Towards Effective Masquerade Attack Detection

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ABSTRACT

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Data theft has been the main goal of the cybercrime community for many years, and more and more so as the cybercrime community gets more motivated by financial gain establishing a thriving underground economy. Masquerade attacks are a common security problem that is a consequence of identity theft and that is generally motivated by data theft. Such attacks are characterized by a system user illegitimately posing as another legitimate user.

Prevention-focused solutions such as access control solutions and Data Loss Prevention tools have failed in preventing these attacks, making detection not a mere desideratum, but rather a necessity. Detecting masqueraders, however, is very hard. Prior work has focused on user command modeling to identify abnormal behavior indicative of impersonation. These approaches suffered from high miss and false positive rates. None of these approaches could be packaged into an easily-deployable, privacy-preserving, and effective masquerade attack detector.

In this thesis, I present a machine learning-based technique using a set of novel features that aim to reveal user intent. I hypothesize that each individual user knows his or her own file system well enough to search in a limited, targeted, and unique fashion in order to find information germane to their current task. Masqueraders, on the other hand, are not likely to know the file system and layout of another user's desktop, and would likely search more extensively and broadly in a manner that is different from that of the victim user being impersonated. Based on this assumption, I model a user's search behavior and monitor deviations from it that could indicate fraudulent behavior. I identify user search events using a taxonomy of Windows applications, DLLs, and user commands. The taxonomy abstracts the user commands and actions and enriches them with contextual information.

Experimental results show that modeling search behavior reliably detects all simulated masquerade activity with a very low false positive rate of 1.12%, far better than any previously published results. The limited set of features used for search behavior modeling also results in considerable performance gains over the same modeling techniques that use larger sets of features, both during sensor training and deployment.

While an anomaly- or profiling-based detection approach, such as the one used in the user search profiling sensor, has the advantage of detecting unknown attacks and fraudulent masquerade behaviors, it suffers from a relatively high number of false positives and remains potentially vulnerable to mimicry attacks. To further improve the accuracy of the user search profiling approach, I supplement it with a trap-based detection approach. I monitor user actions directed at decoy documents embedded in the user's local file system. The decoy documents, which contain enticing information to the attacker, are known to the legitimate user of the system, and therefore should not be touched by him or her. Access to these decoy files, therefore, should highly suggest the presence of a masquerader. A decoy document access sensor detects any action that requires loading the decoy document into memory such as reading the document, copying it, or zipping it. I conducted human subject studies to investigate the deployment-related properties of decoy documents and to determine how decoys should be strategically deployed in a file system in order to maximize their masquerade detection ability. Our user study results show that effective deployment of decoys allows for the detection of all masquerade activity within ten minutes of its onset at most.

I use the decoy access sensor as an oracle for the user search profiling sensor. If abnormal search behavior is detected, I hypothesize that suspicious activity is taking place and validate the hypothesis by checking for accesses to decoy documents. Combining the two sensors and detection techniques reduces the false positive rate to 0.77%, and hardens the sensor against mimicry attacks. The overall sensor has very limited resource requirements (40 KB) and does not introduce any noticeable delay to the user when performing its monitoring actions.

Finally, I seek to expand the search behavior profiling technique to detect, not only malicious masqueraders, but any other system users. I propose a diversified and personalized

user behavior profiling approach to improve the accuracy of user behavior models. The ultimate goal is to augment existing computer security features such as passwords with user behavior models, as behavior information is not readily available to be stolen and its use could substantially raise the bar for malefactors seeking to perpetrate masquerade attacks.

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I dedicate this thesis to my mother and to the soul of my father, for their tireless support and abundant love...

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Chapter 1

Introduction

According to the 2010 e-crime watch survey [CERT, 2010][1] conducted by the Computer Emergency Response Team (CERT), 35% of the 523 security executives and law enforcement officials surveyed experienced unauthorized access and use of their information, systems, and networks. This type of intrusions, known as *a masquerade attacks*, was second in the top five list of electronic crimes perpetrated by outsiders after virus, worms and other malicious code attacks. Knowing that the authors of the survey report defined an outsider as 'someone who has never had authorized access to an organization's systems or networks', we know that the 35% number is just an underestimation of the scale of masquerade attacks, as these types of attacks may be performed by former employees, service providers, or contractors.

Also, according to the same survey, 31% of insiders who commited electronic crimes used password crackers or sniffers, 39% compromised an account, while only 35% used their own account to commit the electronic crime. These numbers are validated by Richardson in the 2008 CSI Computer Crime & Security Survey [Richardson, 2008] and by Randazzo et al. in their insider threat study of illicit cyber activity in the banking and finance sector [Randazzo *et al.*, 2005][1]. The authors concluded that the most important driver for such attacks is financial gain.

Masquerade attacks can occur in several different ways. In general terms, a masquerader

[1]Note that it is very difficult to get representative data from such surveys due to the limited number of responses. Note also that many cybercrimes go unreported, and that affected organizations usually choose not to report them due to the expected negative impact on their reputation and image.

may get access to a legitimate user's account either by stealing a victim's credentials through password sniffing and cracking tools, or through a break-in and installation of a rootkit or keylogger. In either case, the user's identity is illegitimately acquired. Another case is obtaining the credentials through a social engineering attack, or by taking advantage of a user's misplaced trust when he or she leaves his or her terminal open and logged in allowing any nearby co-worker to pose as a masquerader. In the first two cases, the identity thief must log in with the victim's credentials and begin issuing commands within the bounds of one user session, while in the latter the masquerader's activity could take place at any time within the user session. Victims range from ordinary individuals to regular employees and senior company executives, who are the subjects of highly-targeted attacks.

Symantec's 2010 Internet security threat report highlighted that targeted attacks directed at large enterprises and governmental organizations, as well as small businesses (SMBs), and individuals, are evolving to be a leading cause of data breaches. The report indicated that data breaches caused by outsiders 'resulted in an average of over 260,000 identities exposed per breach, far more than any other cause'. An example of such targeted attacks is *Hydraq*, the malware that attempts to steal intellectual property from large corporations [Symantec, 2010]. The 2010 e-crime watch survey [CERT, 2010] also reports that 22% of the respondents experienced Intellectual Property (IP) theft, and 20% reported Personally Identifiable Information (PII) theft, showing the extent of data theft attacks.

Traditional perimeter security technologies such as access controls had little effect in preventing masquerade attacks. Passwords can be easily sniffed or cracked by the numerous password crackers readily available through the web such as *L0phtcrack*. Biometric solutions, whether using fingerprint, iris, or face recognition, can all be easily defeated [Lane and Lordan, 2005].

Data Loss Prevention (DLP) tools [Verdasys, 2011; Vontu, 2009; Edge, 2011], which were designed to prevent data theft as their name suggests, are not effective in preventing information leakage, which constitutes the objective of most masquerade attacks. Such tools typically focus on detecting exfiltration rather than all information (mis-)use. Furthermore, in order for these tools to work, the organization using them has to locate the data that has to be protected. The 2010 Verizon Data Breach Investigations Report [Baker *et al.*, 2010] shows that 90% of the data breaches involved data that the organization did not know existed on the compromised asset.

Moreover, DLP tools work through simple rules defined by the user. Discovered data that matches these rules are tagged as confidential. So, these tools are effective only when the defined rules are accurate and comprehensive. For many types of sensitive data, it is difficult to define such rules. For example, while it may be easy to implement rules that discover data containing credit card or social security numbers, it is difficult to capture information that contains intellectual property using a few simple rules.

The failure of such systems in preventing masquerade attacks attempting to steal information calls for the use of monitoring, detection, and mitigation technologies in order to counter masquerade attacks motivated by data theft. According to Verizon's 2010 Data Breach report, 70% of data breaches were caused by external agents, i.e. outsiders to the victim organization. One interesting finding of this report is that discovering the breach took months in 63% of cases, with 61% of the breaches discovered by a third party. Another surprising fact is that 85% of the data theft incidents were not the result of highly-difficult attacks. This further demonstrates the lack of detection mechanisms within the compromised organizations and the need to deploy more monitoring and detection systems. The report also indicates that most of data breaches result from default, stolen, or weak credentials. Therefore, some mechanisms are needed for distinguishing the legitimate user actions from actions performed by masqueraders once the user is logged in, and for detecting relatively simple attacks with very low latency, so that the incurred costs to victims can be limited.

A major consequence of masquerade attacks that are motivated by data theft is Identity (ID) fraud. The Forbes magazine [Greenberg, 2010] reported that in 2009 alone, 11.2 million consumers were affected by fraud incidents in USA alone, causing $54 billion in ID fraud costs.

