizing log streams in entity intervals



compare current entity behavior with its historic behavior
compare entity behavior with group behavior
entity
time

Figure 10. Historic vs group profiling

Building profiles to characterize "normal" behaviour can be done along two axes (or combinations thereof, see Figure 10):

- ***Historic profiling***: by collecting information about an entity (e.g. a computer) during a number of time intervals, a profile can be built that describes how that entity has behaved in the past. An anomaly score for a new measurement can be determined by calculating how much it deviates from this profile. The assumption here is of course that the entity was not compromised during the initial training period, which will be true for the vast majority of cases, but not all.
- ***Group profiling***: if entities have similar functions, they can be expected to behave similarly. If one user behaves different from his colleagues, or if one DNS server behaves different than its peers, this can be reason to suspect an anomaly. The assumption here is that only a small percentage of entities is compromised. To implement this kind of profiling, entities have to be

clustered in groups of which similar behaviour would be expected. This can be achieved by domain knowledge (e.g. from an HR system that contains job titles of employees), or by data clustering techniques.

Both approaches to profiling are valid and can be used simultaneously, or even combined into historic profiling of groups. This thesis will focus on historic profiling, because the added complexity of having to define relevant groups for group profiling does not contribute to the goal of validating the basic model.

Figure 11 shows the basic, five step model that is proposed to implement anomaly detection based on historic profiling. It consists of the following steps:

- ***Data priming***
  Incoming logs will be in different formats, and not all messages may be relevant for upstream analysis. Normalization and filtering ensures that messages can be analysed efficiently.
- ***Buffer***
  Incoming logs are stored in buffer storage during the time interval over which a feature vector is to be calculated.
- ***Feature vector construction***
  At the end of a time interval, data is retrieved and the feature vectors can be calculated.
- ***Detection of anomalies***
  The new feature vector for each entity is compared to its historic profile to determine an anomaly score.
- ***Profile maintenance***
  As a final step in the process, the historic profile is updated.

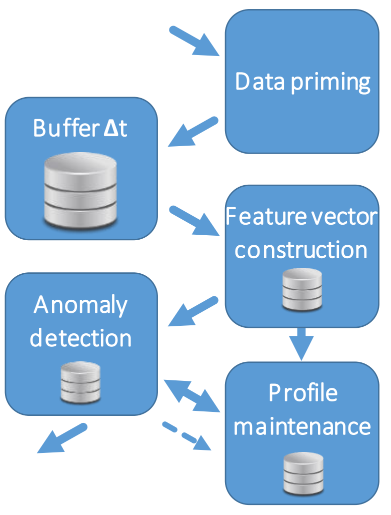


Figure 11. Anomaly detection based on historic profiling

Each of these steps has different design considerations, which will be explained in more detail in the following paragraphs. For clarity's sake, the design steps will be presented here in the sequence they are presented above, which is the order that the steps will be performed once the solution is operational. In practice the design process will follow a different route, and will start at the end by determining what kind of anomalies should be detected, then move to the beginning to match the desired outcome with the available data. After this, the different design choices will be made in an iterative process which should continue even after the solution is operational.

3.5 Data priming

The first step in the proposed anomaly detection method is data priming, which is used as container term for different manipulations that can be performed on the log messages when they enter the system:

Filtering and aggregation can be applied to reduce the total volume of logging to be stored and processed. Log messages that are not considered relevant in security context can be filtered out altogether. High-frequency logs with a large level of redundancy can be sampled, summarized (e.g. "*n* messages received with average value *x*") or similarly processed (e.g. only forward status changes and filter messages reporting that status is unchanged). Data compression can be achieved by e.g. translating strings to integer representations using a dictionary.

Normalization is the arduous but essential task of translating different log dialects into a universal syntax. Naming conventions must be aligned between different sources with the help of a master data-dictionary. Cleaning up or discarding damaged or incomplete data is also part of this process.

Tagging can enrich the information in logs, for instance by adding a time- and location stamp describing when and where each log message was collected.

Pre-processing can ease the computational peak at the end of each interval, when feature vectors are determined, anomalies detected and profiles updated. As a rule, any required processing that can be done on a single log should be done immediately when it is collected.

Priming will often be implemented in a combined decentralized/centralized fashion. As a rule, some forms of tagging (e.g. time-stamps) should be implemented as close to the source as possible, while others (e.g. parsing message content) should be performed centrally because they inflate the volume of the logs and would require bigger collection bandwidth when performed decentralized. Messages that are not used in any upstream process can be filtered out close to the source, while messages that are used for other processes but not for security analysis will usually be filtered out in the central log collection facility.

3.6 Buffer size

The choice of the time interval, over which events are collected to form a single feature vector, is an important design step. As illustrated in Figure 12, choosing a too short interval (Δt_3) will result in a vector based on a small number of events, which means that perfectly normal random fluctuations may contribute heavily to the vector and interfere with the anomaly detection mechanism. Choosing the interval too long may mean that shorter anomalies or trends remain invisible because they are averaged out (Δt_1). The optimal interval times may depend on the technical domain and the entity that is profiled and should, like the other design choices, be established in cooperation with domain experts. If necessary, different time intervals can be tried to experimentally discover which one yields the best results. At the cost of making the system more complex, it would also be feasible to use different intervals for different parameters or entities.

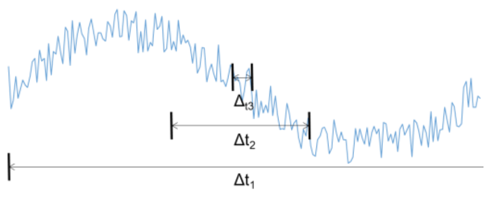


Figure 12. Illustration of time interval selection

3.7 Feature vector construction

The definition of a vector that describes the behaviour of an entity (e.g. a computer) during a specific time interval requires close cooperation between domain experts, security experts and the engineers implementing the detection system. Not all envisioned information may be available and not all analyses can be implemented. The assessment made for this thesis, together with domain experts (see chapter 4), revealed that different kinds of parameters can be defined, with different degrees of computational complexity:

Parameter type	Description
Direct internal parameters	Straightforward parameters that can be derived directly from the available logging, e.g. the number of failed authentication events, the number of computers logged on to or the average byte count of a communication event during a specified interval.
Distinct element count	Parameters that count the number of distinct elements encountered during a time interval (e.g. users, computers, processes)
External/global parameters	Parameters recorded from outside, which may help to explain the behaviour of the entity observed. As an example, recording companywide internet usage as a reference may help to determine if an individual's bandwidth usage is due to a peak in business activity or is something that needs to be examined.
Calculated parameters	These can include simple ratio's (e.g. the average number of events per interactive logon) or conditional events (e.g. the number of interactive logons using Kerberos authentication).
Stateful parameters	Events that occurred previous to the timeframe observed may be relevant to define the entity profile for that timeframe. A simple example is the number of processes running at a specific time. This can be derived by keeping track of the processes started and stopped since the entity was first observed. A more complex example would be a parameter that records how many different computers have been logged on to by a user that he/she did not log on to during the past week.
Analysis based parameters	In order to predict the spread of potential intrusions, results from previous analyses can be included, e.g. in a parameter that counts the number of entities a user has interacted with that have been labelled "suspect" during the previous n analysis rounds.

3.8 Profile maintenance

The previous paragraph described how a feature vector can describe the behaviour of an entity during a specific time interval. By combining feature vectors over a series of time intervals during a training period, a profile can be built that characterizes the "normal" behaviour of an entity over a longer period of time. The assumption here is of course that the behaviour during the training period is "normal", i.e. contains no evidence of malicious activities. Chances are that this assumption is not valid for all entities. This implies that historic anomaly detection is blind to malicious activities that were already going on when the system was first activated. However, given that that average time that an intrusion remains undetected is in the order of months, this effect will gradually fade out if anomaly detection is continued.

A side effect of anomalies is that they also pollute the profile. "Echo's" are a well-known effect in network management, where anomaly alarms are sometimes triggered not only when an anomaly occurs, but also when things return to normal.

Because entity behaviour may change gradually over time for various reasons (job change, software updates, network growth), it makes sense to give recent input a stronger weight in the profile than older data. This can be done in various ways. For the sake of simplicity this thesis assumes a sliding window approach in which the last *n* feature vectors all have an equal weight in the profile and older data is forgotten (see Figure 13).

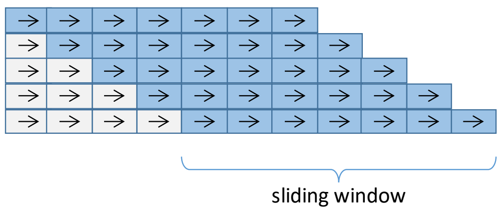


Figure 13. Sliding window approach

3.9 Detecting anomalies

After the initial training period, a profile is available that describes the expected behaviour of an entity over all the dimensions of the feature vector. Now anomaly scores can be computed by comparing behaviour during the most recent interval to this profile. As explained in chapter 2, there are many mathematically sound anomaly detection techniques available to make this comparison, each with its own strengths and weaknesses. For the sake of conceptual and computational simplicity, this study only considers basic statistical methods. Moreover, anomaly detection is implemented in a one-dimension-at-the-time approach: First, an anomaly score is calculated for every parameter in the feature vector. Second, an overall entity anomaly score is calculated by combining the anomaly scores for each parameter. This considerably reduces computational load, but has the disadvantage that complex anomalies might be missed, given that values for different parameters might not be unlikely by themselves but unusual in combination. This disadvantage can be partially mitigated in the design process: if (for instance in an in depth, off-line analysis of historic data), anomalies are found that involve a combination of parameters, a new parameter can be added to the feature vector that reflects this interaction. As a simple example: a student may enter a building in The Hague, and log in to a physical terminal in Leiden. Logs registering these events would not be anomalous in themselves, but if they occurred within seconds of each other it should be cause for alarm. Such anomalies could be detected by defining a new parameter that specifically registers this kind of mismatches.

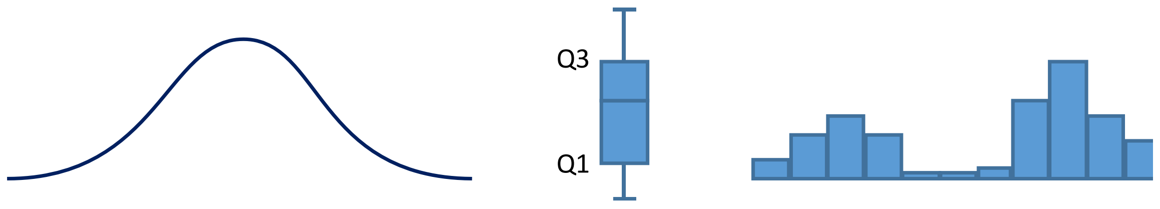


Figure 14. Different methods for modelling profiles. From left to right: statistical distribution, inter quartile range, histogram

The first objective is to measure the deviation from normal behaviour for a single parameter and express it in a single number: the anomaly score. There are many ways to do this; the optimal way depends on the nature of the data (amongst other things). Figure 14 shows three basic methods:

- When a specific ***statistical distribution*** is expected or assumed (e.g. Gaussian, Poisson, binomial), its parameters can be estimated from the data in the profile. For any new point, the likelihood that it belongs to the dataset can be determined. The definition of the anomaly score will depend on the actual distribution. For instance, a Gaussian/normal distribution would be modelled by its mean μ and the standard deviation σ, and the obvious measure for deviation is the *z-score*, the number of standard deviations that a data point lies away from the mean.
- When assuming a specific statistical distribution cannot be justified, ***the Inter Quartile Range*** (IQR) can be used as a measure of deviation. In this method, one dimensional data instances are sorted from lowest to highest. The data-points are then divided in four equal parts, or quartiles, named Q1-Q4. The difference between the highest values in Q3 and Q1 is called the interquartile range (IQR). This can be visualized in so called “box-and-whisker” plots (see Figure 14). Different methods exist to define quartile boundaries. This thesis will use the method described by Mendenhall and Sincich, in which the Q1 and Q3 boundaries lie at

$\frac{1}{4}(n+1)$ and $\frac{3}{4}(n+1)$ respectively[1]. This has the advantage that boundaries always lie at one of the data-points and no interpolation is required (Mendenhall & Sincich, 1995). The anomaly score is determined by the number of IQRs a data point x lies below Q1 or above Q3. Often a threshold value *t* is applied, where *t* is usually chosen as 1.5.

- As an alternative, for instance when data is distributed along several clusters, the probability distribution of data points in the profile can be modelled in ***histograms***. Usually evenly spaced bins are used, but with very uneven distributions dynamic bin width can be used to ensure that each bin contains a minimum number of samples. A rule of thumb is to set the number of bins at the square root of the number of samples. From this it follows that this method is less suitable for smaller samples. The anomaly score for a new sample can be found by determining its likelihood at the hand of the histogram. The anomaly score is the inverse of this value (Goldstein & Dengel, 2012).

Just like the definition of the feature vector itself, deciding how to compare individual parameters with their profiled past should be done with the help of domain experts. Modelling can be different for different parameters: For some parameters exceeding a certain threshold may indicate a security breach by itself, while for others only a deviation from historic behaviour is significant. For some parameters any value outside the normal range is interesting, while for others only upward deviations are relevant. Scores can be a real number or binary (e.g True when a threshold is exceeded). Even though calculations may be different for each parameter, for comparison and further processing it is desirable to define them in such a way that a similar score represents a similar anomaly likelihood.

The ***over-all anomaly*** score is calculated from the one-dimensional parameter anomalies. This can be done in any number of ways. It is important to accommodate some form of weighing of the scores for the different parameters. This gives security experts the means to continuously optimize the model, for instance by processing the results of manual analysis of a suspected anomaly: When the system correctly indicates an anomaly, the parameters that correctly indicated this event can be given a larger weight, while false positive may lead to depreciation of the responsible parameters. Ultimately this may lead to the removal from the model of parameters that do not contribute to accurate anomaly detection.

As a simple solution to obtain a weighed combination of anomaly scores in this thesis, the over-all anomaly score will be determined by summarizing the products of the anomaly scores for each parameter and their respective weights *w* (see Figure 15).

