Enhancing Security Event Management Systems with Unsupervised Anomaly Detection

Markus Goldstein[1], Stefan Asanger[2], Matthias Reif[1] and Andrew Hutchison[3]
[1] *German Research Center for Artificial Intelligence (DFKI), Trippstadterstr. 122, 67663 Kaiserslautern, Germany*
[2] *Department of Computer Science, University of Cape Town, Cape Town, South Africa*
[3] *T-Systems International, 4 Churchill Close Tyger Waterfront, Bellville 7530, South Africa*

Keywords: Anomaly Detection, Event Management, SIEM, Outlier Detection, Windows Events, User Profiling, Behavior Profiling, Behavioral Analysis.

Abstract: Security Information and Event Management (SIEM) systems are today a key component of complex enterprise networks. They usually aggregate and correlate events from different machines and perform a rule-based analysis to detect threats. In this paper we present an enhancement of such systems which makes use of unsupervised anomaly detection algorithms without the need for any prior training of the system. For data acquisition, events are exported from an existing SIEM appliance, parsed, unified and preprocessed to fit the requirements of unsupervised anomaly detection algorithms. Six different algorithms are evaluated qualitatively and finally a global *k*-NN approach was selected for a practical deployment. The new system was able to detect misconfigurations and gave the security operation center team more insight about processes in the network.

1 INTRODUCTION

In today's IT environments, a complex combination of security solutions is typically deployed in order to protect the network from advanced security threats of both external and internal origin. This includes but is not limited to firewalls, intrusion detection and prevention systems as well as anti-virus and patch management solutions. Each of these point solutions performs specific tasks and generates large volumes of log information which is often stored without further consideration. In order to detect security breaches at an early stage, log files from all individual systems should be correlated and analyzed. This is hard to achieve due to the complexity of today's IT systems. The more complex and diverse an IT environment, the more challenging it is to perform log management, threat management and incident response in real-time.

SIEM systems support the aggregation, correlation and analysis of events from diverse sources. Threat management, incident response and log management are key capabilities of today's SIEM solutions. Although SIEM systems have matured in the last years, they still rely on complex rules to detect security threats. However, rule-based correlation is no longer sufficient in protecting an IT environment from continuously evolving dynamic security threats. There is an increasing demand to complement rule-based correlation with more advanced techniques such as anomaly detection (Nicolett, 2011) for several reasons: Obviously, rule-based systems can only detect incidents which have been observed and defined beforehand. In some cases, unknown *zero-day* threats may not be detected by today's appliances and can cause tremendous damage due to network down times or even data leakage. Additionally, the habitual events effect on administrators from standard alarm events recurring over and over can be dangerous. Such regularly occurring events like login failures due to wrong passwords, port scans or detected and removed virus alerts tend to be ignored. However, a certain combination or a trend of such events can reveal a security threat, which cannot be detected by today's appliances if the correlation is not known in advance. Furthermore, rules are often based on manually defined thresholds, which also might not be ideal in many cases. For example, intruders can learn how much data they can smuggle out before being detected in order to "fly under the radar" in future attacks. Also, thresholds need to be adjusted over time due to a changing behavior of the norm.

In this context, anomaly detection (Chandola

Goldstein M., Asanger S., Reif M. and Hutchison A. (2013).
Enhancing Security Event Management Systems with Unsupervised Anomaly Detection.
In *Proceedings of the 2nd International Conference on Pattern Recognition Applications and Methods*, pages 530-538
DOI: 10.5220/0004230105300538

et al., 2009) can help to overcome the above shortcomings. In contrast to rule-based systems, anomaly detection does not rely on statically created rules: Aggregated events are analyzed with a multivariate unsupervised anomaly detection algorithm and an anomaly score is assigned to each instance. Anomaly detection has been successfully applied to many application domains in the field of network security (Garcia-Teodoro and et al, 2009) and is a promising approach to further enhance SIEM systems.

In this paper we present a practical system to apply anomaly detection to the data streams of SIEM systems. Our goal is not to replace SIEM systems, but to have an additional module besides the rule-based engines in order to give security operators hints of potential threats. The main research focus is the detection of suspicious authentication attempts, password guessing attacks and unusual user account activities. The deployment is done within a large-scale SIEM environment, operated as a managed service for a global financial services provider.