In this thesis, I propose a sensor that detects masquerade attacks where stealing data is the objective. The sensor, which is designed for deployment on personal computers, is highly efficient and effective, and is able to detect such attacks with very low latency, allowing the victim to react promptly to the attack, by potentially preventing the data theft, limiting its scope, quickly tracing the source of the attack, and potentially identifying the malefactor potentially.

When monitoring systems to mitigate these attacks, one can collect audit data at the host level, the network level, or both. As the observables at the network level are more distant from the individual user, attributing a network-level event to a specific user is hard. This suggests the need for host-based monitoring.

Unfortunately, many of the state-of-the-art defenses against masquerade attacks operate at the network-layer [GraniteEdge Enterprise Security Platform, 2011; Appliance, 2011; Lancope, 2011], and therefore severely suffer from the difficulty of attribution of malicious activity and difficulty to collect evidence that could be used against the attacker. Detectors that operate at the host level focus on forensics analysis and attribution after an attack has occurred using techniques such as sophisticated auditing [Verdasys, 2011; PacketMotion, 2011; Oakley, 2011]. They suffer from a high operational cost caused by the amount of logging needed and from the upfront costs incurred before deployment. As a matter of fact, these detectors require an extensive amount of expert knowledge in order to specify the rules and policies to be checked by the detector. An effective light-weight masquerade attack detector needs to use anomaly detection as a detection mechanism instead.

1.1 Definitions

Before presenting the hypothesis and the threat model taken in this work, I need to define some key terms:

- A **masquerader** is an attacker who succeeds in obtaining a legitimate user's identity and impersonates another user for illegitimate purposes. Credit card fraudsters are perhaps the best example of masqueraders. Once a bank customer's commercial identity is stolen (*e.g.* his or her credit card or account information), a masquerader presents those credentials for the malicious purpose of using the victim's credit line to steal money.

- A **masquerade attack** is a class of attacks, in which a user of a system illegitimately poses as, or assumes the identity of another legitimate user. Masquerade attacks are extremely serious, especially when sensitive information gets stolen that can ruin the reputation of an enterprise or make it lose its intellectual advantage over competitors.

- A **traitor** is an insider, *i.e.* a legitimate user within an organization, who has been granted access to systems and information resources, but whose actions are counter to policy, and whose goal is to negatively affect confidentiality, integrity, or availability of some information asset or system [Maybury *et al.*, 2005]. The traitor uses his or her legitimate credentials when perpetrating his or her malicious actions

Note that a disgruntled insider employee may act as a traitor and a masquerader after stealing the identity of a coworker.

1.2 Objectives

My goal in this work is therefore to design and develop a light-weight, privacy-preserving, host-based anomaly detector, that effectively detects masquerade attacks and collects related evidence at a low operational cost. Here, I establish a set of objectives that the masquerade attack detector has to meet in order to enable effective masquerade detection and detector deployment:

1. **Achieve high accuracy:** Intrusion Detection Systems (IDS) sensors are typically tuned to minimize false alerts by being less stringent about what is considered malicious. However, it is extremely important for the masquerade attack sensor to detect all masquerade attacks. When prevention is not possible, detection becomes important, so that vulnerabilities in the system can be remedied, and potential extra steps can be performed in order to limit the information leakage. It is also desirable to limit the number of false positives in order to lower the level of annoyance to the legitimate user.

2. **Have low operational costs:** A key criteria for any IDS sensor is its operational cost [Lee *et al.*, 2002]. The sensor should have a low runtime overhead during training, and especially during detection. Moreover, the sensor should have a small footprint

and low storage requirements for saving audit data and evidence of masquerade attacks.

3. **Detect the onset of a masquerade attack:** Most data theft attacks get detected after the attack has been completed by third parties or by reviewing the logs. Not only do I aim to perform online detection of these attacks, my goal is also to detect the onset of the attack, *i.e.* detect the attack at its very early stages, with **very low latency**, only minutes after its beginning.

4. **Support user privacy:** Anomaly detectors aiming at detecting masquerade attacks cannot rely on modeling program behavior [Forrest *et al.*, 1996]. Instead, they have to model *user behavior*. Privacy, then, emerges as an issue, which has to be addressed. A sensor that monitors user's actions and violates user privacy would probably not be widely adopted. A masquerade attack detector has to be able to build and apply user models without sharing any data collected about the user. This can be achieved through one-class modeling techniques, so no data sharing is required.

5. **Collect evidence:** According to the 2010 e-crime watch survey [CERT, 2010], 35% of the respondents reported that intrusions were not referred for legal action due to lack of evidence deemed sufficient to prosecute, while 29% of them stated the inability to identify the individual(s) committing the intrusion as the reason for not taking any legal action. A masquerade attack detector becomes more valuable if it can collect evidence against the attacker, and not just detect the occurrence of an attack, so that the attack can be referred for legal action, therefore deterring other attackers from committing the same crime.

1.3 Hypotheses

In this work, I aim to verify the following hypotheses:

1. Profiling classes of user activities improves masquerade detection accuracy as it reflects malicious intent through monitoring of search activities.
2. Profiling classes of user activities lowers the operational costs of the detector.
3. Combining user behavior profiling with baiting improves detection accuracy, enables the early detection of masquerade attacks, and hardens the masquerade detector against mimicry attacks.

1.4 Threat Model

Masqueraders impersonate legitimate users after stealing their credentials when they access a system. When presenting the stolen credentials, the masquerader is then a legitimate user with the same access rights as the victim user. To that extent, masquerade attacks represent one type of insider attacks. However, masquerade attacks can be characterized by the low amount of knowledge the attacker has about the victim's system and policies in place. In this work, I focus on outside masqueraders and assume that the attacker has little knowledge about the single-user system under attack. In particular, I assume that the attacker does not know the structure of the local file system and whether the system is baited or not. I do not focus on whether an access by some user is authorized since I assume that the masquerader does not attempt to escalate the privileges of the stolen identity, rather the masquerader simply accesses whatever the victim can access.

My objective is to detect data theft attempts performed by masqueraders on single-user systems. It can also be expanded to detect "need-to-know"policy violations perpetrated by traitors on multi-user systems. Note that such violations may also be due to an innocent mistake by a legitimate user.

Masquerade attacks can be characterized by the amount of knowledge a user has about the system and policies in place as well as by the intent of the user's actions. Figure 1.1 is a notional figure that shows the relationship between each type of attacker, his or her knowledge about the attacked system, and the intent of his or her actions.

I assume that the adversary knows that his or her activity on the victim's system is monitored. In all cases, I assume that the attacker can access the assets to be protected

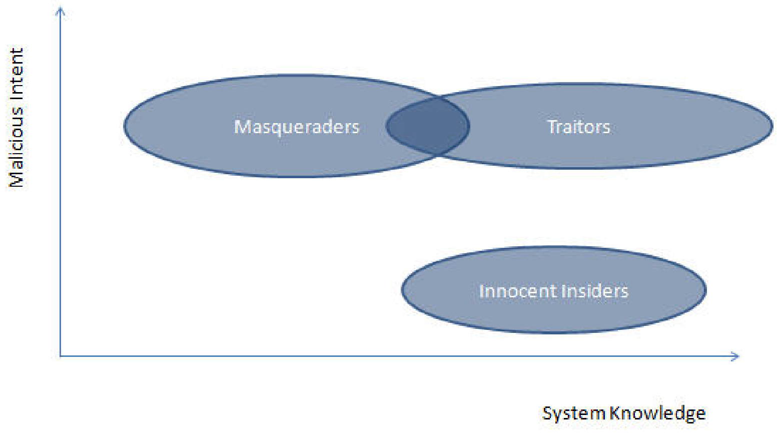

Figure 1.1: Malicious Intent and System Knowledge for different Types of Attackers

from inside the system via trusted access or system compromise. Therefore, I do not focus on monitoring access attempts to the system. The protected assets could range from PII information (*e.g.* customer records and employee personal data), to user credentials, to IP files, and other sensitive data (*e.g.* financial records) stored on the target system. I do not address the case of traitors that have full administrator privileges and full knowledge of the system in multi-user systems such as file servers.

1.5 Contributions

The contributions of this work include scientific contributions and technical contributions.

1.5.1 Scientific Contributions

- Classes of different user activities on information systems that can be used to accurately model user behavior on these systems and to characterize fraudulent behavior, such as masquerader behavior.

- A **taxonomy of Windows applications and DLLs**: The taxonomy elicits the classes of user activities. It is used to abstract and enrich the meaning of user activities performed on the host system. This abstraction enables the reduction of features used for user behavior profiling, and therefore a significant decrease in computational complexity.