[1] To be entirely accurate: in case the Q1 boundary falls exactly between two data points it should be rounded up. If this is the case with Q3 it should be rounded down

	parameter 1	parameter 2	parameter ..	parameter n
anomaly score	A_1	A_2	$A_{..}$	A_n
weight factor	w_1	w_2	$w_{..}$	w_n

$$\boxed{\sum_{i=1}^{n} w_i A_i}$$

Figure 15. Calculating the over-all anomaly score

The next step after the over-all anomaly scores are determined depends on factors such as the maturity of the system, the sensitivity of the affected assets and the resources that are available to manually follow up on alarms. When the system still produces a lot of false positives it can make sense to analyse the top n of anomaly scores every day, or to reserve a fixed amount of time for analysis. When anomaly scores become more reliable they can be treated like regular security alarms.

4 Feedback from security experts

Domain knowledge is generally considered to be essential for the implementation of any successful security solution. In order to get feedback on the different design aspects covered in this thesis, semi-structured interviews were held with 10 domain experts within the authors' organization (a large ISP in the Netherlands). Interviewees included 3 SOC seniors (including the SOC manager), 2 CERT members, 2 Innovation architect/designers, 1 RED team member and 2 operators that maintain the existing detection infrastructure. This intensive interaction proved extremely rewarding, and confirms the importance of talking to experts. Their feedback and suggestions are reflected throughout this thesis. A brief summary is included below.

4.1 On the environment and business needs

All professionals are, by the nature of their jobs, acutely aware of the threat landscape and the responsibilities they carry on their shoulders as an ISP and provider of critical infrastructure. There is a general feeling that a large and/or sophisticated attack can strike at any moment. This leads to a broad sense of urgency to further improve the existing detection and mitigation capabilities. The observation that a diversity of detection applications becomes increasingly difficult to manage as the number of solutions grows is, not coincidentally, widely recognized by the interviewed experts. The SOC operators are confronted by this reality in their daily work: even though alarms are presented in a single interface through a generic presentation layer, for follow up actions they still have to access the underlying applications. Operations and innovation experience a comparable burden, as they are required to maintain an increasing number of systems, interfaces and vendors. CERT experts currently require the suspicion of an incident from an outside source as a starting point before they can effectively start a manual analysis of log data.

4.2 On the knowledge base and applicable knowledge

There is an apparent gap between the academic and the business world: almost none of the professionals interviewed regularly study academic publications. They do, however, keep up to date by reading professional literature and online publications, and by frequent interaction with peers and vendors. When asked for their professional assessment of where the detection industry is heading, big data and machine learning are generally recognized as the important themes. As a group, they have high expectations for SIEM-like solutions in the future, but admit that current functionality is limited.

4.3 On the proposed model

The proposed method of aggregating individual log messages into feature vectors represents a fundamentally new approach, because the current way of working is predominantly based on parsing individual log messages. This noticeably required a shift in the way of thinking about anomaly detection: The current manual approach is based on loosely defined decision trees and does not always directly translate into an approach where many messages are aggregated into a single feature vector. Once this mind-shift was made, there was a general enthusiasm for the ambition to detect anomalies across a much wider scope than currently is possible. Even without reliable anomaly detection, the possibility to get quick insight in essential aspects of infrastructure behaviour is considered an important benefit.

A concern that was voiced is that it might not always be possible to distinguish between security related anomalies and more generic fault and performance related incidents. This would imply the need for a closer cooperation between network- and security-operations to follow up on alarms.

4.4 On the design choices

In the eyes of experts, ***both historic profiling and group profiling are useful***. Group profiling is viewed as specifically promising for groups of machines that have identical functions, and can thus be expected to behave similarly (e.g. parallel DNS servers). Other systems are expected to behave very differently depending on the task they are given (e.g. generic servers), and are therefore less suitable for group profiling. The general opinion was the diversity in user-types is too big to cluster them into groups at all, without generating a lot of false anomalies.

Users, systems and applications are mentioned most frequently as entities for which profiles can be constructed. Of course, the latter categories are somewhat fluid, as network functionality is shifting from hardware to software. Also, profiles could be generated for entities in different layers of software stacks (e.g. network, host OS, hypervisor, OS, application).

It is clear that ***data preparation requires substantial domain expertise***. When examining sample data (see next chapter), single fields in log messages turned out to carry multiple meanings that could be mapped to multiple parameters. Other, complex fields could be simplified into a limited number of categories.

Concerning the discretization time interval over which vectors are collected: ***both day and hour were suggested as an appropriate aggregation interval***, with the caveat that the time of day would have to be factored in somehow since user behaviour changes significantly during the day (e.g. office hours vs. non-office hours). Another suggestion was to make the time configurable, so that experiments could show which interval produces the best results.

Much of the discussion went into possible definitions of feature vectors and which anomalies should lead to alarms. Details of this input are reflected both in the previous and the following chapter. At a high level three groups of clusters were identified

- ***Absolute indicators***: events that regardless of their context or history reflect strange behaviour that should be investigated (e.g. source ports below 1024, users performing local login on different locations at the same time)
- ***Context related indicators***: certain events are normal in one context but not in another (e.g a user process that starts when no user is logged in or a successful Kerberos logon that is not followed by more Kerberos messages).
- ***Indicators that mark a change in behaviour***: These are perhaps the most interesting, as they are hard to capture using conventional methods.

Of course it depends on the way definitions are chosen, but for most (but not all) of the parameters suggested, upward deviations are more interesting than downward deviations. Lower-than-historic values can have many mundane reasons (e.g. an off-site day or sick leave), but legitimate scenarios for a sharp rise are considerably less likely.

5 Model verification with a real-life dataset

An important part of the design process is the verification of the proposed solution, by implementing it in code and testing it on a realistic dataset. Regrettably, no real ISP data could be used. This type of data is extremely security-and privacy-sensitive, and can therefore only be processed within a secured environment, and only for the purpose for which it was collected. The effort required for normalizing and anonymizing a sufficiently large volume to test the proposed model falls beyond the boundaries for this study. Fortunately, after a survey of publicly available databases, a good alternative was found in the Los Alamos dataset.

5.1 The Los Alamos dataset

The Los Alamos National Laboratory is a national facility in the New Mexico desert, where fundamental research is conducted relating to national security of the USA. It employs over 10.000 staff and nearly 1000 students (Wikipedia, 2016). The Los Alamos dataset was created by Alexander Kent (Kent, 2015), and consists of logging from different sources collected at Los Alamos, during 58 consecutive days in 2015. The data was painstakingly anonymized and normalized. The result is that an entity with a certain name in logging from one source carries the same name in another data set, which makes correlation between events from different sources possible. Another feature that makes the set suitable for the purpose of this study is its size: With over 1.6 billion events it provides a good test to ascertain that the proposed algorithms scale effectively. Finally, the data was collected from five different sources that give a realistic representation of what will be found in an ISP infrastructure:

- ***Authentication*** is by far the largest subset. It contains over 1 billion authentication events collected from individual windows based PC's and Active Directory Servers. Events can be initiated both by computers and by users, and can be both local (within one machine) or non-local.
- The ***processes*** set contains start and stop events of Windows processes, also collected on desktop PC's and servers. The processes are anonymized: As an example, all "install.exe" events are represented by "P16", regardless of the location they were executed from.
- ***Network Flow*** events are recorded only for the first 29 days, due to a configuration error. Kent describes flow data as potentially very valuable, but hard to obtain with sufficient quality in real life conditions. Apparently, this is an aspect in which enterprise- and ISP-operations differ: In ISP's Netflow logging is closely monitored because it is essential for adequate DDoS protection. However, Netflow data is often sampled because logging every individual event has too much impact on operational performance.
- ***DNS*** data is collected from three central DNS servers in the network. To avoid performance impact, logging was created using passive network taps. Unfortunately, two out of three taps did not generate logging until the 28th day of the recording period due to invalid configurations. Only DNS lookups inside the Los Alamos infrastructure are represented; there are no records of queries to or from the Internet.
- The ***RedTeam*** data consists of time and target descriptions of ethical hacking events initiated by the Los Alamos Red Team. They used "stolen" credentials to gain access to accounts; other than that no information is available on the Red Teams' exploits.

The table below gives an overview of the data contained in the different sets:

	auth.txt	proc.txt	flows.txt	dns.txt	redteam.txt
File size (kB, uncompressed)	71.692.402	15.036.672	5.114.443	793.689	23
# Events	1.051.430.459	426.045.096	129.977.412	40.821.591	749
Time	x	x	x	x	x
Duration			x		
Source user	x	x			x
Source computer	x	x	x	x	x
Source port			x		
Destination user	x				
Destination computer	x		x	x	x
Destination port			x		
Authentication type	x				
Logon type	x				
Auth. orientation	x				
Success/failure	x				
Process name		x			
Start/end		x			
Protocol			x		
Packet count			x		
Byte Count			x		

5.2 Experimental setup

The Los Alamos dataset is distributed in five comma separated text files (one for each sub set), each containing data for the entire test period of 58 days. As depicted in Figure 16, the software to process it was constructed in three main modules, reflecting the steps in which operations would be performed in a truly stream based setting. Data for visualization was prepared using Python scripts, but the actual graphs were created in Microsoft Excel. Programming was done in Python v2.7, using the standard Pandas and Pytables Libraries. The code (all in all several thousand lines) was edited and run using Jupyter notebook.

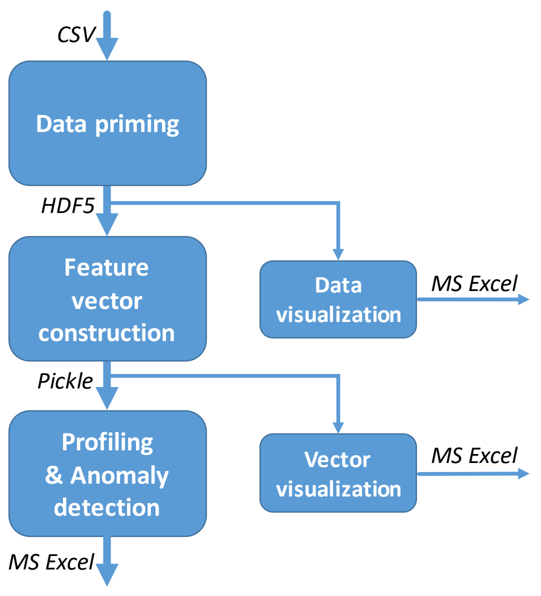


Figure 16. Modular construction of the test solution

Computing was performed on a server at the Leiden Institute of Advanced Computer Science (LIACS), the Octiron server (octiron.liacs.nl), containing 16 Intel Xeon E5-2630v3 CPU's @ 2.40Ghz and 512 GB RAM. For remote access both the Putty and WinSCP SSH clients where used.

5.3 Data understanding

The remainder of this chapter will closely follow the steps described in chapter 3, and apply them to the Los Alamos data. The first, important step is data understanding. One part of this is visualization, another is reading the available documentation. Perhaps the most important element is talking to domain experts. Although these steps have each been followed, is important to note here that the data understanding that can be achieved with anonymized, external data, without access to the responsible people, does not come close to what would be possible with in-company data. Nevertheless, it proved an essential step toward the application of the model.

5.3.1 Authentication

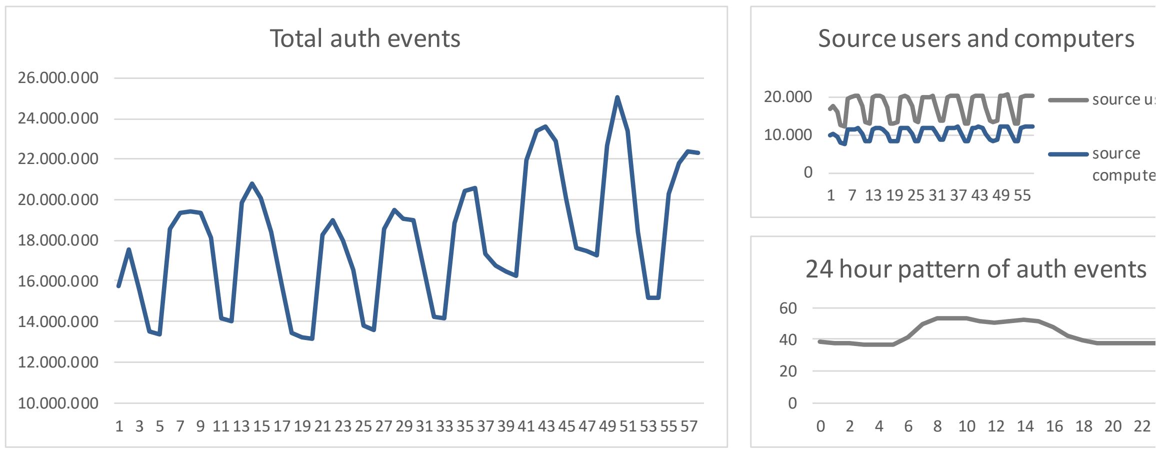


Figure 17. Authentication events during the test period

The authentication data has been gathered during the whole collection period of 58 days. As can be seen in Figure 17, the weekday/weekend cycle is clearly visible. However, the fluctuations are relatively small (the y-axis has been cut). This could imply that roughly half the staff works through the weekend, of that a significant part of the authentication events is unrelated to direct human activity. The same can be concluded from the 24 hour pattern shown on the bottom right.

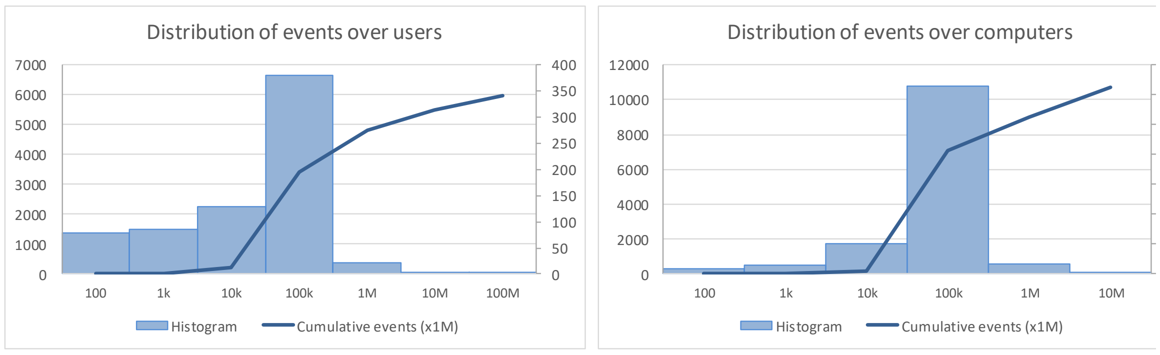


Figure 18. Histogram of events over users and computers

In Figure 18 two histograms are shown that illustrate that there is a wide spread in the activity of users and computers. The bars depict the number of user/of computers per activity bin (left y-axis). Note that the bin sizes on the x-axis are logarithmic. On the lower extreme, there are users and computers that generate only a single event during the entire 58 collection period. At the other end of the scale there are entities that appear in millions of logs. The curves depict the cumulative contribution of each group to the total number of events (right y-axis). The top 5% users generate 48% of all events. For computers this is 35%.