2 BACKGROUND AND RELATED WORK

2.1 Anomaly Detection

Anomaly Detection is a sub-area of machine learning which aims to find outlying records in data sets. It is also known as intrusion detection, fraud detection, misuse detection or outlier detection according to different application domains. However, the basic idea remains the same: Normal multivariate data is modeled and instances being different from the majority should be identified. This leads to the two basic assumptions in anomaly detection:

- anomalies are very rare compared to normal data (typically $< 2\%$) and
- their feature values significantly deviate from normal data.

In the survey articles of (Chandola et al., 2009; Hodge and Austin, 2004) attempts are made to classify the different fields of anomaly detection as summarized in the following. The most important difference is with respect to the availability of labels in the data, leading to three different categories. *Supervised anomaly detection* uses labeled training and test data and traditional machine learning methods such as SVMs or Neural Networks can be applied. In practice, this scenario is hardly of interest since annotated anomalies are often not known. Second, *semi-supervised anomaly detection* refers to the scenario where training data only contains the normal class and thus a model of the normal behavior is learned. In contrast, the test data contains normal data and anomalies which can then be identified. In some modern SIEM systems this scenario has been used, which we will discuss in Subsection 2.3. In terms of machine learning algorithms, one class classifiers can be used, e.g. One-Class-SVMs. Finally, *unsupervised anomaly detection* does not make any assumptions about the data and no separation between training and test set is performed. The unlabeled data set is only analyzed according to its intrinsic nature and records are usually scored according to outlier probability. Of course, this scenario is the most flexible one but this comes at the price of being sensitive to irrelevant information. Thus it requires an appropriate preprocessing which is usually done by generating *data views*. In this paper we present an approach based on unsupervised anomaly detection.

Another important question is whether a *global* or *local* anomaly detection problem should be addressed. Simply speaking, global anomalies are records being "far away" from the normal data whereas local anomalies are suspicious with respect to their local neighborhood. Local anomalies can thus occur in data sets with different dense clusters as illustrated in Figure 1. It is important to know which anomaly problem has to be solved, since local anomaly detection methods fail on global anomaly detection problems (Amer and Goldstein, 2012).

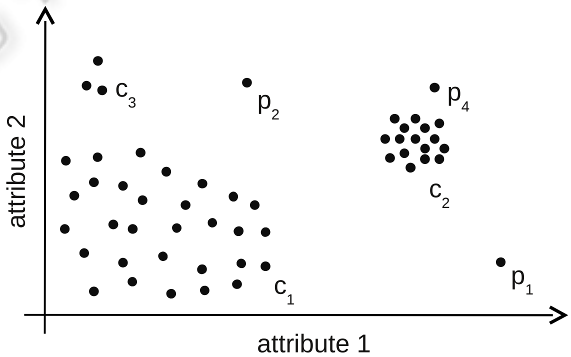


Figure 1: Global and local outliers. p_1 and p_2 are global outliers since their distance to other points is large. The clusters c_1 and c_2 represent normal data points with different (local) densities. p_4 is a local outlier with respect to cluster c_2. Cluster c_3 is called a *microcluster*, a case often not obvious if it should be treated as an anomaly or not.

The approaches in unsupervised anomaly detection can be categorized in three main classes: (1) Nearest-neighbor based methods, (2) Clustering-based methods and (3) Statistical methods. Statistical methods comprise parametric or non-parametric methods and include histograms, kernel-density-estimation methods or the well known univariate Grubb's outlier test (Grubbs, 1969). They often assume a certain distribution of the data or assume independability of features making them not ideal for real-world data. Clustering-based methods are ideal for very large data sets, especially when k-means as a clustering algorithm is used. A well-known algorithm is the Clustering-based Local Outlier Factor (CBLOF) (He et al., 2003). Unfortunately the precision is worse when comparing with nearest-neighbor based algorithms (Amer and Goldstein, 2012). Nearest-neighbor based approaches are by far the most used methods today. Besides the global *k*-NN algorithm (Ramaswamy et al., 2000; Angiulli and Pizzuti, 2002), the well-known Local Outlier Factor (LOF) (Breunig et al., 2000) was the basis for many other algorithms, such as the Connectivity-Based Outlier Factor (COF) (Tang et al., 2002), the Local Outlier Probability (LoOP) (Kriegel et al., 2009) or the Influenced Outlierness (INFLO) (Jin et al., 2006). For the reason of having a higher precision, we also decided to evaluate nearest-neighbor based methods in this work.

2.2 SIEM Solutions

The acronym *SIEM* is a combination of the terms Security Event Management (SEM) and Security Information Management (SIM). Whereas the former offers real-time event monitoring, threat management and incident response capabilities, the latter primarily focuses on centralized log management and compliance reporting. A SIEM system integrates both distinct technologies into one complete solution.