- A **small set of search-related features** used for effective masquerade attack detection: The limited number of these features reduces the amount of sampling required to collect training data. Reducing the high-dimensional modeling space to a low-dimensional one allows for the improvement of both accuracy and performance over prior approaches. I shall use standard machine learning techniques to evaluate the performance of a system composed of these features. Other work has evaluated alternative algorithms. My focus in this work is on the features that are modeled. The best masquerade attack detection accuracy was achieved using a modern ML algorithm, Support Vector Machines (SVMs). SVM models are easy to update, providing an efficient deployable host monitoring system. I shall use one-class SVM (ocSVM) models in this work.

- Real-time monitoring of user search behavior in order to detect the onset of a masquerader attack.

- An empirical evaluation and measurement of how effectively these classes of user activities can be used in modeling distinctive user behavior and detecting fraudulent behavior.

- A personalized and diversified user behavior profiling approach using the defined classes of user activities for improved model accuracy and generalizabiliy.

- A **Windows dataset** [Ben-Salem, b] collected specifically **to study the masquerade attack detection problem**: Real-world data collection poses an important challenge in the security field. Insider and masquerader attack data collection poses even a greater challenge. Very few organizations acknowledge such breaches because of liability concerns and potential implications on their market value. This caused the scarcity of real-world datasets that could be used to study insider and masquerader attacks. Moreover, user studies conducted to collect such data lacked rigor in their design and execution. The collected dataset consists of normal user data collected from a homogeneous user group of 18 individuals as well as simulated masquerader data from 40 different individuals. The dataset, collected on Windows XP machines, is the first publicly available dataset for masquerade attack detection since the Schonlau dataset [Schonlau, 2001], which is rather suitable for the study of author identification problems, instead of masquerade attacks.

- An **integrated approach for masquerade attack detection** that combines user behavior profiling with a baiting approach that makes use of highly-crafted and well-placed decoy documents to bait attackers. The approach improves detection accuracy over prior techniques and is less vulnerable to mimicry attacks.
- A set of best practices and recommendations related to the strategic deployment of decoy documents on local file system for an effective detection of masquerade attacks.
- A **prescription for conducting human subject studies** applied to a computer security problems: Following this prescription enables the correct design and execution of these user studies and increases the power of the experiment and the generalizability of its results.

1.5.2 Technical Contributions

- A host-sensor that implements the integrated detection approach and collects potential evidence that could be used to identify the attacker. The sensor monitors a user's search activity and accesses to decoy documents with embedded HMAC tags when loaded in memory. The sensor reliably detects masquerade attacks with a very low false positive rate, a very low latency, a small minimal footprint, and low operational costs.

1.6 Thesis Outline

The rest of this thesis is organized as follows:

- I start by reviewing prior work related to the topics addressed in this dissertation in Chapter 2. The prior work discussed is related to user behavior profiling, the use of honeypots and trap-based techniques for intrusion detection, and the application of diversity in the field. I also discuss work related to mimicry attacks on anomaly detectors, and review various techniques for feature selection, software-based tamper-resistance, and inductive multi-task learning.

- A novel user search behavior profiling technique is introduced in Chapter 3, where I also discuss the masquerade detection accuracy and performance improvements achieved by this profiling technique.

- In Chapter 4, I evaluate different decoy document properties. I identify and rank the decoy properties that are most important for masquerade attack detection. I also demonstrate that decoy documents can be effectively used for masquerade attack detection without interference with normal user activities.

- Chapter 5 evaluates the impact of diversifying intrusion detection approaches. I experimentally demonstrate how user search behavior profiling can be combined with monitoring accesses to decoy documents to form a very accurate masquerade detection approach. Furthermore, I show that combining the two techniques can be used as a defense mechanism against mimicry attacks targeting the user behavior profiling sensor. In this chapter, I also present the architecture of the masquerade attack detector, which implements the search profiling and decoy access monitoring techniques, and measure its footprint and operational costs.

- Chapter 6 presents an approach for personalizing and diversifying user behavior models. I show that feature diversity improves the accuracy of user models and reduces their vulnerability to mimicry attacks.

- The thesis concludes with Chapter 7, where I summarize the contributions of this work and present directions for future work, both immediate and long-term

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Chapter 2

Related Work

In this chapter, I present the literature related to the main areas of this thesis. I start by discussing various approaches to masquerade and insider threat detection in Section 2.1. In Section 2.2, I review how the concept of diversity has been applied in the field of information and system security. I apply the same concept in this work by diversifying masquerade attack detection techniques and model features for profiling user behavior. I present various feature selection methods in Section 2.3. In Chapter 6, I apply a novel inductive-leaning based feature selection method to select the best discriminating features while customizing the features per user model, therefore diversifying the user models. Various inductive leaning methods are presented in Section 2.4. In Section 2.5, I present the types of mimicry attacks against anomaly-based intrusion detection systems, and I discuss in Chapter 5, how the masquerade attack sensor that is proposed in this dissertation can be hardened against such attacks. Finally, I conclude the chapter with Section 2.6, by discussing tamper-resistant software techniques. I show how the masquerade attack detection sensor is protected from shutdown and tampering by the attacker using a self-monitoring infrastructure that is integral to the sensor.

2.1 Masquerade and Insider Attack Detection

The insider attack detection research, and particularly the masquerade attack detection research work is primarily focused on various methods of profiling user actions and the systems they use. Much of the work reports on studies describing various audit sources and algorithms to profile users that are tested on simulated masquerade attack data, while distinguishing between network-level and host-level detection systems. Most of this work is specific to masquerade attack detection, although some work is reported on trap-based defenses aimed to the traitor detection problem using honeypots and honeytokens. An extensive literature exists reporting on approaches that profile user behavior as a means of detecting insider attacks, and identifying data theft in particular.

There are two main categories of user behavior profiling: (1) profiling based on biometrics such as keystroke dynamics, voice, gait, and speaking rhythm or diction [Gunetti and Picardi, 2005; Maiorana *et al.*, 2011], and (2) profiling based on user goals in performing computer commands, where profiling user command sequences is a dominant approach. Behavioral biometrics-based profiling approaches have limitations when dealing with changes in keystroke behavior, for instance, due to a broken arm or hand for example. Similarly, the user may exhibit different keystroke dynamics in different environments, such as when using a laptop at a desk or on his or her lap. Other behavioral biometric techniques face similar challenges.

The user behavior modeling approach presented in this work considers the means of estimating or inferring the intent of a series of user commands and profiling the users behavior on that basis and falls within the second category. In this section, I present user profiling approaches that fall under the same category [1]. .

2.1.1 Host-based User Profiling

One approach reported in the literature is to profile users by the commands they issue [Davison and Hirsh, 1998]. In the general case of computer user profiling, the entire audit source can include information from a variety of sources:

- Command line calls issued by users
- System call monitoring for unusual application use and events
- Database and file access monitoring

[1] A thorough survey of this work was published in [Ben-Salem *et al.*, 2008].

- Organization policy management rules and compliance logs

The type of analysis used is primarily the modeling of statistical features, such as the frequency of events, the duration of events, the co-occurrence of multiple events combined through logical operators, and the sequence or transition of events. However, most of this work failed to reveal or clarify the user's intent when issuing commands. The focus is primarily on accurately detecting change or unusual command sequences. I begin by presenting the work whose primary focus is command sequence modeling, which can be classified as either two-class or one-class modeling techniques.

Two-Class Modeling of Unix Shell Commands: Ju and Vardi proposed a hybrid high-order Markov chain model [Ju and Vardi, 2001] . A Markov chain is a discrete-time stochastic process. The authors aimed at identifying a 'signature behavior' for a particular user, based on the command sequences that the user executed. In order to overcome the high-dimensionality that is inherent in high-order Markov chains, they used a 'mixture transition distribution' (MTD) approach to model the transition probabilities from one command to another. When the test data contains many commands unobserved in the training data, a Markov model is not usable. Here, a simple independence model with probabilities estimated from a contingency table of users versus commands may be more appropriate. The authors used a method that automatically toggled between a Markov model and an independence model generated from a multinomial random distribution as needed, depending on whether the test data was 'usual' (*i.e.* previously seen commands), or 'unusual' (*i.e.* Never-Before-Seen Commands or NBSCs).