The authentication set contains some details about the authentication request. Figure 19 shows which different types of authentication protocols and logons are present in the dataset. Logon and logoff are roughly in equilibrium.

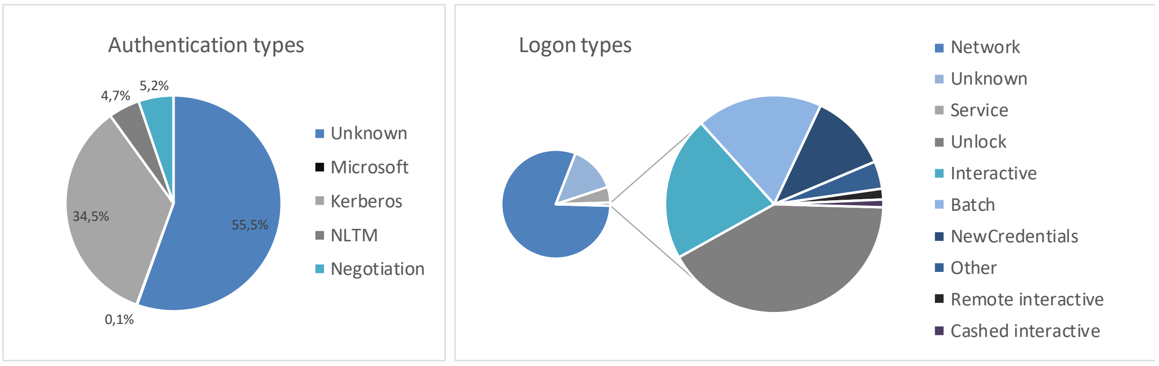


Figure 19. Authentication- and logon type distribution in the authentication dataset

5.3.2 Process start and stop events

Figure 21 shows three time series for the process start- and stop events. It is immediately visible that there are two volume peaks, on day 15 and 51. Closer inspection shows that these are exclusively caused by computer accounts, and that the rise is spread over many different accounts that as a group start more distinct processes. This is an example where background information is lacking: It is likely that two network related events took place (for instance a monthly Windows update), but the author of the dataset does not mention it in his accompanying text. Because he uses an exponential scale the peaks are far less visible in his graph.

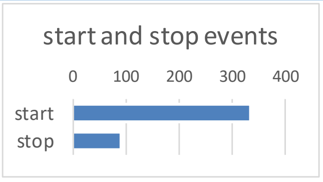


Figure 20 Start vs stop events

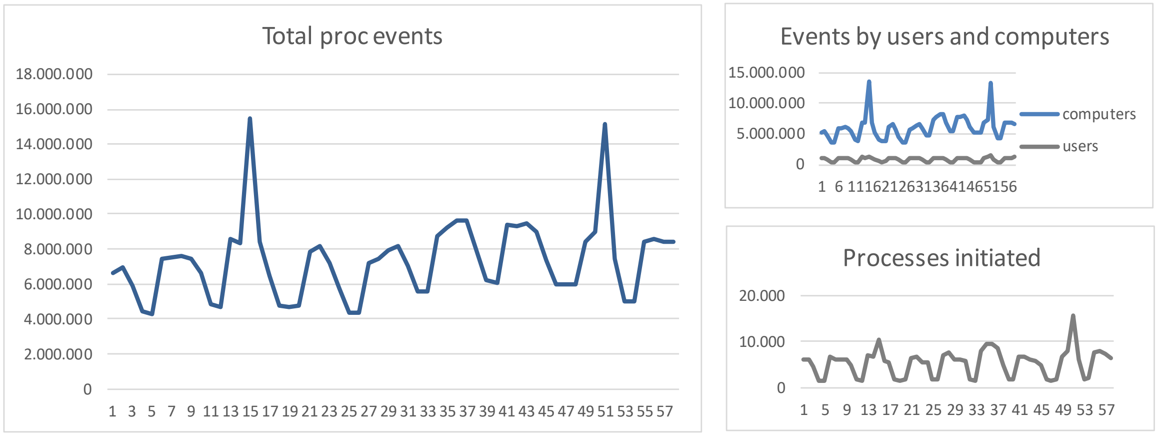


Figure 21 Time series for the process start/stop data

The logging shows a significant imbalance between the logged start-and stop events. Regrettably, it appears that not all stop events are logged (see Figure 20). This makes it impossible to reliably keep track of the processes that are running under each account.

5.3.3 Netflow data

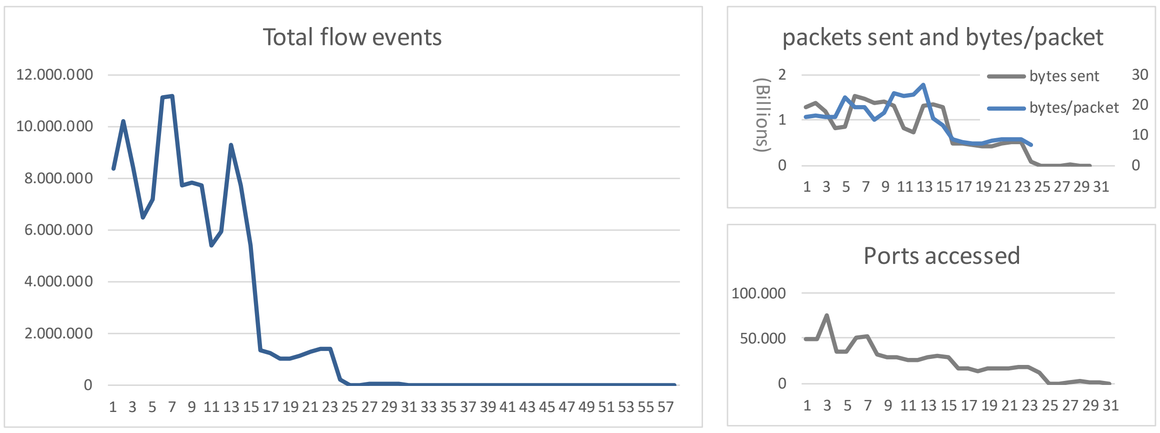


Figure 22 Time series for the netflow dataset

As already indicated by the author of the dataset, netflow data was only recorded for the first 29 days. Judging from the graphs in Figure 22, effective collection stopped before even that. The bytes per packet show interesting fluctuations, but given the questionable data collection, it is unsure whether this represents real network behaviour or is an artefact created by the collection mechanism.

5.3.4 DNS events

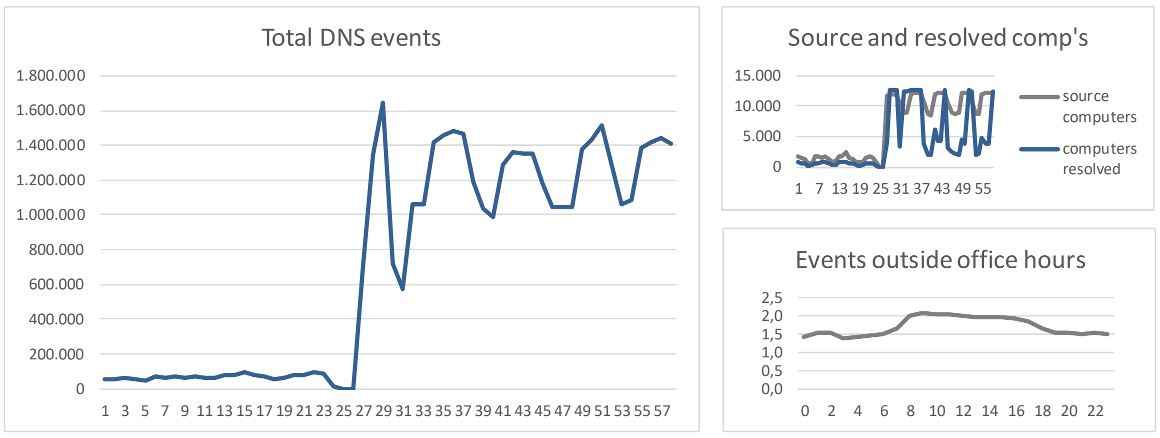


Figure 23. Time series for DNS events

Although Kent indicated that two out of three DNS loggers only became operational after 27 days, this does not fully explain how events developed over time, as shown in Figure 23 (unless the first DNS carried about a fifth of the load of the other two and handled only traffic that was totally weekday/weekend agnostic). After day 27, the data shows clear week- and day patterns, but only as a fluctuation on a much larger, stable baseline. The figure on the top right shows that the number of distinct source computers per day shows a regular pattern, while the number of computers resolved fluctuates much more.

Combining this paragraph with the previous one, it is evident that there is no overlap between the days that DNS and the netflow logging are fully operational.

5.3.5 Red Team Events

No regular pattern was expected in the Red Team data, and none was found. The team had two peaks in activity, unfortunately in the beginning of the recording period. 749 events were initiated from 98 different user accounts. Only four source computers were used, but 301 different destination computers were targeted.

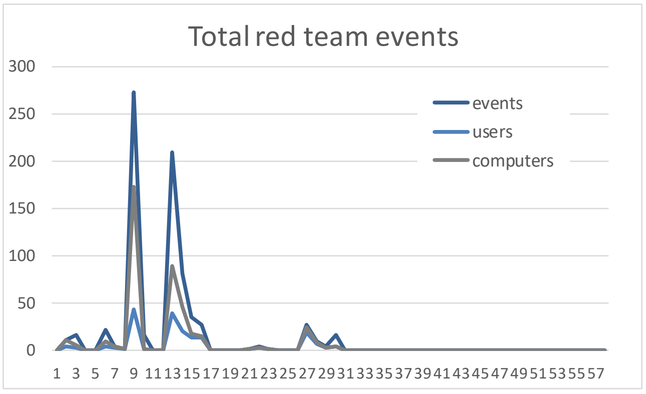


Figure 24. Time series of red team events

5.4 Interdependencies

Another way of looking at the data is by looking at the interdependencies between variables. Figure 25 shows two examples of scatterplots. From the graph on the left it can be read that there is a clear relation between the number of authentication events in a given hour (x-axis) and the number of distinct source computers (y-axis) initiating these events. On the other hand, the relation between the number of authentication events and the number of flow events is much less clear (graph on the right). Given the fact that different areas with strong correlation seem visible, this may be an artefact of the deficient collection of flow data. Figure 26 depicts the calculated interdependencies between all the parameters in a correlation matrix. A darker colour implies a stronger correlation and negative correlations are depicted in red. A larger version of this plot in included in Appendix C.

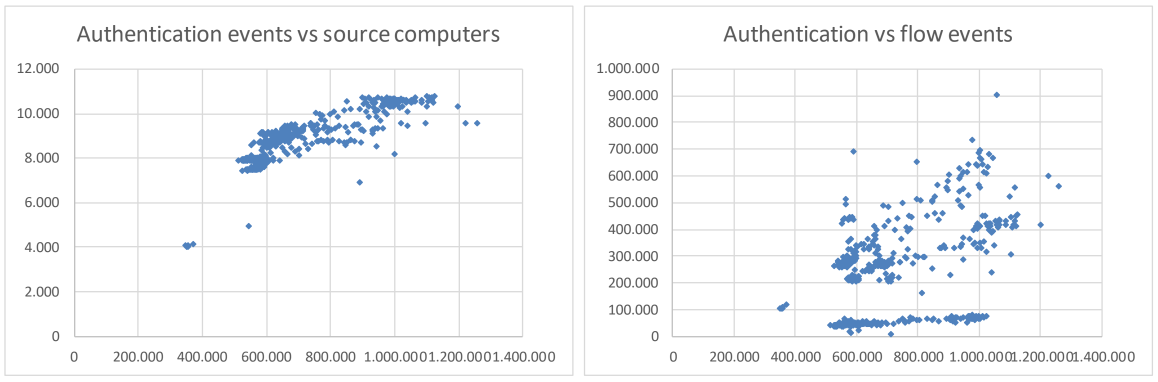
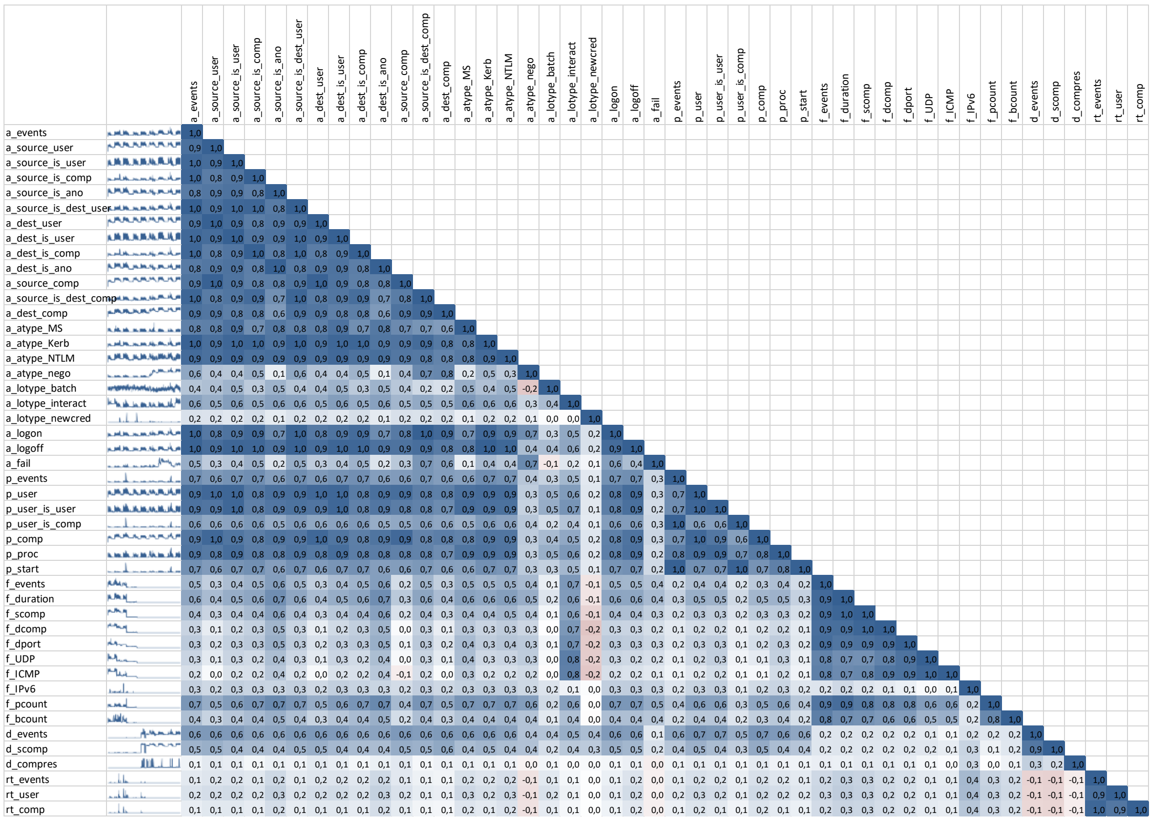