In the past, compliance regulations were the main driver for SIEM systems. Nowadays, more and more SIEM systems are deployed due to their enhanced threat management and incident response capabilities. SIEM systems assist in understanding and interpreting massive volumes of log files and increase visibility, enabling security operators to possibly prevent or react to security breaches in time. The key goal of SIEM systems is to turn raw, diverse events into meaningful information, also known as actionable intelligence. A concise understanding and overview of security-threatening event activities is essential in order to achieve situational awareness (Endsley, 1987). In the SIEM context, situational awareness means to detect a security threat, assess its implications and respond to it in time. Situational awareness is necessary to transition from current reactive to future predictive SIEM solutions.

2.3 Semi-supervised Anomaly Detection in SIEM Systems

According to a market evaluation conducted by (Nicolett, 2011; Nicolett and Kavanagh, 2012b), the SIEM market has matured and become very competitive in the last few years and is comprised of more than twenty individual vendors. Capabilities that are well-supported are log and threat management as well as compliance reporting. However, the majority of SIEM systems still rely on rule-based correlation techniques. In times of advanced persistent threats and targeted attacks, enhanced correlation techniques are needed to protect IT networks from these emerging threats. An increased trend can be identified to complement rule-based correlation techniques with anomaly detection capabilities (Nicolett and Kavanagh, 2012b).

In this context, semi-supervised anomaly detection is used, which requires an "anomaly-free" training phase, also known as *behavior profiling* (Nicolett and Kavanagh, 2012a). As an example, NetIQ[1] incorporates a dedicated anomaly detection engine which detects trend deviations from normal, expected behavior. Normal behavior is defined using a baseline of events requiring at least one week of collected data. A similar approach is followed by NitroSecurity[2] which detects anomalous trend deviations by dynamically calculating baseline behavior. Furthermore, AlienVault[3] incorporates anomaly-based detectors in order to complement pattern or signature based detectors (Miller, 2011). In literature, time-series analysis is also used for this task (Rodriguez and de los Mozos, 2010).

3 EVENT MANAGEMENT SYSTEM/FRAMEWORK

3.1 SIEM Environment

In support of the managed security service, IBM's Tivoli Security Operations Manager (TSOM) is deployed as a SIEM system in the enterprise network. TSOM gathers data from systems and network appliances in an agent-less manner, using transport protocols such as the Simple Network Management Protocol (SNMP) and Syslog. Alternatively, agent-based communication is supported by the Universal Collection Module (UCM). Table 1 gives an overview of the

[1]http://www.netiq.com
[2]http://www.nitrosecurity.com/
[3]http://www.alienvault.com/

diverse data sources which feed security event information into TSOM.

Table 1: Overview of data sources and conduits.

#	*Source*	*Conduit*
421	UNIX/Linux servers	Syslog
108	Cisco routers/switches	Syslog
57	Windows servers	SNMPv2c, UCM
8	IDS solutions	Syslog
2	Anti-virus solutions	SNMPv2c

The focus of this work is currently based on specific authentication events originating from 57 Windows servers, the majority of which are Windows domain controllers hosting Active Directory (AD) instances. The servers and workstations that are deployed in the managed services environment are based on diverse Windows operating systems including Windows Server 2003 (R2), Windows Server 2008 (R2), Windows XP, Windows Vista and Windows 7.

In order to forward Windows security events from TSOM to an external application such as our anomaly detection engine, the *send trap* action was configured (IBM, 2008; Buecker, 2008). The send trap action makes use of SNMPv2c as a transport protocol and allows the content of the SNMP trap message to be customised. Nevertheless, we decided to forward the entire, native Windows security event. Within our framework, the content of the SNMP message is then preprocessed and transformed into a well-structured data set.

3.2 Anomaly Detection Engine

Our framework is an agent-based platform for collecting, aggregating and interpreting audit trails using advanced anomaly detection techniques. It is based on the Java Intelligent Agents Component (JIAC) framework (Albayrak and Wieczorek, 1998) and consists of three main components which acquire, process and exploit event information from diverse systems. Figure 2 gives an overview of all components which are part of our anomaly detection engine.

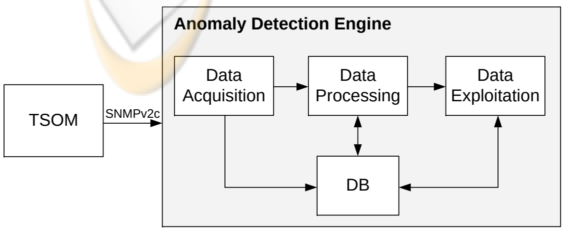


Figure 2: Overview of the anomaly detection engine.