Schonlau *et al.* applied six masquerade detection methods to a dataset of 'truncated' UNIX shell commands for 70 users [Schonlau *et al.*, 2001] collected using the UNIX *acct* auditing mechanism. Each user had 15,000 commands collected over a period of time ranging between a few days and several months. 50 users were randomly chosen to serve as intrusion targets. The other 20 users were used as simulated masqueraders. The first 5000 commands for each of the 50 users were left intact or clean, the next 10,000 commands were randomly injected with 100-command blocks issued by the 20 masquerade users. When commands are grouped into blocks of 100 commands each, the block is either 'clean', or 'dirty' (*i.e.* all 100 commands were originated by a masquerader) [Schonlau, 2001]. The complete dataset and more information about it can be found at `http://www.schonlau.net`. The objective of their experiments was to accurately detect the 'dirty' blocks and classify them as masquerader blocks. This dataset was widely used by several authors that investigated different detection methods and has served as the standard benchmark dataset for this line of research. It is important to note that this dataset does not constitute ground truth masquerade data, but rather simulates impersonation.

One detection method explored by Schonlau, called 'uniqueness' relies on the fact that half of the commands in the training data are unique (*i.e* used by one user only), and many more are unpopular amongst the users (*i.e.* used only by a few users). The second method investigated was the Bayes one-step Markov approach. It was based on one-step transitions from one command to the next. The approach, originally proposed by DuMouchel [Dumouchel, 1999], uses a Bayes factor statistic to test the *null* hypothesis that the observed one-step command transition probabilities were consistent with the historical transition matrix. The two hypotheses modeled were the null hypothesis, which assumed that the observed transitions probabilities stem from the historical transition matrix, and the alternative hypothesis which assumed that they were generated from a Dirichlet distribution.

Schonlau *et al.* also applied a hybrid multi-step Markov method similar to the one introduced by Ju and Vardi [Ju and Vardi, 2001], and a fourth method, called the 'compression' method. The latter was based on the premise that test data appended to historical training data compressed more readily when the test data stemmed from the very same user rather than from a masquerader. They applied the method to the Schonlau dataset using the UNIX tool 'compress' which implements a modified version of the Lempel-Ziv algorithm.

IPAM (Incremental Probabilistic Action Modeling), was another method applied to the same dataset. The method is based on one-step command transition probabilities estimated from the training data, and was first introduced by Davidson and Hirsch to build an adaptive command line interface [Davison and Hirsh, 1998; Davison and Hirsh, 1997]. The transition probabilities were continuously updated following an exponential decay scheme with the arrival of a new command.

Lane and Brodley proposed a sequence-match approach, where upon the arrival of each new command, a similarity measure between the most 10 recent commands and a user's profile is computed [Lane and Brodley, 1997]. A user's profile consists of all 10-command sequences that the user has issued in the past. For the Schonlau dataset, the initial user profiles are therefore made up of 4991 command sequences. The number of matches in a command-by-command comparison of two command sequences constitutes the similarity measure. The matches are weighted and adjacent matches are assigned a higher weight. With each new command, the test sequence of the last 10 commands is therefore scored against all 4991 command sequences available in the user's profile. The maximum of all scores computed is then assigned to the test command sequence. As these scores are noisy, and since the masquerade data in the Schonlau data comes in blocks of 100 commands, the last 100 scores are averaged out. The average score is compared to a threshold that varies by user model. If the score is lower than the threshold, the 100-command block is classified as a masquerade block.

Maxion and Townsend applied a naïve Bayes classifier, which had been widely used in text classification tasks, to the same dataset [Maxion and Townsend, 2002]. They provided a thorough and detailed investigation of classification errors of the classifier in a separate paper [Maxion and Townsend, 2004], highlighting why some masquerade victims were more vulnerable than others, and why some masqueraders were more successful than others. Killourhy and Maxion also investigated a shortcoming of the naïve Bayes classifier when dealing with NBSCs [Killourhy and Maxion, 2008].

Seo and Cha experimented with combinations of sequence-based SVM kernels including the K-gram kernel and the string kernel with some success. They managed to increase the classification accuracy compared to the widely used RBF kernel with relatively high false positive rates [Seo and Cha, 2007].

Table 2.1 presents the estimated accuracy of the two-class based modeling methods which are all based on a supervised training methodology whereby data is labeled as 'self' or 'non-self' (with True Positive rates displayed rather than True Negatives). Performance is shown to range from 1.3% - 10.4% False Positive rates, with a False Negative rate ranging from 2.6% to 73.2% (alternatively, True Positive rates from 26.8% to 97.4%). Clearly, these results are far from ideal.

The Schonlau data used is a mixture of command sequences from different users. The classifiers produced in these studies essentially identify a specific user from a set of known users who provided training data. Furthermore, mixing data from multiple users to train classifiers to detect masqueraders is complicated and fraught with problems. Besides potential privacy threats, requiring the mixture of data from multiple users requires substantial retraining of classifiers as users join and leave an organization.

One-Class Modeling of Unix Shell Commands: In a real-world setting, it is probably more appropriate to use a one-class based anomaly detection training approach. Wang and Stolfo experimented with one-class based training methods using a naïve Bayes classifier and a Support Vector Machine (SVM) model of user commands to detect masqueraders [Wang and Stolfo, 2003]. The authors also investigated SVMs using binary features and frequency-based features. The one-class SVM algorithm using binary features performed best among four one-class training algorithms. It also performed better than most of the two-class algorithms listed in Table 2.1, except the two-class multinomial naïve Bayes algorithm with updating. In summary, Wang and Stolfo's experiment confirmed that, for masquerade attack detection, one-class training is as effective as two-class training.

Szymanski and Zhang proposed recursively mining the sequence of commands by finding frequent patterns, encoding them with unique symbols, and rewriting the sequence using this new coding [Szymanski and Zhang, 2004]. A signature was then generated for each user using the first 5000 user commands. The process stopped when no new dominant patterns in the transformed input could be discovered. They used a one-class SVM classifier for masquerade detection. The authors used an individual intrusion detection approach with 4 features (the number of dominant patterns in levels 1 and 2, and the number of distinct dominant patterns in levels 1 and 2), as well as a 'communal' intrusion detection approach, where they added new features, such as the number of users sharing each dominant pattern in a block. Again, the latter approach demands mixing user data and may not be ideal or easily implemented in a real-world setting.

Dash *et al.* developed user profiles from command sequences [Dash *et al.*, 2005]. Thirteen temporal features were used to check the consistency of patterns of commands within a given temporal sequence. Probabilities were calculated for movements of commands within

Table 2.1: Summary of Accuracy Performance of Two-Class Anomaly Detectors Using the Schonlau Dataset

Method	**True Pos. (%)**	**False Pos. (%)**
Uniqueness [Schonlau *et al.*, 2001]	39.4	1.4
Bayes one-step Markov [Schonlau *et al.*, 2001]	69.3	6.7
Hybrid multi-step Markov [Schonlau *et al.*, 2001]	49.3	3.2
Compression [Schonlau *et al.*, 2001]	34.2	5.0
IPAM [Davison and Hirsh, 1998] [Davison and Hirsh, 1997; Schonlau *et al.*, 2001]	41.1	2.7
Sequence Match [Lane and Brodley, 1997; Schonlau *et al.*, 2001]	26.8	3.7
Naïve Bayes (with updating) [Maxion and Townsend, 2002]	61.5	1.3
Naïve Bayes (without updating) [Maxion and Townsend, 2002]	66.2	4.6
SVM with K-gram kernel [Seo and Cha, 2007]	89.6	10.4
SVM with string kernel [Seo and Cha, 2007]	97.4	2.6

a sequence in a predefined reordering between commands. The authors achieved a detection rate of 76%, but did not report a false positive rate.

Coull *et al.* [Coull *et al.*, 2001] modified the Smith-Waterman local alignment algorithm and developed the semi-global alignment method, which uses a scoring system that rewards the alignment of commands in a test segment. The bioinformatics-inspired method, however, does not necessarily penalize the misalignment of large portions of the signature of the user. The authors enhanced it and presented a sequence alignment method using a binary scoring and a signature updating scheme to cope with concept drift [Coull and Szymanski, 2008]. The computational complexity of the sequence alignment algorithm is $O(m * n)$ where where m is the length of the sequence of audit data gathered from the normal user and n is the length of the test sequence.

Yung chose experiment with a probabilistic method, called the self-consistent naïve Bayes classifier [Yung, 2004]. The method is a combination of the naïve Bayes classifier and the Expectation-Maximization (EM) algorithm. The new classifier is not forced to make a binary decision for each new block of commands, *i.e.* a decision whether the block is a masquerade block or not. Rather, it assigns a score that indicates the probability of a masquerader block. Moreover, it can change scores of earlier blocks as well as later blocks of commands.