Figure 25. Examples of two scatterplots visualizing the relationships between parameters



	a_events	a_source_user	a_source_is_user	a_source_is_comp	a_source_is_ano	a_source_is_dest_user	a_dest_user	a_dest_is_user	a_dest_is_comp	a_dest_is_ano	a_source_comp	a_source_is_dest_comp	a_dest_comp	a_atype_MS	a_atype_Kerb	a_atype_NTLM	a_atype_nego	a_lotype_batch	a_lotype_interact	a_lotype_newcred	a_logon	a_logoff	a_fail	p_events	p_user	p_user_is_user	p_user_is_comp	p_comp	p_proc	p_start	f_events	f_duration	f_scomp	f_dcomp	f_dport	f_UDP	f_ICMP	f_IPv6	f_pcount	f_bcount	d_events	d_scomp	d_compres	rt_events	rt_user	rt_comp
a_events	1,0																																													
a_source_user	0,9	1,0																																												
a_source_is_user	1,0	0,9	1,0																																											
a_source_is_comp	1,0	0,8	0,9	1,0																																										
a_source_is_ano	0,8	0,9	0,9	0,8	1,0																																									
a_source_is_dest_user	1,0	0,9	1,0	1,0	0,8	1,0																																								
a_dest_user	0,9	1,0	0,9	0,8	0,9	0,9	1,0																																							
a_dest_is_user	1,0	0,9	1,0	0,9	0,9	1,0	0,9	1,0																																						
a_dest_is_comp	1,0	0,8	0,9	1,0	0,8	1,0	0,8	0,9	1,0																																					
a_dest_is_ano	0,8	0,9	0,9	0,8	1,0	0,8	0,9	0,9	0,8	1,0																																				
a_source_comp	0,9	1,0	0,9	0,8	0,8	0,9	1,0	0,9	0,8	0,8	1,0																																			
a_source_is_dest_comp	1,0	0,8	0,9	0,9	0,7	1,0	0,8	0,9	0,9	0,7	0,8	1,0																																		
a_dest_comp	0,9	0,9	0,8	0,8	0,6	0,9	0,9	0,8	0,8	0,6	0,9	0,9	1,0																																	
a_atype_MS	0,8	0,8	0,9	0,7	0,8	0,8	0,8	0,9	0,7	0,8	0,7	0,7	0,6	1,0																																
a_atype_Kerb	1,0	0,9	1,0	1,0	0,9	1,0	0,9	1,0	1,0	0,9	0,9	0,9	0,8	0,8	1,0																															
a_atype_NTLM	0,9	0,9	0,9	0,9	0,9	0,9	0,9	0,9	0,9	0,9	0,9	0,8	0,8	0,8	0,9	1,0																														
a_atype_nego	0,6	0,4	0,4	0,5	0,1	0,6	0,4	0,4	0,5	0,1	0,4	0,7	0,8	0,2	0,5	0,3	1,0																													
a_lotype_batch	0,4	0,4	0,5	0,3	0,5	0,4	0,4	0,5	0,3	0,5	0,4	0,2	0,2	0,5	0,4	0,5	-0,2	1,0																												
a_lotype_interact	0,6	0,5	0,6	0,5	0,6	0,6	0,5	0,6	0,5	0,6	0,5	0,5	0,5	0,6	0,6	0,6	0,3	0,4	1,0																											
a_lotype_newcred	0,2	0,2	0,2	0,2	0,1	0,2	0,2	0,2	0,2	0,1	0,2	0,2	0,2	0,1	0,2	0,2	0,1	0,0	0,0	1,0																										
a_logon	1,0	0,8	0,9	0,9	0,7	1,0	0,8	0,9	0,9	0,7	0,8	1,0	0,9	0,7	0,9	0,9	0,7	0,3	0,5	0,2	1,0																									
a_logoff	1,0	0,9	1,0	1,0	0,9	1,0	0,9	1,0	1,0	0,9	0,9	0,9	0,8	0,8	1,0	1,0	0,4	0,4	0,6	0,2	0,9	1,0																								
a_fail	0,5	0,3	0,4	0,5	0,2	0,5	0,3	0,4	0,5	0,2	0,3	0,7	0,6	0,1	0,4	0,4	0,7	-0,1	0,2	0,1	0,6	0,4	1,0																							
p_events	0,7	0,6	0,7	0,7	0,6	0,7	0,6	0,7	0,7	0,6	0,6	0,7	0,6	0,6	0,7	0,7	0,4	0,3	0,5	0,1	0,7	0,7	0,3	1,0																						
p_user	0,9	1,0	1,0	0,8	0,9	0,9	1,0	1,0	0,8	0,9	0,9	0,8	0,8	0,9	0,9	0,9	0,3	0,5	0,6	0,2	0,8	0,9	0,3	0,7	1,0																					
p_user_is_user	0,9	0,9	1,0	0,8	0,9	0,9	0,9	1,0	0,8	0,9	0,8	0,8	0,7	0,9	0,9	0,9	0,3	0,5	0,7	0,1	0,8	0,9	0,2	0,7	1,0	1,0																				
p_user_is_comp	0,6	0,6	0,6	0,6	0,5	0,6	0,6	0,6	0,6	0,5	0,5	0,6	0,6	0,5	0,6	0,6	0,4	0,2	0,4	0,1	0,6	0,6	0,3	1,0	0,6	0,6	1,0																			
p_comp	0,9	1,0	0,9	0,8	0,9	0,9	1,0	0,9	0,8	0,9	0,9	0,8	0,8	0,8	0,9	0,9	0,3	0,4	0,5	0,2	0,8	0,9	0,3	0,7	1,0	0,9	0,6	1,0																		
p_proc	0,9	0,8	0,9	0,8	0,8	0,9	0,8	0,9	0,8	0,8	0,8	0,8	0,7	0,9	0,9	0,9	0,3	0,5	0,6	0,2	0,8	0,9	0,2	0,8	0,9	0,9	0,7	0,8	1,0																	
p_start	0,7	0,6	0,7	0,7	0,6	0,7	0,6	0,7	0,7	0,6	0,6	0,7	0,6	0,6	0,7	0,7	0,3	0,3	0,5	0,1	0,7	0,7	0,2	1,0	0,7	0,7	1,0	0,7	0,8	1,0																
f_events	0,5	0,3	0,4	0,5	0,6	0,5	0,3	0,4	0,5	0,6	0,2	0,5	0,3	0,5	0,5	0,5	0,4	0,1	0,7	-0,1	0,5	0,5	0,4	0,2	0,4	0,4	0,2	0,3	0,4	0,2	1,0															
f_duration	0,6	0,4	0,5	0,6	0,7	0,6	0,4	0,5	0,6	0,7	0,3	0,6	0,4	0,6	0,6	0,6	0,5	0,2	0,6	-0,1	0,6	0,6	0,4	0,3	0,5	0,5	0,2	0,5	0,5	0,3	0,9	1,0														
f_scomp	0,4	0,3	0,4	0,4	0,6	0,4	0,3	0,4	0,4	0,6	0,2	0,4	0,3	0,4	0,4	0,5	0,4	0,1	0,6	-0,1	0,4	0,4	0,3	0,2	0,3	0,3	0,2	0,3	0,3	0,2	0,9	1,0	1,0													
f_dcomp	0,3	0,1	0,2	0,3	0,5	0,3	0,1	0,2	0,3	0,5	0,0	0,3	0,1	0,3	0,3	0,3	0,3	0,0	0,7	-0,2	0,3	0,3	0,2	0,1	0,2	0,2	0,1	0,2	0,2	0,1	0,9	0,9	1,0	1,0												
f_dport	0,3	0,2	0,3	0,3	0,5	0,3	0,2	0,3	0,3	0,5	0,1	0,3	0,2	0,4	0,3	0,4	0,3	0,1	0,7	-0,2	0,3	0,3	0,3	0,2	0,3	0,3	0,1	0,2	0,3	0,2	0,9	0,9	0,9	0,9	1,0											
f_UDP	0,3	0,1	0,3	0,2	0,4	0,3	0,1	0,3	0,2	0,4	0,0	0,3	0,1	0,4	0,3	0,3	0,3	0,0	0,8	-0,2	0,3	0,2	0,2	0,1	0,2	0,3	0,1	0,1	0,3	0,1	0,8	0,7	0,7	0,8	0,9	1,0										
f_ICMP	0,2	0,0	0,2	0,2	0,4	0,2	0,0	0,2	0,2	0,4	-0,1	0,2	0,0	0,3	0,2	0,2	0,2	0,0	0,8	-0,2	0,2	0,2	0,1	0,1	0,2	0,2	0,1	0,1	0,2	0,1	0,8	0,7	0,8	0,9	0,9	1,0	1,0									
f_IPv6	0,3	0,2	0,3	0,3	0,3	0,3	0,2	0,3	0,3	0,3	0,2	0,3	0,2	0,3	0,3	0,3	0,3	0,2	0,1	0,0	0,3	0,3	0,3	0,2	0,3	0,3	0,1	0,2	0,3	0,2	0,2	0,2	0,2	0,1	0,1	0,0	0,1	1,0								
f_pcount	0,7	0,5	0,6	0,7	0,7	0,7	0,5	0,6	0,7	0,7	0,4	0,7	0,5	0,7	0,7	0,7	0,6	0,2	0,6	0,0	0,7	0,7	0,5	0,4	0,6	0,6	0,3	0,5	0,6	0,4	0,9	0,9	0,8	0,8	0,8	0,6	0,6	0,2	1,0							
f_bcount	0,4	0,3	0,4	0,4	0,5	0,4	0,3	0,4	0,4	0,5	0,2	0,4	0,3	0,4	0,4	0,4	0,4	0,1	0,4	0,0	0,4	0,4	0,4	0,2	0,4	0,4	0,2	0,3	0,4	0,2	0,8	0,7	0,7	0,6	0,6	0,5	0,5	0,2	0,8	1,0						
d_events	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,4	0,4	0,5	0,4	0,6	0,6	0,1	0,6	0,7	0,7	0,5	0,7	0,6	0,6	0,2	0,2	0,2	0,2	0,2	0,1	0,1	0,2	0,2	0,2	1,0					
d_scomp	0,5	0,5	0,4	0,4	0,4	0,5	0,5	0,4	0,4	0,4	0,5	0,5	0,6	0,4	0,5	0,4	0,4	0,2	0,4	0,3	0,5	0,5	0,2	0,4	0,5	0,4	0,3	0,5	0,4	0,4	0,2	0,2	0,2	0,2	0,2	0,2	0,1	0,3	0,1	0,2	0,9	1,0				
d_compres	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,0	0,1	0,0	0,0	0,1	0,1	0,0	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,0	0,3	0,0	0,1	0,3	0,2	1,0			
rt_events	0,1	0,2	0,2	0,1	0,2	0,1	0,2	0,2	0,2	0,2	0,1	0,1	0,1	0,2	0,2	0,2	-0,1	0,1	0,1	0,0	0,1	0,2	0,0	0,1	0,2	0,2	0,1	0,2	0,2	0,1	0,2	0,3	0,3	0,2	0,2	0,1	0,1	0,4	0,3	0,2	-0,1	-0,1	-0,1	1,0		
rt_user	0,2	0,2	0,2	0,2	0,3	0,2	0,2	0,2	0,2	0,3	0,2	0,1	0,1	0,3	0,2	0,3	-0,1	0,2	0,1	0,0	0,1	0,2	0,0	0,2	0,3	0,2	0,1	0,2	0,2	0,2	0,3	0,3	0,3	0,2	0,2	0,1	0,1	0,4	0,3	0,2	-0,1	-0,1	-0,1	0,9	1,0	
rt_comp	0,1	0,1	0,1	0,1	0,2	0,1	0,1	0,1	0,1	0,2	0,1	0,1	0,1	0,2	0,1	0,2	-0,1	0,1	0,1	0,0	0,1	0,2	0,0	0,1	0,2	0,1	0,1	0,2	0,1	0,1	0,2	0,3	0,3	0,2	0,2	0,1	0,1	0,4	0,3	0,2	-0,1	-0,1	-0,1	1,0	0,9	1,0

Figure 26. Correlation matrix between all primed variables in the dataset

5.5 Design and implementation of the model

The implementation of the model for the Los Alamos dataset is presented here as a chronological process. In reality there was an iterative progression through the different steps, starting from the output desired by domain experts, tracing back to the available input and then back and forth as intermediate results became available.

5.5.1 Data priming

The bulk of the data priming for the Los Alamos dataset was already performed by the creator of the set, Alexander Kent. However, additional priming was implemented to speed up data retrieval and simplify downstream processing. Loading and parsing large comma separated text files takes considerable time, while other formats load much faster. After some experimentation, the HDF5 format was selected to store the primed datasets (HDF5 Home Page, 2016), which enabled loading data into memory in minutes rather than hours from the original CSV files.

Some other pre-processing was done to prepare data for easy calculation of the feature vectors:

- The time in seconds was translated into day and hour values and a boolean indicating whether an event took place outside office hours (chosen as 18:00-7:00).
- "User/computer@domain" parameters were parsed to obtain the distinct user and computer identifiers (the part before the "@" sign).
- Booleans were added to indicate whether accounts belonged to a user or a computer.
- Fields with a limited number of potential values were translated to booleans for easy aggregation. As an example: the "protocol" field in the netflow data was translated into three separate booleans (f_UDP, f_ICMP and f_ IPv6), which are True if respectively UDP, ICMP or IPv6 are used as a protocol.
- In some cases, details that were not considered relevant by domain experts were dropped. For instance, all variations of Microsoft authentication protocols were clustered into a single "MS" property.