Agent technology is a key component of the framework and provides functionality for data acquisition, data preprocessing, anomaly detection as well as exploitation. The JIAC framework allows each component to be distributed amongst individual agents which can be located on different agent nodes, thus providing load balancing capabilities. The data acquisition component currently supports Comma Separated Value (CSV) files as well as the Attribute-Relation File Format (ARFF) and is capable of processing SNMP traps. All event data is stored in a MySQL database.

The SNMP traps forwarded from TSOM consist of 24 managed objects, including the native Windows security event. Within our framework, the content of all managed objects is preprocessed and transformed into a well-structured data set which can be effectively analyzed by anomaly detection techniques. The parsing of SNMP traps is carried out by the SNMP4J[4] API which transforms each trap according to a specific format that is discussed in the following section.

3.3 Event Parsing

In order to detect suspicious authentication attempts, password guessing attacks and unusual user account activities, specific Windows security events need to be analyzed. Relevant events are provided by the *Logon/Logoff* and *Account Logon* security auditing policies in Windows domain environments. Logon/Logoff events enable administrators to track all successful and failed logon and logoff attempts. Account Logon events document attempts to authenticate user and computer accounts. Out of both auditing categories, thirteen Logon/Logoff and four Account Logon events were selected, as illustrated in Table 2.

Windows security events which are not listed in Table 2 are neglected by our data acquisition component. Within our framework, the event content, entailed in SNMP traps, is transformed into a well-structured data set according to a specific format. It consists of a comprehensive set of attributes which is grouped into two parts: TSOM-specific and event-specific attributes. TSOM-specific attributes are based on event information provided by TSOM itself. Event-specific attributes are based on attributes which originate from the native Windows security event.

Additionally, the resulting data set was augmented by various attributes to increase the contextual background information. As an example, certain attributes are useful to distinguish between standard and privileged users as well as domain controllers, member

[4] http://www.snmp4j.org/

Table 2: Overview of Windows security events.

Logon/Logoff		
Use Case	*Event ID*	*Description*
1	528 / 4624	Successful Logon
2	540 / 4624	Successful Network Logon
3	529 / 4625	Logon Failure: Unknown user name or bad password
4	530 / 4625	Logon Failure: Account logon time restriction violation
5	531 / 4625	Logon Failure: Account currently disabled
6	532 / 4625	Logon Failure: The specified user account has expired
7	533 / 4625	Logon Failure: User not allowed to logon at this computer
8	534 / 4625	Logon Failure: The user has not been granted the requested logon
9	537 / 4625	Logon Failure: An unexpected error occurred during logon
10	539 / 4625	Logon Failure: Account locked out
11	576 / 4672	Special privileges assigned to new logon
12	538 / 4634	User Logoff
13	551 / 4647	User initiated logoff
Account Logon		
Use Case	*Event ID*	*Description*
14	672 / 4768	A Kerberos authentication ticket (TGT) was requested
15	673 / 4769	A Kerberos service ticket was requested
16	675 / 4771	Kerberos pre-authentication failed
17	680 / 4776	A domain controller attempted to validate account credentials

servers and workstations. Furthermore, geographical IP information was added for all records containing external IP addresses.

4 GLOBAL ANOMALY DETECTION ALGORITHM

4.1 Data Views

As already pointed out previously, unsupervised anomaly detection algorithms rely on an appropriate preprocessing. In contrast to supervised algorithms which are able to learn which features are important, this is not possible in an unsupervised setting. For this reason, *data views* need to be generated which guide the anomaly detection algorithm to find outliers. Since single records in the data set are not an anomaly but a combination of multiple records might represent one, an appropriate data aggregation is used. In (Chandola et al., 2009) this is referred to as a *complex anomaly detection* problem, whereas anomaly detection algorithms can only deal with *point anomaly detection* problems. We defined the following five data views based on aggregation as follows:

Per User and Day: Events of single users are aggregated with a time unit of one day,

Per User and Hour: Events of single users are aggregated on an hourly basis. This could potentially identify users using a workstation during non-business hours,

Per User, Day and Hour: Same as above with adding the day as additional feature,

Different Workstations per User: Events generated at different workstations for each user. This could for example help to identify fraudulent users "scanning" the network shares,

Different Users per Workstation: Events of a single workstation for each single user. The idea behind this data view is to identify password guessing attempts (in combination with use cases 3-10) or to identify violations against company rules for servers (e.g. in combination with use case 2 one could identify non-authorized server applications).