Oka *et al.* attempted to capture the dynamic behavior of a user that appears in a command sequence by correlating not only connected events, but also events that are not adjacent to each other while appearing within a certain distance (non-connected events). They developed the layered networks approach based on the Eigen Co-occurrence Matrix (ECM) [Oka *et al.*, 2004b; Oka *et al.*, 2004a]. The ECM method extracts the causal relationships embedded in sequences of commands, where a co-occurrence means the relationship between every two commands within an interval of sequences of data. This type of relationship cannot be represented by frequency histograms nor through n-grams. While this method provided relatively good accuracy results compared to all other one-class modeling techniques, it is computationally intensive. It takes 22.15 seconds to classify a single command sequence as normal or anomalous.

The disadvantage of the last three methods lies in their lack of scalability due to their high computational cost. The size of the user profile grows linearly in the former two and exponentially in the latter with each command used by the user for the first time. Model training and update time as well as command sequence test time grows accordingly. Furthermore, such approaches would be even harder to apply in an operational environment, particularly when using other operating systems such as Windows, where the number of unique applications, processes, and user actions is orders of magnitude higher than the number of commands in Unix.

The detection results achieved by the one-class modeling techniques using the Schonlau dataset are summarized in Table 2.2.

Table 2.2: Summary of Accuracy Performance of One-Class Anomaly Detectors Using the Schonlau Dataset

Method	**True Pos. (%)**	**False Pos. (%)**
Recursive Data Mining [Szymanski and Zhang, 2004]	63	7
one-class SVM using binary features [Wang and Stolfo, 2003; Ben-Salem and Stolfo, 2010]	72.7	6.3
Semi-Global Alignment [Coull *et al.*, 2001]	75.8	7.7
Sequence Alignment (with Updating) [Coull and Szymanski, 2008]	68.6	1.9
Eigen Co-occurrence Matrix [Oka *et al.*, 2004b; Oka *et al.*, 2004a]	72.3	2.5
Naïve Bayes + EM [Yung, 2004]	75.0	1.3

Other Modeling Techniques and Analyses of Unix Shell Commands: Tan and Maxion investigated which detector window size would enable the best detection results [Tan and Maxion, 2001]. They uncovered that the best detector window size was dependent on the size of the minimal foreign sequence in test data, which is not determinable *a priori*. A foreign sequence is one that is not contained in the alphabet set of the training data, but each of its individual symbols is. A minimal foreign sequence is a foreign sequence that contains within it no smaller foreign sequences.

It was shown that the Schonlau dataset was not appropriate for the masquerade detection task. Maxion listed several reasons [Maxion and Townsend, 2004]. First, the data was gathered over varied periods for different users (from several days to several months), and the number of login sessions varied by user. Second, the source of data is not clear. One does not know whether the users perform the same jobs or are widely spread across different job functions. Moreover, in *acct*, the audit mechanism used to collect the data, commands are not logged in the order in which they are typed, but rather when the application ends. Hence the methods applied that focus on strict sequence analysis may be faulty.

In order to alleviate some of the problems encountered with the Schonlau dataset, Maxion applied naïve Bayes classifier to the Greenberg dataset, a user command dataset enriched with flags and arguments [Maxion, 2003]. He compared the performance of the classifier on the Greenberg dataset by using enriched commands and truncated commands. The hit rate achieved using the enriched command data was more than 15% higher than with the truncated data. However, the false positive rate was approximately 21% higher as well. Nevertheless, when plotting the ROC curves for both datasets, the one for enriched data runs above the ROC curve for truncated data, showing that a better detection performance can be achieved using the user commands enriched with flags and arguments.

As noted, several types of attributes and statistical features can be used for modeling a user's actions. Ye *et al.* studied the attributes of data for intrusion detection [Ye *et al.*, 2001]. The attributes studied included the occurrence of individual events (audit events, system calls, user commands), the frequency of individual events (e.g. number of consecutive password failures), the duration of individual events (CPU time of a command, duration of a connection), and combinations of events, as well as the frequency histograms or distributions of multiple events, and the sequence or transition of events. The goal was to find out whether the frequency property was sufficient for masquerader detection, and if so whether there was a single event, at a given time, that is sufficient for detecting a masquerader. Five probabilistic techniques were investigated on system call data: a decision tree, Hotelling's T^2 test, the chi-square test, the multivariate test, and the Markov chain. The dataset used was made up of 250 auditable security-relevant events collected by the Solaris Basic Security Module (BSM) and 15 simulated intrusions on the background of normal activities. The investigation confirmed the importance of both the frequency property, and the ordering property of events.

User Behavior and Program Profiling by Monitoring System Call Activity:

Nguyen *et al.* investigated whether monitoring system call activity is effective in detecting insider threats [Nguyen *et al.*, 2003]. Their results showed that profiling program system call activity could be effective in detecting buffer overflow attacks. They also showed that user file access patterns varied from day to day, and hypothesized that such patterns would not be effective in insider threat detection. The authors did not evaluate their hypothesis. Counter to their conjecture, I show that file access volume can be used, in conjunction with file system search-related features, in building accurate and masquerade classifiers.

User Profiling in Windows Environments: Less research work has been applied to Windows environments compared to work done for the Unix environment. Much of the difference lies in the auditing methods available on each platform. Linux apparently has cleaner auditing mechanisms (*acct*, BSM, etc.), whereas Windows has a plethora of system actions that can be captured by various monitoring subsystems.

Shavlik *et al.* presented a prototype anomaly detection system that created statistical profiles of users running Windows 2000 [Shavlik and Shavlik, 2004]. Their algorithm measured more than two-hundred Windows 2000 properties every second, and created about 1500 features from the measurements. The system assigned weights to the 1500 features in order to accurately characterize the particular behavior of each user. Every user, therefore, is assigned his or her own set of feature weights as his or her unique signature. Following training, each second all of the features 'vote' as to whether an intrusion has occurred. The weighted votes 'for' and 'against' an intrusion were compared, and if there were enough evidence, an alarm would be raised.

Li and Manikopoulos explored modeling user profiles trained with SVMs using audit data from a Windows environment gathered over a year [Ling and Manikopoulos, 2004]. They modeled the sequence of windows and processes over time in a manner similar to what a process sensor would see. They simulated attack data by mixing data between legitimate user sessions, and reported some success at modeling the user profiles. Their approach suffered from high false positive rates though.

In most of the approaches surveyed above, either user command data or system calls data were used. User command data fail to capture window behavior and do not include commands executed inside a script, whereas system call data are not particularly humanreadable, nor easily attributed to direct user action. On the other hand, process table data includes window behavior and anything running in a script, and can easily be interpreted when read by a human. Moreover, window tracing provides information at a level of granularity somewhere between the levels of a command line and a system call, while most of the system noise can be filtered out (a formidable challenge when tracing Windows), which makes it a good candidate for user profiling. This lead Goldring to collect user data consisting of successive window titles with process information (from the process table) for a group of users over two years [Goldring, 2003]. The combination of data sources allowed the use of the process tree structure to filter out system noise. However, it complicated the feature selection task. The proposed system reduced the stream of data to a single feature vector that consisted of a mixture of different feature types per session. A record was generated each time a new window was opened including information about the window title, and all contents in a window title's bar. Besides that, the window's process and parent process IDs were saved. The window titles' data allowed one to distinguish between the operating system's programs such as *Control Panel* and *Find Files*, which would not be distinguishable from inspecting the process table alone. Goldring reported no performance results, but rather presented a proof-of-concept system.

2.1.2 Network-Based User Profiling

When an insider accesses information that they do not need to know, one may have good evidence of an insider attack. A system for detecting insiders who violate need-to-know policies, called ELICIT, was developed by Maloof and Stephens [Maloof and Stephens, 2007]. The focus of their work was on detecting activities, such as searching, browsing, downloading, and printing, by monitoring the use of sensitive search terms, printing to a non-local printer, anomalous browsing activity, and retrieving documents outside of one's social network. Five malicious insider scenarios were tested, that represented need-to-know violations. Contextual information about the user identity, past activity, and the activity of peers in the organization or in a social network were incorporated when building the models. HTTP, SMB, SMTP, and FTP traffic was collected from within a corporate intranet network for over 13 months, but no inbound or outbound traffic was gathered. In order to identify the information deemed outside the scope of an insider's duties, a social network was computed for each insider based on the people in their department, whom they e-mailed, and with whom they worked on projects. A Bayesian network for ranking the insider threats was developed using 76 detectors. Subject matter experts defined the thresholds for these detectors, at which an alarm gets set. A single threat score was computed for each user based on the alerts from these detectors.

Caputo *et al.* studied differences in user behavior when gathering information for malicious *vs.* benign purposes [Caputo *et al.*, 2009a]. They conducted experiments in a commercial setting with 50 human subject study participants, and found that malicious users broke their information gathering activities into more separate sessions than the benign users, and downloaded large amounts of data indiscriminately.