Since storage or system memory were not seen as limiting factors, no effort was made to reduce the volume of the dataset. Appendix A gives a full overview of how the original data set was primed for further processing.

5.6 Buffer

Domain experts proposed buffering times in the range from one hour to one day. After a visual examination of the data it was decided to start with a 24 hour interval. Figure 27 demonstrates why: the graph shows the time series for a single parameter (the number of authentication events per minute), for four typical user accounts during the first 3 days. With a time interval of an hour many of the observed, seemingly random, peaks would appear anomalous, potentially clogging up the system with false alarms. Of course, this is only an informed way to select a sensible interval to start trials with. In a real implementation, this first estimate would be followed by experiments with different time intervals to find the optimum value.

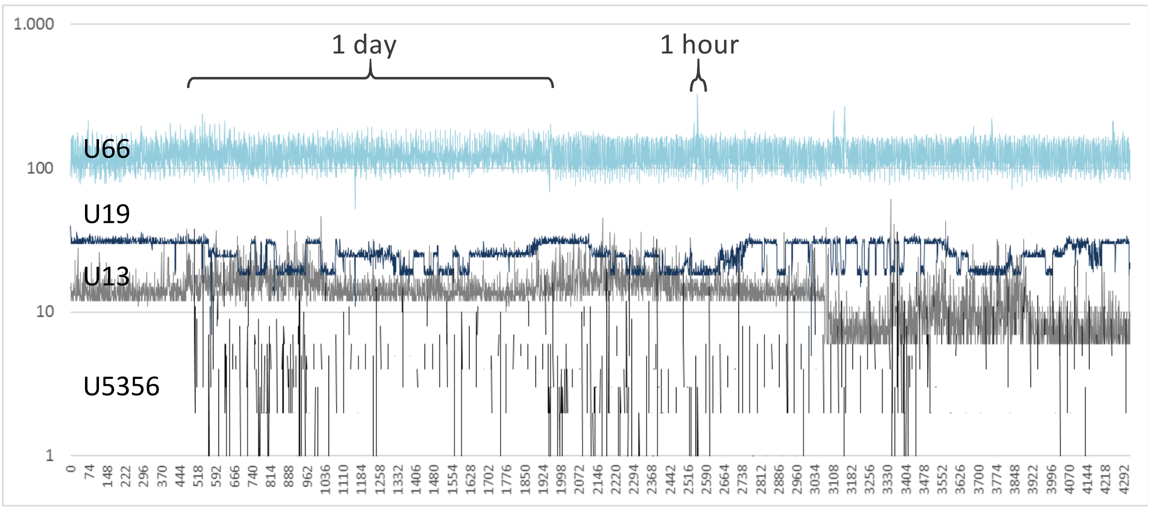


Figure 27. Three-day event time series for four typical user accounts

5.6.1 Feature vector construction

In consultation with domain experts, it was decided to construct feature vectors for both user and computer entities. As can be seen in the table in paragraph 5.1, the “user” parameter appears in only 3 datasets. This means that user feature vectors were constructed from authentication and process data, with Red Team data added as a reference. Since computer names appear in all 5 sets, the computer feature vectors are built from all five sources, with the caveat that the DNS and Flow sets are incomplete.

Feature vectors were composed based on expert input and the available data. Because of the experimental nature of this study, many different parameters were included without advance selection. This resulted in feature vectors that are perhaps un-economically long, with the assumption that parameters that turn out not to contribute to successful anomaly detection can be discarded later. Initial length is 29 parameters for the user vectors and 45 for the computer vectors.

The table below summarizes how the different parameter types described in paragraph 3.7 are implemented for the Los Alamos dataset. A full overview of the user- and computer vectors can be found in Appendix B.

Parameter type	Description
Direct internal parameters	Straightforward parameters were included for most of the elements in the primed data (e.g. the number of authentication events or the percentage of events using the NLTM protocol)
Distinct element count	Domain experts consider distinct element count an important way to describe entity behaviour. Counts were included for: - Users (both as source and as destination) - Computers (idem) - Port-numbers - Processes Element count was implemented by building sets for each parameter for each user and establishing their length at the end of each interval.
External parameters	No external parameters were included with the dataset.
Calculated parameters	Several conditional parameters were included in the vectors, for instance: - The number of events initiated with a low port number (<1024) - Percentage of authentication events where source- and destination-domain are not the same - A conditional parameter that represents the number of distinct user domains the user has unsuccessfully tried to access. - Another parameter that gives the number of computers that have been communicated with without a DNS request
Stateful parameters	Four stateful parameters were implemented: - The number of successful logons minus logoffs accumulated over the logging period (with a minimum value of zero) - The number of processes started minus the processes stopped, accumulated over the logging period (min=0) - The number of computers the user has accessed that have not been accessed in the previous n days - The number of processes the user started for the first time in n days These last two parameters were implemented by building a sliding window of sets for both parameters, with window size n=7 days.
Analysis based parameters	This is left for future work

5.7 Profile maintenance

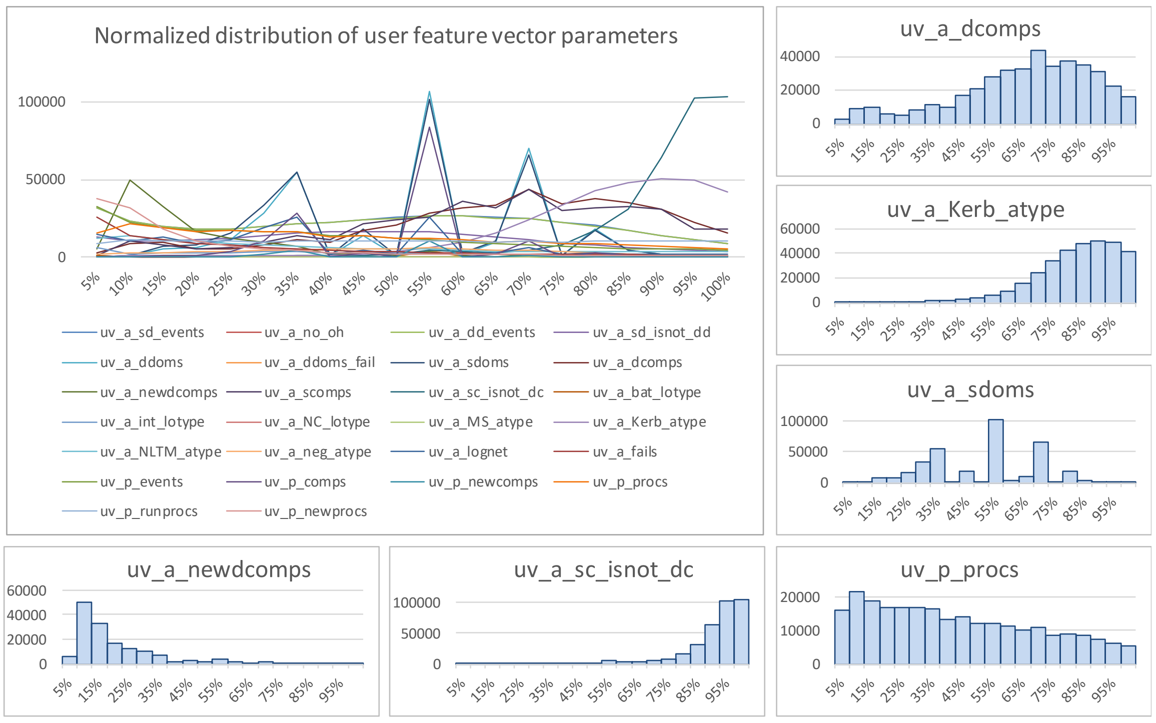


Figure 28. Normalized distribution of user feature vectors

To help understand how to detect anomalies based on the feature vectors in a profile, a visualization was made of the distribution of parameter values over the full 58 days of the test period[2]. Figure 28 shows the end result for all parameters in the user feature vector. Six typical parameters are also depicted as proper histograms for clearer reading. A similar graph for the computer vector can be found in Appendix D. Several aspects stand out:

- Most parameters show quite regular, "nice", distributions, but some (e.g. the number of distinct source domains shown on the right) have irregular histograms that are difficult to interpret without additional domain knowledge. Distributions for single users are likely to show more irregularities than the accumulated versions presented here.
- Parameters that are defined as percentages tend to be cut off on the right because no values over 100% are possible (e.g. the share of Kerberos authentication shown on the right or the percentage of events were source and destination computer are different at the bottom).
- Even the regular distributions have no common shape.

These arguments led to the conclusion that describing profiles by mapping values to one (or a few) standard statistical distributions appears unfeasible. The Python code for profile maintenance and anomaly detection is prepared for the use of different statistical methods per parameter; however only the interquartile range method was actually implemented.

In consultation with domain experts the training period was initially set to 14 days, which means that the hinges of the Q1 and Q3 quartiles lie at position 4 and 11. As can be seen from the graphs in paragraph 5.3, training 14 days before starting actual anomaly detection means that little use can be

[2] To prevent the most active entities from dominating the outcome, distributions were first normalised per user/parameter and then added together to yield the final result. This required a two-pass approach: A first pass to determine the maximum value per user per parameter throughout the test period, and a second pass to calculate the normalized distributions.

made of the Netflow and Red Team data in the analysis. For this reason, analysis will also be attempted with a shorter sliding window of 7 days, with hinges at positions 2 and 6.

5.8 Anomaly detection

Anomaly scores for the test set were calculated as described in paragraph 3.9, following this structure (in pseudo code with user as the chosen entity):

```
for each day:
   for each user with a complete profile:
      for each parameter in the users feature vector:
         determine parameter anomaly score
      determine over-all anomaly score from parameter anomalies
```

Since not all users/computers are active during every day, not all training periods end on the same day and the start of actual anomaly detection differs from entity to entity. No provisions were made for entities with missing intervals after their first appearance: for days that no input was received all vector values were set to zero.

The anomaly scores per day/entity/parameter were calculated by calculating the distance of the current parameter value from Q3, and comparing this distance to the Inter Quartile Range (IQR, the difference between Q3 and Q1). Because an analog anomaly score was preferred over a simple binary outlier test, the score was calculated as a ratio minus a threshold value *t*:

$$Anomaly\ score_{day,entity,parameter} = max\left(\frac{Current\ value\ -\ Q_3}{Q_3 -\ Q_1} - t_{parameter}, 0\right) \qquad (Q3 > Q1)$$

In line with common practice the value of the threshold was initially set at 1.5 for all parameters. For values below this point the anomaly score was set at zero. Only upward deviations were calculated.

A special measure had to be taken to account for divisions by zero. The first anomaly calculation attempt returned a number of infinite values. Analysis showed that these were caused by parameters that remained constant (often zero) for enough days for Q3 to become equal to Q1, resulting in an inter-quartile range of zero. After some experimentation and analysis of data samples, a new variable *z* was introduced to prevent these exceptions from muddying the overall scores:

$$Anomaly\ score_{day,entity,parameter} = max\left((Current\ value - Q3)\cdot z_{parameter}, 0\right) \qquad (Q3 = Q1)$$

Total anomaly scores per day/entity were calculated by taking the sum of the products of the parameter-anomaly scores and their weight factors *w*:

$$Anomaly\ score_{day,entity} = \sum_{parameters} Anomaly\ score_{day,entity,parameter} \cdot w_{parameter}$$

The resulting model has three sets of variables for each parameter that can be tuned to optimize model performance: the threshold *t*, weight factor *w* and parameter *z* that determines how steps after a period of stability are scored.

5.9 Results

To determine the initial values of the values in the model, some pragmatic choices were made:

- Sliding window size was set at 14 days.
- The threshold value in the IQR anomaly detection was set at *t*=1.5 for al parameters, in line with common practice.
- A more complex puzzle was how to score the exceptional cases were IQR=0. After some trial and error, a pragmatic choice was made: The values of *z* were chosen in such a way that the highest "exception" anomaly score was awarded twice the value of the highest observed "normal" score for each parameter[3]. The reasoning behind this heuristic is that sudden steps are important, but should not entirely dominate the overall outcome.
- The weight factors were determined in two steps: First, the values of *w* were chosen in such a way that all parameters in the vector contributed evenly to the overall anomaly score[4]. Second, five parameters that were considered specifically relevant by domain experts[5] were awarded a double weighting in the over-all score.

5.9.1 User anomaly scores

The over-all user anomaly scores, calculated with the system parameters initialized as described in the previous paragraph, are shown in Figure 29. After the initial 2-week training period, the week pattern is clearly recognizable (there are fewer anomalies in the weekends, because only upward deviations are scored). The rising peaks at first resemble an artefact, but on closer inspection seem plausible when the trends in the source data are considered (see Figure 17 and Figure 21). Especially the peak on day 51 in the process start/stop data is clearly recognizable.

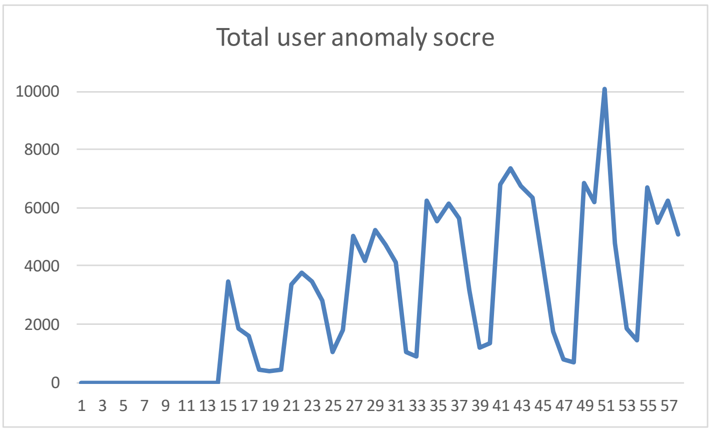


Figure 29. Total user anomaly score with 14 day sliding window

Figure 30 shows the breakdown of the over-all anomaly score to the contributing scores per parameter. Some interesting peaks are observed, that could serve as a starting point for further investigation. As an example, an analysis was made based on the interesting observation that there was a peak of failed logon anomalies on day 43. It turns out that 21 users generate the same, maximum anomaly score for that day. Their feature vector histories were extracted; Figure 31 shows the logon history for two of them. User U1040 has a regular pattern of successful logon attempts,

[3] This required two pre-detection runs: one where the anomaly scores of all "normal" cases were set at zero and *z*=1 (giving the maximum "steps" after a period of stability), and one where the exception values were set at zero (giving the values for "normal" scores). The value of *z* for each parameter was determined by dividing the two.