Each of the data views was created for all of the 17 event types (use cases) as defined in Table 2. Furthermore, each of the data views above was created for standard users and privileged users separately since we assume a different behavior of both groups. Users to be known as system users (such as backup jobs, administrative jobs) were filtered out and not processed any further. In total, we generated 170 different data views (17 use cases with 5 different aggregations for standard and privileged users), whereas some do not contain enough data and are not processed further, in particular use cases 4,6,7 and 11. This is most likely due to the setup of policies in the used infrastructure. However, if such events will occur in the future they will be processed automatically.

4.2 Sliding Window

Within our anomaly detection engine, data is streamed into the database. The anomaly detection algorithm is then applied immediately after the data of a new time unit is complete (e.g. one hour or one day). A sliding window with an appropriate length guarantees that old data is not used any more in the live system in order to adapt to changing user behavior or infrastructure changes. Also, anomalies are only reported once when they occur for the first time.

4.3 Global *k*-NN Algorithm

The choice of the used anomaly detection algorithms is crucial, especially if a local or a global anomaly detection method needs to be used. Although we presume that our problem is global, we tried out different methods. A very efficient and parallel implementation of anomaly detection algorithms can be found in the *Anomaly Detection Extension*[5] of RapidMiner (Mierswa et al., 2006). Since we know from (Amer and Goldstein, 2012) that clustering based methods perform not as well as nearest-neighbor based approaches, we focused on the latter. In particular, we investigated the local approaches LOF (Breunig et al., 2000), COF (Tang et al., 2002), LoOP (Kriegel et al., 2009) and INFLO (Jin et al., 2006). For global algorithms, the k-nearest-neighbor (Angiulli and Pizzuti, 2002) and the k^{th}-nearest-neighbor (Ramaswamy et al., 2000) approach was used. The difference between both is that the latter uses only one nearest neighbor for anomaly scoring whereas the first estimates the score by averaging over all N_k neighbors:

$$anomaly\_score(p) = \frac{\sum_{o \in N_k(p)} d(p,o)}{|N_k(p)|} \qquad (1)$$

Our investigation showed that *global* methods perform best, especially the k-NN approach averaging over all neighbors. Since we do not have a labeled data set, the evaluation was done qualitative based on if "interesting" outliers are found as discussed later in Section 5. Furthermore, the parameter k has to be determined, which is important for the detection of microclusters. Recalling the example of Figure 1, the microcluster c_3 could be identified as normal for $k = 2$ or as outlier for $k \geq 3$. In practice, values smaller then $k = 10$ are not used in order to cope with statistical fluctuation in the data. We performed experiments for $10 \leq k \leq 30$ and did not find significant changes in the outlier scores of the algorithm. Thus we can conclude that microclusters are not contained in the data.

Before the anomaly detection algorithm was applied, the data was normalized to [0,1] for each single feature to ensure equal influence on the result. This also results in anomaly scores in the range of [0,1] with zero indicating a very normal record and records close to one indicating anomalies.

5 RESULTS

Our developed anomaly detection framework is able to run either live in an actual deployment via receiving SNMP traps in a network infrastructure or as an offline application with previously collected data. For the ease of evaluation, we are presenting the results of a three months data collection with a sliding window of two months. In the next subsection, the data within

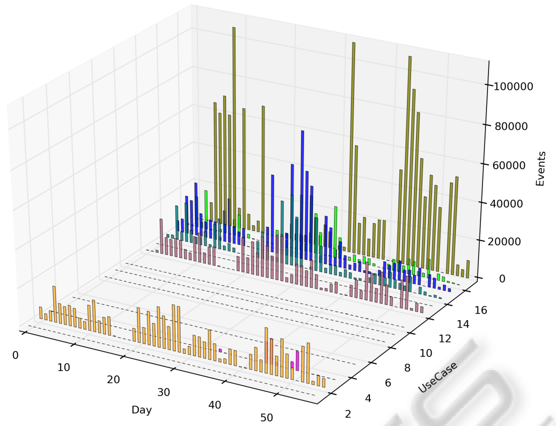


Figure 3: The number of events of standard users per use case and day.