Identifying specific users from observable network events consumed considerable effort. Event attribution proved to be a major challenge: 83% of events initially had no attribution, and 28.6% of them remained un-attributed, even after the use of two off-line methods to determine the originator of a particular event. The evaluation of the system used scenarios that were executed over a short period of time, less than one day. However, attacks by insiders who violate need-to-know policy usually occur over days, months, and even decades, such as in the case of Robert Hanssen. Therefore, it is important to evaluate the ELICIT system using other scenarios that occur over longer periods of time.

2.1.3 Honeypots and Deception Techniques

Honeypots are information system resources that are designed to attract malicious users. Honeypots have been widely deployed in De-Militarized Zones (DMZs) to trap attempts to penetrate an organization's network carried out by external attackers. Their typical use is for early warning and slowing down or stopping automated attacks from external sources, and for capturing new exploits and gathering information on new threats emerging from outside the organization.

Spitzner presented several ways to adapt the use of honeypots to the insider attack detection problem [Spitzner, 2003]. Since insiders probably know what information they are after, and in many cases, where that information is to be found, and how it could be accessed, he recommended implanting honeytokens with perceived value in the network or in the intranet search engine. He defined a honeytoken as 'information that the user is not authorized to have or information that is inappropriate' [Spitzner, 2003]. This information could then direct the insider to the more advanced honeypot that could be used to discern whether the insider's intention was malicious or not, a decision that may be determined by inspecting the insider's interaction with the honeypot. In order to reach such interaction that can be used to gather information, it is important to ensure that the honeypot looks realistic to the insider.

Decoy files, or 'honeyfiles', were further developed by Yuill *et al.* [Yuill *et al.*, 2004; Yuill *et al.*, 2006]. The authors created a system that allowed users to select files from the user space on a network file server, and change them into decoy files. Illegitimate accesses to the honeyfiles could then be monitored by consulting a record that associated the honeyfile with the legitimate *userid*.

Bowen *et al.* extended the notion of a decoy document system, and developed an automated system for generating decoy documents [Bowen *et al.*, 2009b; Bowen and Hershkop, 2009]. The system generated files from different templates with various themes, including a health-related information theme, a financial account theme, and a tax return theme. They also proposed several decoy properties as general guidelines for the design and deployment of decoys, such as the decoy's conspicuousness, believability, enticingness to the adversary, as well as the decoy's non-interference with the the defender's regular activities.

Cohen *et al.* developed a 'framework for deception' [Cohen *et al.*, 2001]. In their study of deception techniques, they identified factors affecting the nature of deceptions and listed requirements for the success of any deception operation. They also presented a cognitive model for higher-level deception. Although they did not conduct any experiments or user studies, they recommended evaluating the effectiveness of deception techniques against systems combining both people and computers.

Honeypots and baiting techniques suffer from certain shortcomings. First, the attacker may not ever use or interact with the honeypot or honeytoken, especially if their identity is known to or discovered by the insider. Moreover, if an attacker discovers the honeypot or the bait, he or she can possibly inject bogus or false information to complicate detection.

2.1.4 Integrated Approaches

Among the first integrated systems was the one presented by Maybury *et al.* [Maybury *et al.*, 2005]. The integrated system used honeypots, network-level sensors for traffic profiling to monitor scanning, downloads, and inside connections, and 'Structured Analysis', a real-time and top-down structural analysis tool using the models of insiders and pre-attack indicators to infer the malicious intent of an insider. Moreover, several data sources were used in addition to auditing of cyber assets. Physical security logs, such as employee badge readers, were also integrated to keep track of the location of a user. The program funding this effort apparently ended prematurely. Insufficient test and evaluations were performed on an approach that seemed quite promising.

2.1.5 Search Behavior Profiling

Search behavior has been recently studied in the context of web usage mining. Most literature focused on the behavior of a user after a web search engine returned a list of potentially sponsored search results, *i.e.* the focus was on user behavior when browsing and retrieving the search query results [O'Brien and Keane, 2007; Attenberg *et al.*, 2009]. However, a few studies investigated user behavior prior to the submission of a search query. Baeza-Yates *et al.* analyzed web queries and modeled keywords, query and session lengths, as well as click and query refinement patterns [Baeza-Yates *et al.*, 2005]. Kamvar and Baluja noted how the device used to submit a web search query influenced the user's search behavior [Kamvar and Baluja, 2006]. They showed that, when using a wireless device, users tended to have directed search goals with specific URLs and short sessions with a few queries. However, when using desktops, searchers engaged in undirected exploration.

2.2 Redundancy and Diversity in Security

Diversity is an approach that has been widely used in fault-tolerant and self-healing systems [Kelly, 1982; Kelly and Avizienis, 1983; Avizienis, 1995]. Kelly and Avizienis advocated n-version programming and claimed that it would improve system robustness if the n programs were mutually independent. Knight and Leveson, however, showed that design diversity had a limited effect on robustness [Knight and Leveson, 1986], as developers tended to make the same errors in their designs and code. The results of n different approaches are thus not independent of each other, because students are trained in similar ways with similar techniques.

Littlewood and Strigini were among the first researchers to apply the concept of *diversity* to computer security [Littlewood and Strigini, 2004]. Motivated by the application of models of diversity in system and process design and by the work on formal probability modeling of reliability and safety [Mitra *et al.*, 2002], the authors studied the roles and limits of redundancy and diversity in intrusion detection systems. They suggested that model diversity could be utilized to build anomaly-based IDS systems that could provide more coverage to intrusion attacks. They argued for a formal mathematical approach to estimating the effectiveness of both approaches and for a metric for measuring the independence of various intrusion detection systems (IDSs) by category of attack rather than by some average mixture of attacks.

Gashi *et al.* [Gashi *et al.*, 2009] studied the actual gains in detection rates that could be obtained through the use of *diverse* or *different* off-the-shelf anti-virus engines. They showed that when using two anti-virus engines only, almost a third of the engine pairs performed better than the best individual engine.

Tan and Maxion studied the anomaly space of various sequence-based anomaly detectors when presented with a 'foreign sequence', *i.e.* a never-before-seen-sequence of events, as an anomaly [Tan and Maxion, 2005]. They showed that the anomaly spaces of these anomaly detectors are highly overlapping, which limited or prevented any potential detection accuracy gains that could be achieved by combining several anomaly detectors into one classifier.

Bloomfield and Littlewood argued that that general diversity was not enough. They advocated the *three-legged stool* approach, where each approach had to use a a very different technique and perspective from the others [Bloomfield and Littlewood, 2003].

Despite the increasing recognition of the value of diversity of sensors in intrusion detection, no experiments have been conducted to measure the effectiveness of the use of detectors with diverse detection techniques (*e.g.* behavior profiling and trap-based detection) as advocated by Bloomfield and Littlewood[Bloomfield and Littlewood, 2003]. Furthermore, this concept of diversity has not yet been applied to models used in anomaly detectors. I conjecture that diversity in user models through the selection of different features for different users could enable modeling the unique behavior of specific users. Moreover, it could bring additional performance gains to the sensor.

2.3 Feature Selection

There has been extensive work on feature selection approaches. Feature selection methods can be categorized in two ways: as filter or as wrapper methods [Kohavi and John, 1997]. The former methods do not take into account the effects of the selected features on the accuracy performance of the modeling algorithm. The latter overcome this shortcoming by searching through the space of feature subsets while estimating the accuracy of the modeling algorithm. This, obviously, comes with a higher computational complexity.

Guyon and Elisseeff surveyed variable and feature selection methods [Guyon and Elisseeff, 2003]. Due to the lack of a benchmark between the various feature selection methods, the authors recommended the use of a linear prediction technique, such as a linear SVM, when tackling a new problem, and then selecting features using two different methods: a variable ranking method that uses a correlation coefficient or mutual information, and a nested subset selection method with multiplicative updates.

Bi *et al.* proposed an approach for dimensionality reduction using sparse support vector machines [Bi *et al.*, 2003]. The approach benefits from the variable selection capability inherent in sparse linear SVM, as well as non-linear induction. The results achieved by this approach maintained or improved generalizability and outperformed SVMs trained with the full set of features or the features selected by correlation ranking.

The problem of feature selection or dimensionality reduction is more challenging in an unsupervised learning setting, as the features discarded could have a negative impact on the accuracy of the modeling algorithm. Globerson and Tishby proposed extracting approximate sufficient statistics for one variable about another from the co-occurrence matrix. The method is used for dimensionality reduction in unsupervised learning [Globerson and

Tishby, 2003].