[4] This was done by first calculating anomalies with all weight factors at *w*=1. The total of all anomaly scores over all users and all day was then calculated for each parameter. Finally, the weight factors were determined by taking the inverse of this value.

[5] uv_a_ddoms_fail, uv_a_newdcomps, uv_a_fails, uv_p_newcomps and uv_p_newprocs

until on day 42/43 the volume drops and the success rate drops to near, but not totally, zero. U6242 has a more erratic history, but also drops both in volume and success rate on day 42. The dotted line shows that the percentage of Kerberos logons drops to zero on the same day.

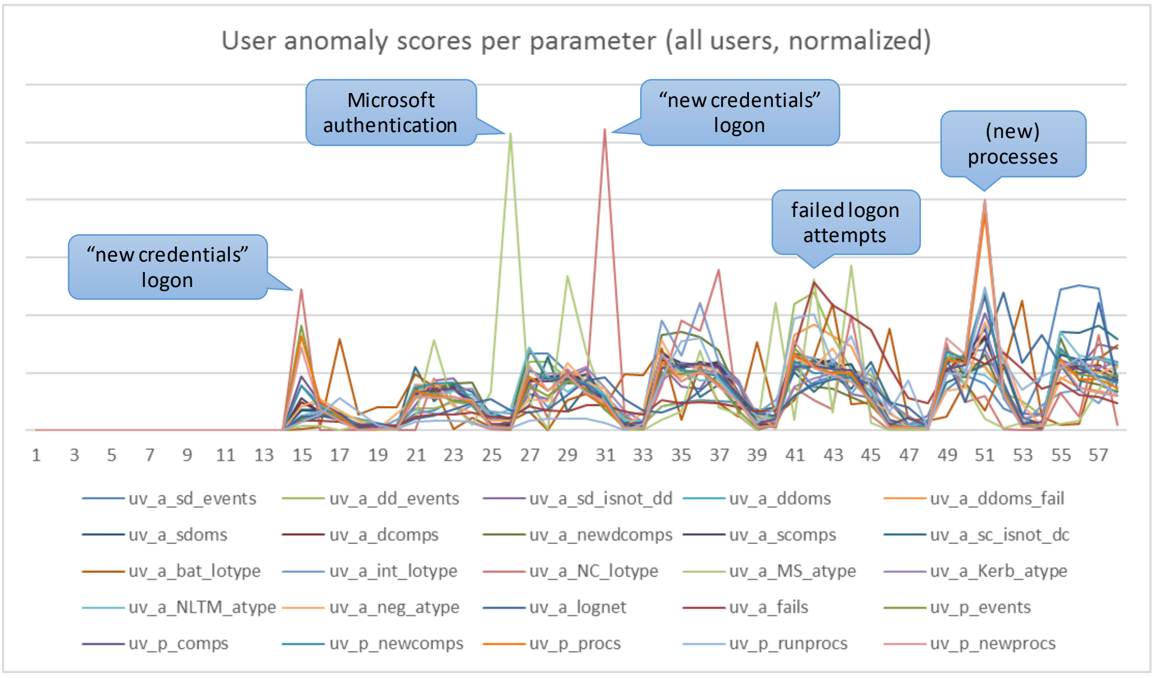


Figure 30. Normalized user anomaly scores per parameter, totalled over all users.

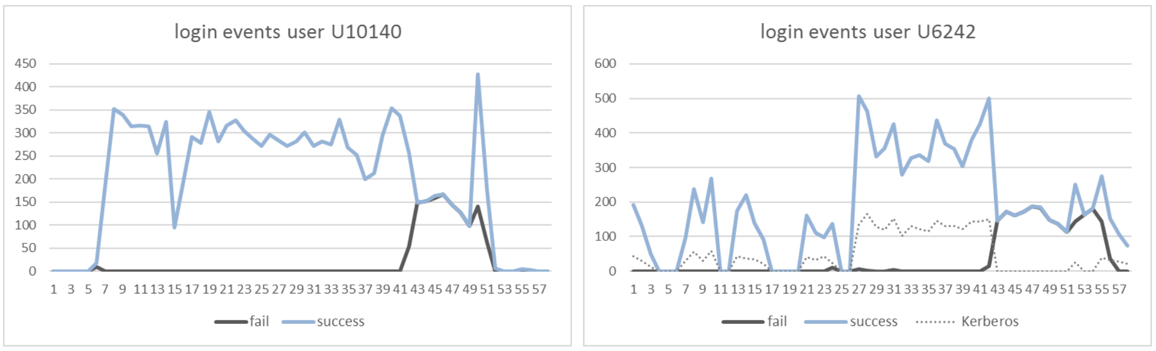


Figure 31. Logon history for two users contributing to the observed peak in failed logon anomalies on day 43

Without access to more detailed logs or operational staff it is impossible to determine whether this behaviour indicates a security issue or is simply the result of e.g. a configuration error. Still, this example demonstrate that this way of modelling offers a quick method of zooming in from global observations to the details of the underlying data.

In regular operation, this model could be used to generate a daily top x of users that are eligible for manual analysis. For instance, on day 25, the ten users with the most anomalous behaviour are U1464, U1560, U1582, U1678, U4510, U4732, U583, U8373, U849 and U927. Figure 32 shows selected parameters for two of those users. User U4510 the anomaly score is determined by a peak in new destination computers. U1464 is more interesting: on day 24 there is a peak in new processes, followed by a sudden rise in the percentage of failed logon attempt on day 25. Somewhat disappointingly, the users that were targeted by the Red Team did not appear among the top scores for the days they occurred.

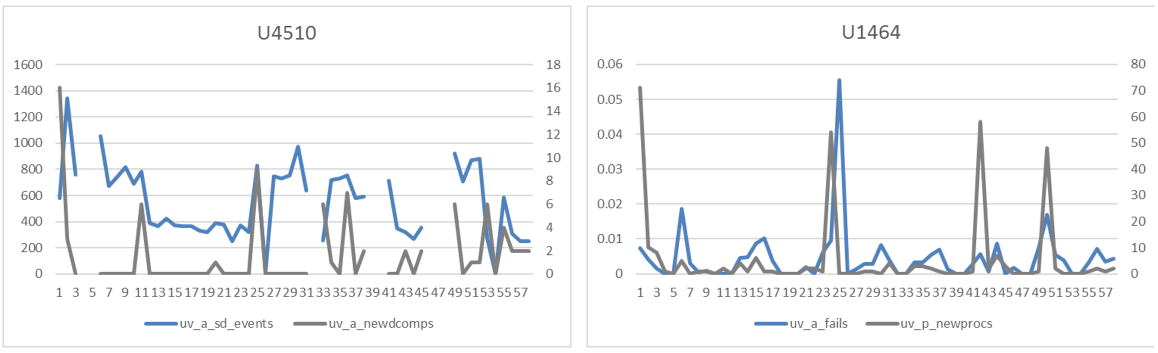


Figure 32. Selected parameters from two users appearing in the anomaly top 10 for day 25

5.9.2 Computer anomaly scores

The computer based anomalies were configured and calculated in a similar fashion as the user anomalies. In this case, besides the 14-day sliding window a shorter window of 7 days was also tried, so the netflow data could be included in the analysis. The resulting scores are shown in Figure 33. Figure 34 shows the anomaly scores per parameter and indicates the causes of the most noticeable peaks.

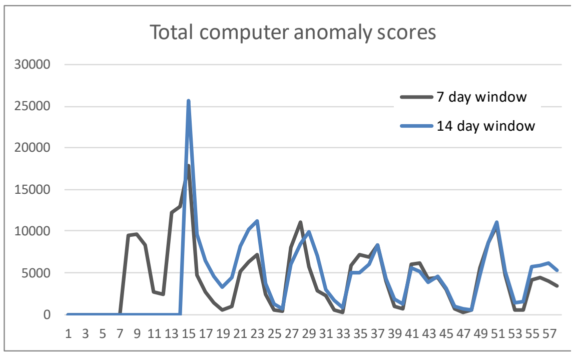


Figure 33. Total computer anomaly score with 2 window sizes

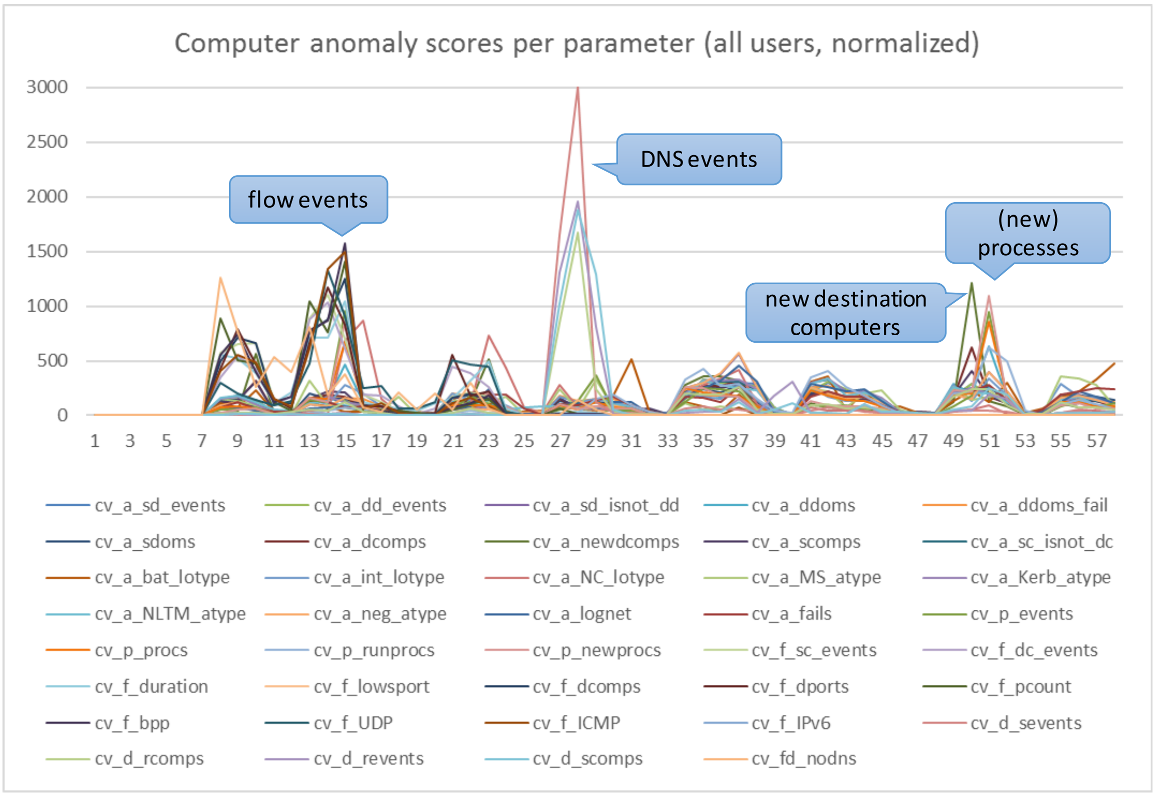


Figure 34. Normalized computer anomaly scores per parameter, totalled over all users (7-day window)

5.10 Computational impact

For the proposed anomaly detection to work, the available computing power must be able to process the data at least as fast as it comes in. Even though the code has not been optimized for performance, this presented no problem for the test implementation.

Data priming involves reading and parsing the text data and performing some simple operations. This was done per source file. The authentication file is by far the largest source; priming it took nearly four hours (13.905 seconds) or 4 minutes per day of data. All other sources took less than an hour to process.

In the test implementation, results were kept in memory until all the parsing was done, but if necessary this could easily be changed to reading and writing line by line, resulting in minimal memory requirements. Of course the Los Alamos data is already pre-processed; in real-life implementations parsing will be more complicated, external sources and data dictionaries may need to be accessed and routines should be implemented to handle missing or corrupted data. However, since there are no interdependencies between variables, processing time will grow linear with the number of events and the number of parameters and should scale well. Network and storage requirements may be significant given the amount of data involved, but should also scale linear with data volume.

Buffering mainly leads to storage requirements. The test implementation was optimized for code transparency and data retrieval speed, not for data volume. This led to binary output that was only ~20% smaller that the text original. This could easily be condensed if storage space is limited. However, in real life implementation data volume typically grows with about a factor 2 after data priming, since the normalized parameters are added as tags to the raw data, which itself is also kept for later reference.

Calculating the user vectors is by far the most computing intensive, since the number of events has not been reduced at this point in the test set-up (in real implementations, data priming may of course include filtering). Significant processing is required for aggregating the data and determining the feature vector parameters. Since parameter calculations can combine input from different datasets, all five sets are processed in parallel. Building the user feature vectors for the entire period took 18:48 hours (67.698 seconds), or 19 minutes per day of data. Computer vectors took 26:22 hours, or 27 minutes per day.

Resource requirements obviously depend heavily on the number of vector parameters and the way they are defined. A parameter that contains the number of times a certain type of event occurred requires only a simple counter per entity, while a parameter like “the number of processes started that have not been started before in the last *n* days” requires maintaining a sliding window for each computer that contains the sets of distinct processes started during this period. Still, because there are no interdependencies between entities, resource demand grows linear with the number of users/computers.

Maintaining profiles and detecting anomalies is considerably less resource intensive, because at this point the volume of data has been significantly reduced. The original dataset contains 12.9 billion individual parameters, the computer feature vectors “only” 34.5 million, a reduction by a factor of 373. Assuming an average of 8 bytes per parameter, storing the profile and the current parameters requires $34.5 \cdot 10^6 / 58 \cdot (14+1) \cdot 8$ = 72MB of memory, which is hardly impressive. The user feature vectors are even smaller.

Detecting anomalies using the quartile approach is quick, and because scoring is done per parameter, scales linear with the numbers of users and parameters. Updating profiles and calculating anomalies for the user vectors takes less than 30 minutes. Computing the computer anomalies takes about twice that time, which is in line with expectations considering that there are more computers and more parameters in the computer vector to process.