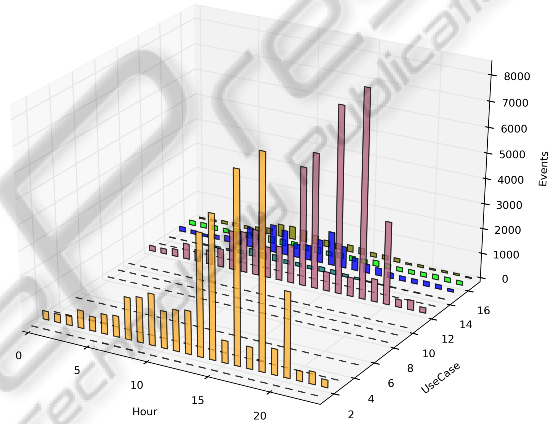


Figure 4: The number of events of privileged users per use case and hour of the day.

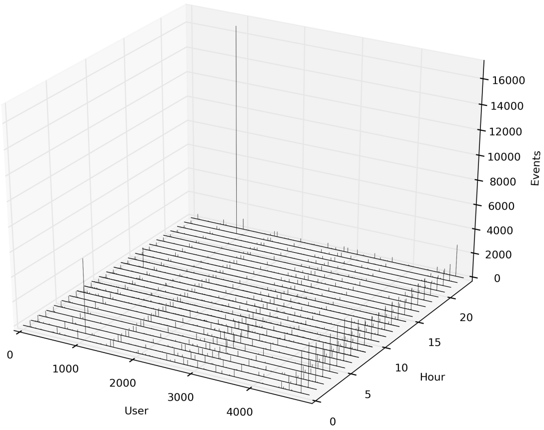
the sliding window is presented first and the detected outliers are finally reported in Subsection 5.2.

5.1 Data Analysis/Manual Investigation

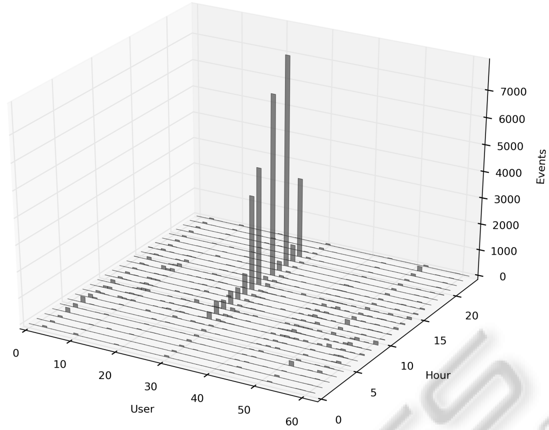
Figure 3 shows the number of events generated by standard users for each single day of the two months sliding window and for each use case separately. It can be seen that the amount of events does not only vary between the use cases but also among the days. Determining whether single users are responsible for such large deviations or if this is indeed a normal behavior is the task of the anomaly detection algorithm.

For a second visualization, the data was aggregated based on 24 time bins in order to investigate the distribution of the events over the day. As expected, Figure 4 shows a typical distribution of events for most of the use cases with a majority of the events within the business hours and only few events during the rest of the day for privileged users. However, use case 2 (successful network logon) and 12 (user log-

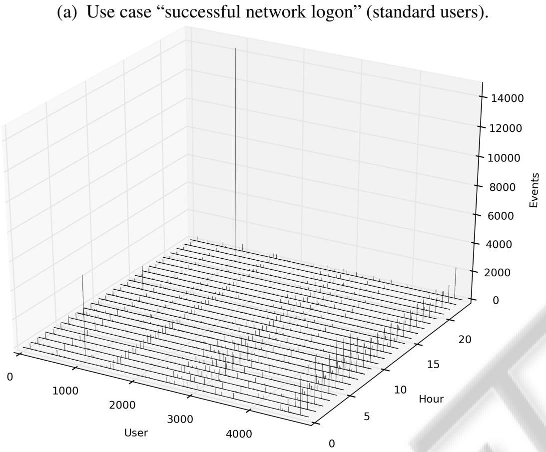
[5] For source code and binaries see http://madm.dfki.de/rapidminer/anomalydetection



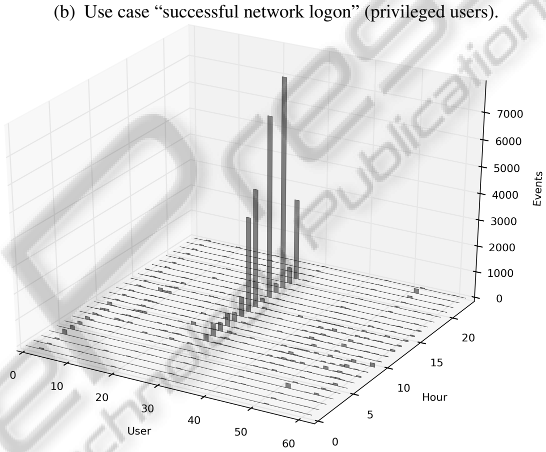
(a) Use case "successful network logon" (standard users).