Grafting is an incremental feature selection approach that operates iteratively to optimize a gradient-based heuristic used to select the most likely feature to improve a model's accuracy. This gradient descent-based algorithm proposed by Perkins *et al.* works as an integral part of the model training or learning, which makes it efficient [Perkins *et al.*, 2003]. It scales linearly with the number of feature vectors and quadratically with the number of features.

Torkkola presented a feature extraction method that maximizes the non-parametric estimate of mutual information between features and class labels without using any simplifying assumptions about the densities of the classes [Torkkola, 2003]. This dimensionality reduction approach falls under the feature transform methods (as opposed to feature selection methods), and therefore is more computationally intensive. However, the author showed that it is computationally usable with training datasets with tens of thousands of samples.

Ranking variables for feature selection can be based on different criteria. Rakotomamonjy presented some of these criteria using SVMs, showing that the derivative of the weight vector criterion performed consistently well over all tested datasets [Rakotomamonjy, 2003].

Most feature selection methods are dependent on the target machine. Stoppoiglia *et al.* proposed a simple variable ranking approach for feature selection that is intuitive and independent of the target machine [Stoppiglia *et al.*, 2003]. The filter method works using the orthogonalization and mutual information between features. It can also be applied to select computed kernels such as wavelets or radial basis functions.

2.4 Inductive Multi-task Learning

Jebara and Jaakola developed a Maximum Entropy Discrimination (MED) framework to solve log-sigmoid problems, which they enhanced later to solve SVMs problems, sparse SVMs, and multi-task SVMs [Jebara and Jaakkola, 2000]. The framework is a generalization of support vector machines, as it returns a distribution of parameter models $P(\theta)$ rather than a single parameter value θ, where the expected value of the discriminant under this distribution agrees with the labeling [Jebara, 2004]. These MED solutions can be further augmented to represent join densities over parameters of several classifiers and feature and kernel selection configurations, rather than parameters of a single classifier. For example, by modifying the discriminant with a binary feature selection switch vector $s = [s_1, s_2, ..., s_D]$, where $s_i \in \{0, 1\}$, $i \in [1..D]$, and D is the number of features, we can learn the SVM model while selecting the best discriminating features for the model. The framework provides an iterative quadratic programming implementation and uses some tight bounds for improved runtime efficiency.

Jacob and Bach investigated clustered multi-task learning using a convex formulation [Jacob *et al.*, 2004]. They showed that multi-task learning could improve classifier accuracy when few training points are available. However, their results also showed, that with large samples of data, the use of the multi-task learning approach would no be longer useful.

Finally, Baxter argued that the average error of M tasks could potentially decrease inversely with M [Baxter, 2000], while Ben-David and Schuller presented generalization guarantees for each individual task for classifiers that are closely related and share a common structure [Ben-david and Schuller, 2003].

2.5 Dealing with Mimicry Attacks

Tan *et al.* [Tan *et al.*, 2002] identified two mechanisms for performing mimicry attacks:

1. Contaminating the learning and/or model update process by inserting attack data into normal user data

2. Intertwining attacks with normal user activity so that the attacks go undetected. This is also known as an evasion attack.

Wagner and Soto investigated the types of mimicry attacks against host-based intrusion detection systems [Wagner and Soto, 2002]. They adopted the generally-accepted assumption that the attacker knows how the system works and which IDS algorithm is being used, as the system's source code can be easily reverse-engineered. They distinguished six types of evasion attacks, assuming that the attack consisted in feeding a malicious sequence of commands or system calls to the IDS:

1. The *lip under the radar* attack: The attacker avoids causing any change to the observable behavior of the application, *i.e.* they do not launch any processes that the legitimate user would not normally run. They use already running processes only, and at the same rate as the victim user.

2. The *be patient* attack: The attacker waits for the time when the malicious sequence is accepted.

3. The *be patient, but make your own luck* attack: This is similar to the previous attack, but forces the application or IDS into a specific execution path in order to speed up the acceptance of the malicious sequence.

4. The *replace system call parameters* attack: As its name suggests, this attack consists in replacing the arguments in a system call in order to achieve a malicious goal.

5. The *insert no-ops* attack: This attack creates variants of the malicious sequence, which may be more likely to get accepted.

6. The *generate equivalent attacks* attack: The authors present a few examples of this type of attack, such as the substitution of the *read()* system call with a call to *mmap()* followed by a memory access. Another equivalent attack can be achieved by forking the IDS and splitting the malicious sequence between the two IDS processes.

In this thesis, I propose diversifying user models and combining orthogonal detection techniques to protect against evasion attacks.

2.6 Tamper-Resistant Software Techniques

A few software-based solutions for verifiable code execution and for code attestation were proposed. Code attestation is a technique, by which a remote party, the verifier, also known as the 'challenger,' can verify the authenticity of the code running on a particular host, the 'attestor.' It is typically implemented through a set of measurements performed on the attesting host and sent to the verifier. The verifier then validates these measurements and the state of the system indicated by them.

One among the first tamper-resistant software techniques, Genuinity achieves code attestation through the use of a subroutine in the program that calculates the checksum of the memory space and sends it to the "verifier [Kennell and Jamieson, 2003]." The technique assumes the existence of a virtually-paged architecture and low-level CPU counters, making it usable in machines with high-end CPUs only. Seshadri *et al.* extended Genuinity, and proposed SWATT, another SoftWare-based ATTestation technique to verify the memory contents of embedded devices [Seshadri *et al.*, 2004]. Later, Seshadri *et al.* presented Pioneer, a software-based protocol to enable verifiable code execution on untrusted legacy systems which lack secure co-processors and virtualization support [Seshadri *et al.*, 2005].

Although the goal of these solutions is tamper-proofing software, *i.e.* preventing the unauthorized use of software, they could presumably be easily modified to detect unauthorized attempts to disable or shutdown the software. However, they all require the presence of a third party which can execute code for verification, on top of their extremely high computational cost. In this thesis, I use embedded self-monitoring monitors to protect the proposed detection against tampering attacks.

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Chapter 3

User Search Behavior Profiling

A common approach to counter masquerade attacks is to apply machine learning (ML) algorithms that produce classifiers, which identify suspicious behaviors that are potentially indicative malfeasance of an impostor. Previous work has focused on auditing and modeling sequences of user commands including work on enriching command sequences with information about arguments of commands [Schonlau *et al.*, 2001; Maxion and Townsend, 2002; Wang and Stolfo, 2003].

I extend prior work on modeling user command sequences for masquerade detection, and propose a novel approach to profile a user's search behavior by auditing search-related applications and accesses to index files, such as the index file of the Google Desktop Search application. Prior techniques for masquerade attack detection, as reviewed in Chapter 2, suffer from low accuracy and/or a high computational cost. This is somewhat expected, as modeling user behavior in general implies a very high-dimensional feature space. In order to improve the accuracy of the user models, one needs to identify ways for dimensionality reduction that apply to all user models.

One possible approach, is to identify specific user behaviors that could be used to classify user activities as legitimate or fraudulent. By focusing on these specific behaviors, or limited aspects of user behavior, I was able to reduce the dimensionality of the feature space. Search behavior is particularly promising to monitor.

I conjecture that a masquerader is unlikely to have the depth of knowledge of the victim's machine (files, locations of important directories, available applications, etc.), nor is he or she likely to know the victim's search behavior when the victim uses his or her own system. This complicates the masquerader's task to mimic the user. Hence, a masquerader would likely first engage in information gathering and search activities before initiating any specific actions. On the other hand, a legitimate user will search within an environment they have created. For example, he or she would search for a file within a specific directory. A programmer, for instance, may search for a symbol within a specific source code file. Since the attacker has little to no knowledge of that environment, that lack of knowledge will be revealed by the masquerader's abnormal search behavior.

It is this key assumption that I rely upon in order to detect a masquerader. I do not focus on whether an access by some user is authorized since I assume that the masquerader does not attempt to escalate the privileges of the stolen identity. Rather, the masquerader simply accesses whatever the victim can access. My focus is rather on monitoring a user's behavior in real time to determine whether current user actions are consistent with the user's historical behavior, primarily focused on his or her unique search behavior.

While it is very difficult to gather ground truth to test my hypothesis, my experiments aim to provide evidence that monitoring search behavior and information gathering activities makes a very useful profiling technique to identify impersonators. In this chapter, I demonstrate that this conjecture is backed up with real user studies. I monitored eighteen users for four days on average and collected more than 10 GBytes of computer user data, which I analyzed and modeled. More specifically, I modeled user search behavior in Windows and tested my modeling approach using a dataset collected at Columbia University, which I claim is more suitable for evaluating masquerade attack detection methods. The results show that indeed normal users display different search behaviors, and that search behavior is an effective tool to detect masqueraders.