5.11 Discussion of the results

Several suspected anomalies were indicated in the data, both by taking a top down approach and by starting from the individual entities. Unfortunately, the correctness of these suspicions could not be confirmed, as no labelled data is available and there is no way to further analyse events.

The test implementation re-enforced the awareness that access to domain knowledge is essential to achieve an effective solution. Access to subject matter experts from another organization, however valuable, is no substitute for true understanding of the data. This is an inherent limitation when using public, anonymized data sets. With in-company data and access to the domains that generate it, much deeper understanding would be possible, enabling a much more targeted implementation.

This being said: The Los Alamos dataset is of high quality and deserves more research. This thesis only scratched the surface of what can undoubtedly be found in that trove of data!

6 Conclusions and recommendations for further study

This study has addressed an important challenge for Internet Service Providers: detecting cyber security anomalies in growing streams of heterogeneous logfiles. After discussing the proposed model with domain experts and applying it to a realistic dataset with over 1.6 billion records, it can be concluded that it is a promising approach to complement existing tooling. The model proved straightforward to implement, intuitively links high level overviews to specific details and scales well. It is also flexible in the sense that there are many ways to gradually augment and improve it as experience with the tooling and the data grows.

It is evident that working with an anonymized test-dataset, without access to infrastructure details or domain experts, has severe limitations. To bring the model to the next level, it should be applied in a real operational setting. Once access to real data has been achieved, many improvements and follow-up experiments are possible:

- Further experimentation with intervals, sliding window sizes and other parameters should help to find optimum values. This can be accomplished with historical data, but should be done in close cooperation with operational staff from both security (SOC and CERT) and the domains that generate the data.
- As a next step, the model can be applied to (near) real-time data. Processes should be implemented to systematically monitor and optimize the model over a longer test period. This should eventually lead to a smarter definition of the feature vectors.
- In ISP infrastructures there are many clusters of appliances that share the same function, and therefore can be expected to behave similarly. Group profiling could easily be applied to these clusters to detect any deviations from standard behaviour.
- Applications and processes generate significant amounts of logging, and should be candidates for both historic-and group-profiling. These entities will only become more important as virtualization and Software Defined Networks accelerate the functionality shift from hardware to software.
- Optimization of the code is certainly possible, which should lead to improvements in both storage requirements and processing speed. There is a subfield in data mining called “mining data steams” that has developed extremely fast and memory efficient algorithms to calculate statistics from streaming data (Leskovec, Rajaraman, & Ullman, 2014). Applying these techniques to the model should drastically improve performance and scalability.
- An important area for follow-up research should be the anomaly detection itself. The simple interquartile range based approach deployed in this study can be supplemented by other, more refined, models to detect anomalies (statistical- or other). This can be applied per parameter, but multi-dimensional approaches should also be investigated if they can be built to scale.
- Including anomaly scores in the feature vectors could create a way to monitor the propagation of anomalies through the network.
- Using contextual knowledge to correlate anomalies in different types of entities could significantly improve resolution.

Given the dynamics in the field of both big data and its application to security, it can be expected that security anomaly detection will see rapid developments during the coming years or even months. This progress will be closely monitored by the ISP community.

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Appendix A. Data Priming

source	normalized	type	definition
auth			
time	a_hour	integer	seconds/60/60
	a_day	integer	seconds/24/60/60
	a_no_officeh	boolean	True if time is between 18:00 and 7:00 (assuming start at 00:00)
source user@domain	a_source_user	string	Part of source user string left of "$" or "@"
	a_source_is_user	boolean	True if source user starts with "U"
	a_source_is_comp	boolean	True if source user starts with "C"
	a_source_is_ano	boolean	True if source uster starts with "A"
	a_source_is_dest_user	boolean	True if source and destination user are the same
destination user@domain	a_dest_user	string	Part of dest user string left of "$" or "@"
	a_dest_is_user	boolean	True if destination user starts with "U"
	a_dest_is_comp	boolean	True if destination user starts with "C"
	a_dest_is_ano	boolean	True if destination uster starts with "A"
source computer	a_source_comp	string	source computer
	a_source_is_dest_comp	boolean	True if source and destionation computer are the same
destination computer	a_dest_comp	string	destination computer
authentication type	a_atype_MS	boolean	True if authentication type starts with "M"
	a_atype_Kerb	boolean	True if authentication type = "Kerberos"
	a_atype_NTLM	boolean	True if authentication type = "NLTM"
	a_atype_nego	boolean	True if authentication type = "Negotiate"
logon type	a_lotype_batch	boolean	True if logon type = "Batch"
	a_lotype_interact	boolean	True if logon type = "Interactive"
	a_lotype_newcred	boolean	True if logon type = "NewCredentials"
authentication orientation	a_logon	boolean	True if authentication orientation = "LogOn"
	a_logoff	boolean	True if authentication orientation = "LogOff"
success/failure	a_fail	boolean	True if success/failure = "Fail"

source	normalized	type	definition
proc			
time	p_hour	integer	seconds/60/60
	p_day	integer	seconds/24/60/60
	p_no_officeh	boolean	True if time is between 18:00 and 7:00 (assuming start at 00:00)
user@domain	p_user	string	Part of user string left of "$" or "@"
	p_user_is_user	boolean	True if user starts with "U"
	p_user_is_comp	boolean	True if user starts with "C"
computer	p_comp	string	computer
process name	p_proc	string	process name
start/end	p_start	boolean	True if start/end = "Start"
flows			
time	f_hour	integer	seconds/60/60
	f_day	integer	seconds/24/60/60
	f_no_officeh	boolean	True if time is between 18:00 and 7:00 (assuming start at 00:00)
duration	f_duration	integer	duration
source computer	f_scomp	string	source computer
source port	f_sport_islow	boolean	True if sourceport < 1024
destination computer	f_dcomp	string	destination computer
destination port	f_dport	string	destination port
protocol	f_UDP	boolean	True if protocol = 17
	f_ICMP	boolean	True if protocol = 1
	f_IPv6	boolean	True if protocol = 41
packet count	f_pcount	integer	packet count
byte count	f_bcount	integer	byte count
dns			
time	d_hour	integer	seconds/60/60
	d_day	integer	seconds/24/60/60
	d_no_officeh	boolean	True if time is between 18:00 and 7:00 (assuming start at 00:00)
source computer	d_scomp	string	source computer
computer resolved	d_compres	string	computer resolved
redteam			
time	rt_hour	integer	seconds/60/60
	rt_day	integer	seconds/24/60/60
user@domain	rt_user	string	Part of user string left of "@"
source computer			
destination computer	rt_comp	string	destination computer

Appendix B. Feature vector definition

A1. Definition of user Feature vector

parameter short	calculation	type	definition
auth			
uv_a_sd_events	count	integer	the total number of authentication events with the user as source
uv_a_no_oh	ratio	float	the number of authentication events (as source) outside office hours (18:00-8:00 and weekends)
uv_a_dd_events	count	integer	the total number of authentication events with the user as destination
uv_a_sd_isnot_dd	ratio	float	% where source domain <> destination domain (= authentication as another user)
uv_a_sd_isano	ratio	float	% of events where the user is accessed by an anonymous user
uv_a_dd_isano	ratio	float	% of events where the user is accessing an anonymous user
uv_a_ddoms	set	integer	number of distinct user domains the user has accessed
uv_a_ddoms_fail	conditional count	integer	number of distinct user domains the user has unsuccessfully tried to access
uv_a_sdoms	set	integer	number of distinct domains the user is accessed by
uv_a_dcomps	set	integer	number of distinct computers the user has accessed
uv_a_newdcomps	historic set	integer	number of computers the user has accessed that have not been accessed in the previous n days
uv_a_scomps	set	integer	number of distinct computers the user has been accessed by
uv_a_sc_isnot_dc	ratio	float	% where source computer <> destination computer (= non-local event)
uv_a_bat_lotype	ratio	float	% of events (with user as source) with login type = "batch"
uv_a_int_lotype	ratio	float	% of events (with user =source) with login type = "interactive"
uv_a_NC_lotype	ratio	float	% of events (with user as source) with login type = "new credential"
uv_a_MS_atype	ratio	float	% of events (with the user as source) with authentication type contains "microsoft"
uv_a_Kerb_atype	ratio	float	% of events (with the user as source) with authentication type = "Kerberos"
uv_a_NLTM_atype	ratio	float	% of events (with the user as source) with authentication type = "NLTM"
uv_a_neg_atype	ratio	float	% of events (with the user as source) with authentication type = "Negotiate"
uv_a_lognet	historic count	integer	number of successful logons-logoffs cumulated over the logging period (min=0)
uv_a_fails	ratio	float	% of unsuccessful events with the user as source domain

parameter short	calculation	type	definition
proc			
uv_p_events	count	integer	the total number of proc events with the user as source
uv_p_comps	set	integer	number of distinct computers the user initiated processes on
uv_p_newcomps	historic set	integer	number of computers the user started processes on for the first time in n days
uv_p_procs	set	integer	number of distinct process types initiated by the user
uv_p_runprocs	historic count	integer	number of processes started cumulated over the logging period (min=0)
uv_p_newprocs	historic set	integer	number of processes the user started for the first time in n days
red team			
uv_rt_hacked	boolean	boolean	= True when user has been involved in RedTeam event

A2. Definition of computer feature vector

parameter short	calculation	type	definition
auth			
cv_a_sd_events	count	integer	total number of authentication events with the user as source
cv_a_no_oh	ratio	float	number of authentication events (as source) outside office hours (18:00-8:00 and weekends)
cv_a_dd_events	count	integer	total number of authentication events with the user as destination
cv_a_sd_isnot_dd	ratio	float	% where source domain <> destination domain (= authentication as another user)
cv_a_sd_isano	ratio	float	% of events where the user is accessed by an anonymous user
cv_a_dd_isano	ratio	float	% of events where the user is accessing an anonymous user
cv_a_ddoms	set	integer	number of distinct user domains the user has accessed
cv_a_ddoms_fail	conditional count	integer	number of distinct user domains the user has unsuccessfully tried to access
cv_a_sdoms	set	integer	number of distinct domains the user is accessed by
cv_a_dcomps	set	integer	number of distinct computers the user has accessed
cv_a_newdcomps	historic set	integer	number of computers the user has accessed that have not been accessed in the previous n days
cv_a_scomps	set	integer	number of distinct computers the user has been accessed by
cv_a_sc_isnot_dc	ratio	float	% where source computer <> destination computer (= non local event)
cv_a_bat_lotype	ratio	float	% of events (with the user as source domain) with login type = "batch"
cv_a_int_lotype	ratio	float	% of events (with the user as source domain) with login type = "interactive"
cv_a_NC_lotype	ratio	float	% of events (with the user as source domain) with login type = "new credential"
cv_a_MS_atype	ratio	float	% of events (with the user as source domain) with authentication type contains "microsoft"
cv_a_Kerb_atype	ratio	float	% of events (with the user as source domain) with authentication type = "Kerberos"
cv_a_NLTM_atype	ratio	float	% of events (with the user as source domain) with authentication type = "NLTM"
cv_a_neg_atype	ratio	float	% of events (with the user as source domain) with authentication type = "Negotiate"
cv_a_lognet	historic count	integer	number of successful logons-logoffs cumulated over the logging period (min=0)
cv_a_fails	ratio	float	% of unsuccessfull events with the user as source domain

parameter short	calculation	type	definition
flows			
cv_f_sc_events	count	integer	number of events where the computer is the source computer
cv_f_dc_events	count	integer	number of events where the computer is the destination computer
cv_f_duration	ratio	float	the average duration of a flow
cv_f_lowsport	conditional count	integer	number of events initiated by the computer with a low port number <1024
cv_f_dcomps	set	integer	number of distinct destination computers accessed by the computer
cv_f_dports	set	integer	number of distinct destination ports accessed by the computer
cv_f_pcount	ratio	float	average packet count of sessions initiated by the computer
cv_f_bpp	ratio	float	average byte per packet of sessions initiated by the computer
cv_f_UDP	ratio	float	% of UDP traffic in sessions initiated by the computer
cv_f_ICMP	ratio	float	% of ICMP traffic in sessions initiated by the computer
cv_f_IPv6	ratio	float	% of IPv6 traffic in sessions initiated by the computer
proc			
cv_p_events	count	integer	total number of proc events with the user as source
cv_p_comps	set	integer	the number of distinct computers the user initiated processes on
cv_p_newcomps	historic set	integer	number of distinct computers the user started processes on for the first time in n days
cv_p_procs	set	integer	number of distinct process types initiated by the user
cv_p_runprocs	historic count	integer	number of processes started cumulated over the logging period (min=0)
cv_p_newprocs	historic set	integer	number of processes the user started for the first time in n days
dns			
cv_d_sevents	count	integer	number of events initiated from the computer
cv_d_rcomps	set	integer	number of distinct destinations resolved
cv_d_revents	count	integer	number of events where the computer was resolved as a destination address
cv_d_scomps	set	integer	number of distinct source computers that initiated a request that resolved to the computer
cv_fd_nodns	set	integer	number of computers that have been communicated with without a dns request
red team			
cv_rt_hacked	boolean	boolean	= True when user has been involved in a Red Team event