(b) Use case "successful network logon" (privileged users).

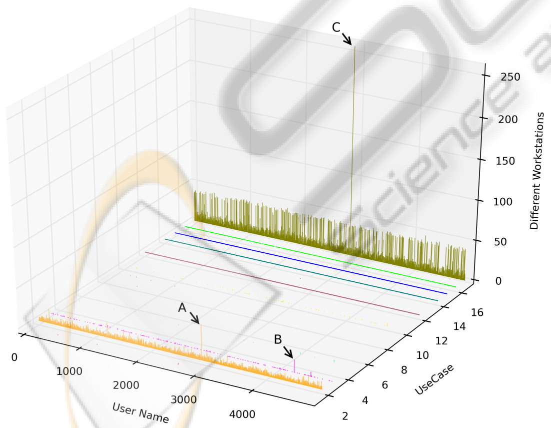


(c) Use case "user logoff" (standard users).

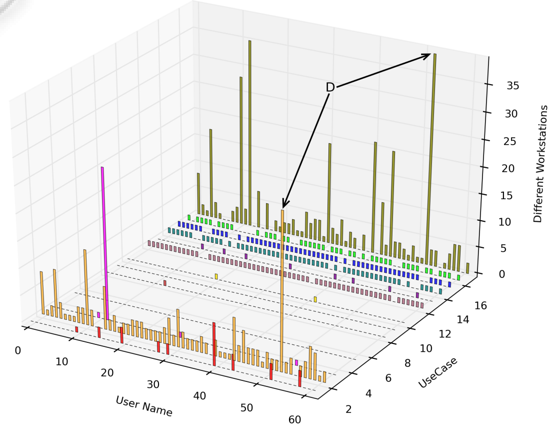


(d) Use case "user logoff" (privileged users).

Figure 5: Data views for different use cases based on an hourly data aggregation.



(a) Standard users.



(b) Privileged users.

Figure 6: The different number of workstations per use case used by each (a) standard and (b) privileged user.

off) already show a non-expected peaky behavior in the afternoon that will also be subject of the anomaly detection.

5.2 Unsupervised Anomaly Detection

Although the system handles 170 data views, we can only describe a few interesting results exemplary in this work. Figure 5 shows four data views for the hourly data aggregation. While Figure 5(a) and 5(b) show the data of use case 2 for standard and privileged users, Figure 5(c) and 5(d) show the data of use case 12.

It can be seen that most of the events of each data view are generated by a few users only. Thus, the applied *k*-NN anomaly detection reports one standard user as anomalous in hour 22, with an anomaly score of 0.93 for use case 2 and 0.92 for use case 12. Similarly, our system reports one privileged user for both use cases 2 and 12. He receives an anomaly score of 0.76 for hour 18 and 0.63 in hour 16. Please note that the visualization of the data can only be performed when having at most three dimensions which is not the case for all of our defined data views. In this case, the results are presented as tables to the security operators.

As a second exemplary result, we look at the number of different workstations per user. Figure 6 shows the aggregated data for (a) standard users and (b) privileged users.

Our system detected the three anomalies A, B and C within the standard users although especially anomaly B contains a rather small absolute amount of events as compared to the amount of normal events of use case 17. Within the data view of privileged users, one account could be identified as anomalous in use cases 2 and 17 (D). Among others, the system detected a “SAS Business Intelligence” account that performed several transactions on multiple workstations and was previously incorrectly categorized as a user account. Additionally, a legacy account that was used to manage all Windows computers in a Novell network was identified as an anomaly because it generated a high logon failure rate due to a mismatch between the Novell password and the account’s password.

6 CONCLUSIONS

In this work we present an unsupervised anomaly detection approach for extending SIEM appliances with two main contributions: (1) The proposed system is applicable in practice and extends already deployed commercial systems with an anomaly detection engine and (2) the usefulness of unsupervised anomaly detection was evaluated qualitatively on real world data in a large enterprise network. In contrast to semi-supervised anomaly detection, which is already part of commercial systems, our proposed unsupervised system does not require any “anomaly-free” training phase and is to our knowledge the first proposed approach combining unsupervised anomaly detection and SIEM systems. Six different anomaly detection algorithms have been evaluated and finally the global *k*-NN approach was selected. The detected anomalies in our field study were valuable to the security operator center team: Besides misconfigurations some interesting insights about the infrastructure have been found. Those results have not been reported by the traditional rule-based SIEM system.

ACKNOWLEDGMENTS

This work is part of ADEWaS, a project of Deutsche Telekom Laboratories supported by German Research Center for Artificial Intelligence (DFKI) GmbH and T-Systems International, South Africa.

REFERENCES

Albayrak, S. and Wieczorek, D. (1998). JIAC - an open and scalable agent architecture for telecommunication applications. *Intelligent Agents for Telecommunication Appl.*

Amer, M. and Goldstein, M. (2012). Nearest-neighbor and clustering based anomaly detection algorithms for rapidminer. In *Proc. of the 3rd RCOMM 2012*.

Angiulli, F. and Pizzuti, C. (2002). Fast outlier detection in high dimensional spaces. In *PKDD*, volume 2431 of *LNCS*, pages 43–78. Springer.

Breunig, M. M., Kriegel, H.-P., Ng, R. T., and Sander, J. (2000). Lof: identifying density-based local outliers. *SIGMOD Rec.*, 29(2):93–104.

Buecker, A., e. a. (2008). *IBM Tivoli Security Operations Manager 4.1*. Deployment Guide Series. IBM Redbooks, 1st edition.

Chandola, V., Banerjee, A., and Kumar, V. (2009). Anomaly detection: A survey. *ACM Comput. Surv.*, 41(3):1–58.

Endsley, M. R. (1987). The application of human factors to the development of expert systems for advanced cockpits. In *Human Factors Society 31st Annual Meeting*.

Garcia-Teodoro, P. and et al (2009). Anomaly-based network intrusion detection: Techniques, systems and challenges. *Computers and Security*, 28:18 – 28.

Grubbs, F. E. (1969). Procedures for detecting outlying observations in samples. *Technometrics*, 11:1–21.

He, Z., Xu, X., and Deng, S. (2003). Discovering cluster-based local outliers. *Pattern Recognition Letters*, 24(9-10):1641 – 1650.

Hodge, V. J. and Austin, J. (2004). A survey of outlier detection methodologies. *Artificial Intelligence Rev.*, 22.

IBM (2008). *Tivoli Security Operations Manager Version 4.1.1 - Administration Guide*. IBM, 1st edition. http://publib.boulder.ibm.com/infocenter/tivihelp/v2r1/topic/com.ibm.netcool_som.doc/tsom411_admin.pdf.

Jin, W., Tung, A., Han, J., and Wang, W. (2006). Ranking outliers using symmetric neighborhood relationship. In *Advances in Knowledge Discovery and Data Mining*, volume 3918 of *LNCS*, pages 577–593. Springer.

Kriegel, H.-P., Kröger, P., Schubert, E., and Zimek, A. (2009). Loop: local outlier probabilities. In *CIKM '09*, pages 1649–1652. ACM.

Mierswa, I., Wurst, M., and et al (2006). Yale (now: Rapidminer): Rapid prototyping for complex data mining tasks. In *Proc. of the ACM SIGKDD 2006*.

Miller, D. R. e. a. (2011). *Security Information and Event Management (SIEM) Implementation*. The McGraw-Hill Companies.

Nicolett, M., e. a. (2011). Magic Quadrant for Security Information and Event Management. *Gartner RAS Core Research*, (ID:G00212454).

Nicolett, M. and Kavanagh, K. M. (2012a). Critical Capabilities for Security Information and Event Management. *Gartner RAS Core Research*, (ID:G00227900).

Nicolett, M. and Kavanagh, K. M. (2012b). Magic Quadrant for Security Information and Event Management. *Gartner RAS Core Research*, (ID:G00227899).

Ramaswamy, S., Rastogi, R., and Shim, K. (2000). Efficient algorithms for mining outliers from large data sets. In *Proce. of the 2000 ACM SIGMOD*, pages "427–438".

Rodriguez, A. C. and de los Mozos, M. R. (2010). Improving network security through traffic log anomaly detection using time series analysis. In *CISIS'10*, pages 125–133.

Tang, J., Chen, Z., Fu, A., and Cheung, D. (2002). Enhancing effectiveness of outlier detections for low density patterns. In *Advances in Knowledge Discovery and Data Mining*, volume 2336 of *LNCS*, pages 535–548. Springer.