Appendix C. Parameter distribution

		a_events	a_source_user	a_source_is_user	a_source_is_comp	a_source_is_ano	a_source_is_dest_user	a_dest_user	a_dest_is_user	a_dest_is_comp	a_dest_is_ano	a_source_comp	a_source_is_dest_comp	a_dest_comp	a_atype_MS	a_atype_Kerb	a_atype_NTLM	a_atype_nego	a_lotype_batch	a_lotype_interact	a_lotype_newcred	a_logon	a_logoff	a_fail	p_events	p_user	p_user_is_user	p_user_is_comp	p_comp	p_proc	p_start	f_events	f_duration	f_scomp	f_dcomp	f_dport	f_UDP	f_ICMP	f_IPv6	f_pcount	f_bcount	d_events	d_scomp	d_compres	rt_events	rt_user	rt_comp
a_events		1,0																																													
a_source_user		0,9	1,0																																												
a_source_is_user		1,0	0,9	1,0																																											
a_source_is_comp		1,0	0,8	0,9	1,0																																										
a_source_is_ano		0,8	0,9	0,9	0,8	1,0																																									
a_source_is_dest_user		1,0	0,9	1,0	1,0	0,8	1,0																																								
a_dest_user		0,9	1,0	0,9	0,8	0,9	0,9	1,0																																							
a_dest_is_user		1,0	0,9	1,0	0,9	0,9	1,0	0,9	1,0																																						
a_dest_is_comp		1,0	0,8	0,9	1,0	0,8	1,0	0,8	0,9	1,0																																					
a_dest_is_ano		0,8	0,9	0,9	0,8	1,0	0,8	0,9	0,9	0,8	1,0																																				
a_source_comp		0,9	1,0	0,9	0,8	0,8	0,9	1,0	0,9	0,8	0,8	1,0																																			
a_source_is_dest_comp		1,0	0,8	0,9	0,9	0,7	1,0	0,8	0,9	0,9	0,7	0,8	1,0																																		
a_dest_comp		0,9	0,9	0,8	0,8	0,6	0,9	0,9	0,8	0,8	0,6	0,9	0,9	1,0																																	
a_atype_MS		0,8	0,8	0,9	0,7	0,8	0,8	0,8	0,9	0,7	0,8	0,7	0,7	0,6	1,0																																
a_atype_Kerb		1,0	0,9	1,0	1,0	0,9	1,0	0,9	1,0	1,0	0,9	0,9	0,9	0,8	0,8	1,0																															
a_atype_NTLM		0,9	0,9	0,9	0,9	0,9	0,9	0,9	0,9	0,9	0,9	0,9	0,8	0,8	0,8	0,9	1,0																														
a_atype_nego		0,6	0,4	0,4	0,5	0,1	0,6	0,4	0,4	0,5	0,1	0,4	0,7	0,8	0,2	0,5	0,3	1,0																													
a_lotype_batch		0,4	0,4	0,5	0,3	0,5	0,4	0,4	0,5	0,3	0,5	0,4	0,2	0,2	0,5	0,4	0,5	-0,2	1,0																												
a_lotype_interact		0,6	0,5	0,6	0,5	0,6	0,6	0,5	0,6	0,5	0,6	0,5	0,5	0,5	0,6	0,6	0,6	0,3	0,4	1,0																											
a_lotype_newcred		0,2	0,2	0,2	0,2	0,1	0,2	0,2	0,2	0,2	0,1	0,2	0,2	0,2	0,1	0,2	0,2	0,1	0,0	0,0	1,0																										
a_logon		1,0	0,8	0,9	0,9	0,7	1,0	0,8	0,9	0,9	0,7	0,8	1,0	0,9	0,7	0,9	0,9	0,7	0,3	0,5	0,2	1,0																									
a_logoff		1,0	0,9	1,0	1,0	0,9	1,0	0,9	1,0	1,0	0,9	0,9	0,9	0,8	0,8	1,0	1,0	0,4	0,4	0,6	0,2	0,9	1,0																								
a_fail		0,5	0,3	0,4	0,5	0,2	0,5	0,3	0,4	0,5	0,2	0,3	0,7	0,6	0,1	0,4	0,4	0,7	-0,1	0,2	0,1	0,6	0,4	1,0																							
p_events		0,7	0,6	0,7	0,7	0,6	0,7	0,6	0,7	0,7	0,6	0,6	0,7	0,6	0,6	0,7	0,7	0,4	0,3	0,5	0,1	0,7	0,7	0,3	1,0																						
p_user		0,9	1,0	1,0	0,8	0,9	0,9	1,0	1,0	0,8	0,9	0,9	0,8	0,8	0,9	0,9	0,9	0,3	0,5	0,6	0,2	0,8	0,9	0,3	0,7	1,0																					
p_user_is_user		0,9	0,9	1,0	0,8	0,9	0,9	0,9	1,0	0,8	0,9	0,8	0,8	0,7	0,9	0,9	0,9	0,3	0,5	0,7	0,1	0,8	0,9	0,2	0,7	1,0	1,0																				
p_user_is_comp		0,6	0,6	0,6	0,6	0,5	0,6	0,6	0,6	0,6	0,5	0,5	0,6	0,6	0,5	0,6	0,6	0,4	0,2	0,4	0,1	0,6	0,6	0,3	1,0	0,6	0,6	1,0																			
p_comp		0,9	1,0	0,9	0,8	0,9	0,9	1,0	0,9	0,8	0,9	0,9	0,8	0,8	0,8	0,9	0,9	0,3	0,4	0,5	0,2	0,8	0,9	0,3	0,7	1,0	0,9	0,6	1,0																		
p_proc		0,9	0,8	0,9	0,8	0,8	0,9	0,8	0,9	0,8	0,8	0,8	0,8	0,7	0,9	0,9	0,9	0,3	0,5	0,6	0,2	0,8	0,9	0,2	0,8	0,9	0,9	0,7	0,8	1,0																	
p_start		0,7	0,6	0,7	0,7	0,6	0,7	0,6	0,7	0,7	0,6	0,6	0,7	0,6	0,6	0,7	0,7	0,3	0,3	0,5	0,1	0,7	0,7	0,2	1,0	0,7	0,7	1,0	0,7	0,8	1,0																
f_events		0,5	0,3	0,4	0,5	0,6	0,5	0,3	0,4	0,5	0,6	0,2	0,5	0,3	0,5	0,5	0,5	0,4	0,1	0,7	-0,1	0,5	0,5	0,4	0,2	0,4	0,4	0,2	0,3	0,4	0,2	1,0															
f_duration		0,6	0,4	0,5	0,6	0,7	0,6	0,4	0,5	0,6	0,7	0,3	0,6	0,4	0,6	0,6	0,6	0,5	0,2	0,6	-0,1	0,6	0,6	0,4	0,3	0,5	0,5	0,2	0,5	0,5	0,3	0,9	1,0														
f_scomp		0,4	0,3	0,4	0,4	0,6	0,4	0,3	0,4	0,4	0,6	0,2	0,4	0,3	0,4	0,4	0,5	0,4	0,1	0,6	-0,1	0,4	0,4	0,3	0,2	0,3	0,3	0,2	0,3	0,3	0,2	0,9	1,0	1,0													
f_dcomp		0,3	0,1	0,2	0,3	0,5	0,3	0,1	0,2	0,3	0,5	0,0	0,3	0,1	0,3	0,3	0,3	0,3	0,0	0,7	-0,2	0,3	0,3	0,2	0,1	0,2	0,2	0,1	0,2	0,2	0,1	0,9	0,9	1,0	1,0												
f_dport		0,3	0,2	0,3	0,3	0,5	0,3	0,2	0,3	0,3	0,5	0,1	0,3	0,2	0,4	0,3	0,4	0,3	0,1	0,7	-0,2	0,3	0,3	0,3	0,2	0,3	0,3	0,1	0,2	0,3	0,2	0,9	0,9	0,9	0,9	1,0											
f_UDP		0,3	0,1	0,3	0,2	0,4	0,3	0,1	0,3	0,2	0,4	0,0	0,3	0,1	0,4	0,3	0,3	0,3	0,0	0,8	-0,2	0,3	0,2	0,2	0,1	0,2	0,3	0,1	0,1	0,3	0,1	0,8	0,7	0,7	0,8	0,9	1,0										
f_ICMP		0,2	0,0	0,2	0,2	0,4	0,2	0,0	0,2	0,2	0,4	-0,1	0,2	0,0	0,3	0,2	0,2	0,2	0,0	0,8	-0,2	0,2	0,2	0,1	0,1	0,2	0,2	0,1	0,1	0,2	0,1	0,8	0,7	0,8	0,9	0,9	1,0	1,0									
f_IPv6		0,3	0,2	0,3	0,3	0,3	0,3	0,2	0,3	0,3	0,3	0,2	0,3	0,2	0,3	0,3	0,3	0,3	0,2	0,1	0,0	0,3	0,3	0,3	0,2	0,3	0,3	0,1	0,2	0,3	0,2	0,2	0,2	0,2	0,1	0,1	0,0	0,1	1,0								
f_pcount		0,7	0,5	0,6	0,7	0,7	0,7	0,5	0,6	0,7	0,7	0,4	0,7	0,5	0,7	0,7	0,7	0,6	0,2	0,6	0,0	0,7	0,7	0,5	0,4	0,6	0,6	0,3	0,5	0,6	0,4	0,9	0,9	0,8	0,8	0,8	0,6	0,6	0,2	1,0							
f_bcount		0,4	0,3	0,4	0,4	0,5	0,4	0,3	0,4	0,4	0,5	0,2	0,4	0,3	0,4	0,4	0,4	0,4	0,1	0,4	0,0	0,4	0,4	0,4	0,2	0,4	0,4	0,2	0,3	0,4	0,2	0,8	0,7	0,7	0,6	0,6	0,5	0,5	0,2	0,8	1,0						
d_events		0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,6	0,4	0,4	0,5	0,4	0,6	0,6	0,1	0,6	0,7	0,7	0,5	0,7	0,6	0,6	0,2	0,2	0,2	0,2	0,2	0,1	0,1	0,2	0,2	0,2	1,0					
d_scomp		0,5	0,5	0,4	0,4	0,4	0,5	0,5	0,4	0,4	0,4	0,5	0,5	0,6	0,4	0,5	0,4	0,4	0,2	0,4	0,3	0,5	0,5	0,2	0,4	0,5	0,4	0,3	0,5	0,4	0,4	0,2	0,2	0,2	0,2	0,2	0,2	0,1	0,3	0,1	0,2	0,9	1,0				
d_compres		0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,0	0,1	0,0	0,0	0,1	0,1	0,0	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,0	0,3	0,0	0,1	0,3	0,2	1,0			
rt_events		0,1	0,2	0,2	0,1	0,2	0,1	0,2	0,2	0,2	0,2	0,1	0,1	0,1	0,2	0,2	0,2	-0,1	0,1	0,1	0,0	0,1	0,2	0,0	0,1	0,2	0,2	0,1	0,2	0,2	0,1	0,2	0,3	0,3	0,2	0,2	0,1	0,1	0,4	0,3	0,2	-0,1	-0,1	-0,1	1,0		
rt_user		0,2	0,2	0,2	0,2	0,3	0,2	0,2	0,2	0,2	0,3	0,2	0,1	0,1	0,3	0,2	0,3	-0,1	0,2	0,1	0,0	0,1	0,2	0,0	0,2	0,3	0,2	0,1	0,2	0,2	0,2	0,3	0,3	0,3	0,2	0,2	0,1	0,1	0,4	0,3	0,2	-0,1	-0,1	-0,1	0,9	1,0	
rt_comp		0,1	0,1	0,1	0,1	0,2	0,1	0,1	0,1	0,1	0,2	0,1	0,1	0,1	0,2	0,1	0,2	-0,1	0,1	0,1	0,0	0,1	0,2	0,0	0,1	0,2	0,1	0,1	0,2	0,1	0,1	0,2	0,3	0,3	0,2	0,2	0,1	0,1	0,4	0,3	0,2	-0,1	-0,1	-0,1	1,0	0,9	1,0

Appendix D. Computer feature vector distribution

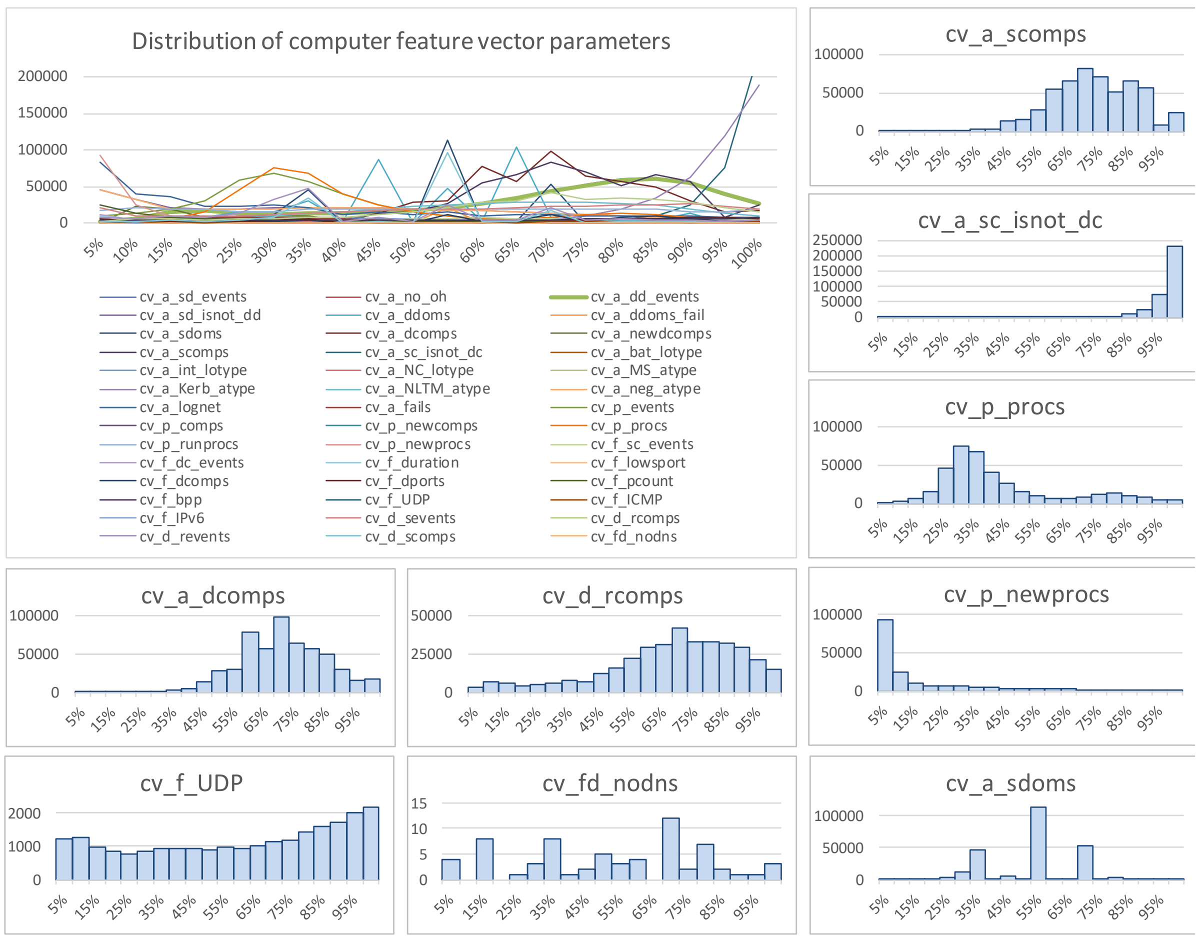

Figure 35. Normalized distribution of computer feature vector parameters