The contributions of this work include:

- A **small set of search-related features** used for effective masquerade attack detection: The limited number of features reduces the amount of sampling required to collect training data. Reducing the high-dimensional modeling space to a low-dimensional one allows for the improvement of both accuracy and performance.

- A **Windows dataset** [Ben-Salem, b] collected specifically **to study the masquer-**

ade attack detection problem as opposed to the author identification problem: The dataset consists of normal user data collected from a homogeneous user group of 18 individuals as well as simulated masquerader data from 40 different individuals. The dataset is the first publicly available dataset for masquerade attack detection since the Schonlau dataset [Schonlau, 2001].

The following section expands on the objective and the approach taken in this work. In Section 3.2, I present the methodology followed while designing and conducting the human subject studies to validate our modeling and detection approach. Then I describe the dataset gathered at Columbia University to study masquerade attack detection techniques in Section 3.3. This dataset is referred to as the RUU dataset. Section 3.4 shows how the malicious intent of a masquerader, whose objective is to steal information, has a significant effect on his or her search behavior. In section 3.5, I discuss experiments conducted by modeling search behavior using the RUU dataset. Section 3.6 presents experiments using the Schonlau dataset for completeness. Section 3.7 discusses the computational performance of the proposed modeling and detection approach. Finally, Section 3.8 concludes the chapter by summarizing our results and contributions, and discussing directions for future work [1].

3.1 User Profiling Approach

When dealing with the masquerader attack detection problem, it is important to remember that the attacker has already obtained credentials to access a system. When presenting the stolen credentials, the attacker is then a legitimate user with the same access rights as the victim user. Ideally, monitoring a user's actions after being granted access is required in order to detect such attacks. Furthermore, if we can infer or estimate the user's intent, we may be able to predict whether the actions of a user are malicious or not more accurately.

Much of the prior work on modeling users and profiling their behavior was purely *syntactic*, as there was no discernible means to extract the semantics of user-initiated events, other than implicitly through a set of pre-defined rules or specifications as in the case of

[1]Portions of this chapter have been published in [Ben-Salem and Stolfo, 2011c] and [Ben-Salem and Stolfo, 2011b].

ELICIT [Maloof and Stephens, 2007]. In this work, I am focused on a specific set of commands and actions issued by users that I posit tease out the user's intent. For instance, search should be an interesting behavior to monitor since it indicates that the user lacks information they are seeking. Although user search behavior has been studied in the context of web usage mining [Baeza-Yates *et al.*, 2005; O'Brien and Keane, 2007], it has not been used in the context of intrusion detection.

I propose an approach to profile a user's behavior, and particularly his or her search behavior, based on a 'taxonomy' of Windows applications, DLLs and user commands. The taxonomy abstracts the audit data and enriches the meaning of a user's profile, thus reflecting the type of activity that the user is performing on the computer. User commands and applications that perform similar types of actions are grouped together in one category making profiled user actions more abstract and meaningful. Commands or user actions are thus assigned a type or a class, and classes of user activity are modeled rather than individual user actions. I use the taxonomy to readily identify and model search behavior, which is manifested through a variety of system-level and application-specific search functions.

In the following subsections, I present the application and command taxonomy that I have developed for the Windows environment and the machine learning algorithm that I use for learning user behavior and building individual user models.

3.1.1 User Command and Application Taxonomy

I abstract the set of Windows applications, Dynamic Link Libraries (DLLs), and Microsoft Disk Operating System (MS-DOS) commands into a taxonomy of application and command categories as presented in Figure 3.1. In particular, I am interested in identifying the specific set of commands that reveal the user's intent to search. Once these commands are identified, I can extract features representing such behavior while auditing the user's behavior.

While the focus of this work is on profiling and monitoring a user's **search behavior**, there are other behaviors that are interesting to monitor. For example, remote access to other systems and the communication or egress of large amounts of data to remote systems may be an indication of illegal copying or distribution of sensitive information. Once again, the taxonomy defined allows a system to automatically audit and model a whole class of commands and application functions that represent the movement or copying of data. Similarly the transfer of large amounts of data to a peripheral device such as a USB drive or a printer is equally interesting to monitor. Another, perhaps more goal-oriented behavior, is the development of new rootkits or installation of malware, if the commands deal with compiling and executing files presumably containing code. One could also monitor the case of changes made to the configuration and settings of security-related applications such as an anti-virus engine, followed by the installation of new software. These behaviors are all examples of user activities that could reveal the malicious intent of an attacker. The taxonomy could be very useful in profiling and detecting such behaviors with a low operational cost. However, in this thesis, I focus on profiling user search behavior. Monitoring other user behaviors that could indicate fraudulent masquerade activity will be the subject of my future work.

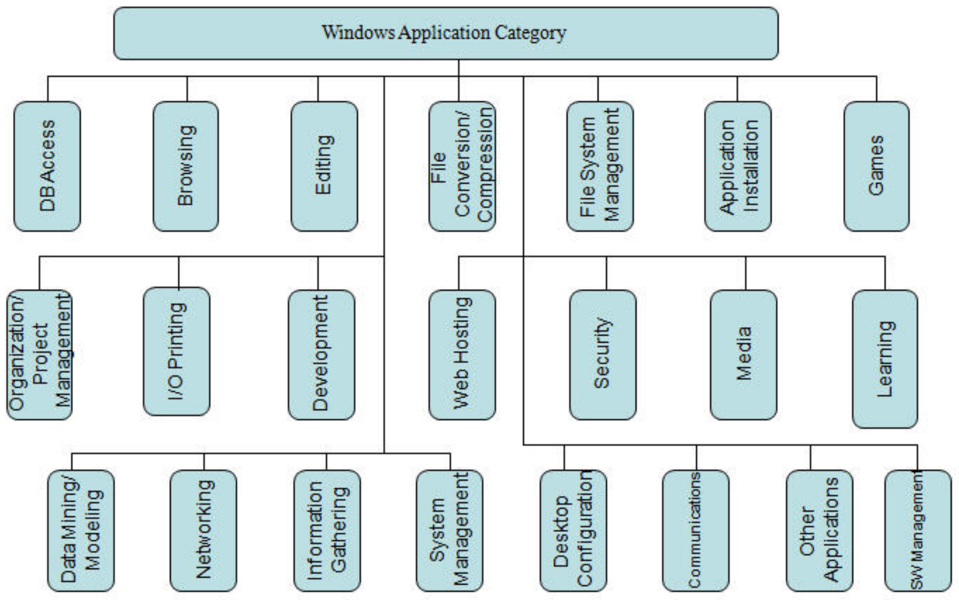

Figure 3.1: Taxonomy of Windows applications

The taxonomy includes 22 different categories or classes: Browsing, Communications, Database Access, Development and Coding, Editing, File Conversion or Compression, File System Management, Games, Application Installation, Media, Networking, Security, Software Management and Licensing, Web Hosting, Information Gathering, Data Mining and Modeling, Desktop Configuration, Learning Applications, I/O Peripherals, System Management, Organization and Project Management, and Other Applications, such as mathematical and scientific applications. The *Information Gathering* or *Search* category includes commands such as **find** and applications such as **Google Desktop Search**.

Most categories were further classified into sub-categories. Each group of commands or class of user activity is further divided into sub-classes. For example, *Communications* includes E-mail, *Instant Messaging*, and *Video Chat* as subclasses. Similarly, *I/O peripherals* includes *Printer*, *Scanner*, *USB Drive*, *DVD Drive*, etc., while a *Networking*-activity can be a *File Transfer*, a *Remote Desktop Access*, or a *Bluetooth Connection* for instance. Certain categories do not require more granularity, however, such as the *Desktop Configuration* or *Software Licensing* category.

I use one-class support vector machines to learn user search behavior. SVMs achieved the best accuracy results when applied to the masquerade attack detection problem. SVM models are easy to update, providing an efficient deployable host monitoring system. Below, I describe how one-class SVMs work.

3.1.2 One-Class Support Vector Machines

SVMs are linear classifiers used for classification and regression. They are known as maximal margin classifiers rather than probabilistic classifiers. Schölkopf et al. proposed a way to adapt SVMs to the one-class classification task [Schölkopf *et al.*, 2001]. The one-class SVM algorithm uses examples from one class only for training. Just like in multi-class classification tasks, it maps input data into a high-dimensional feature space using a kernel function, such as the linear, polynomial, or Radial Basis Function (RBF) kernel. The origin is treated as the only example from another class. The algorithm then finds the hyperplane that provides the maximum margin separating the training data from the origin in an iterative manner. The kernel function is defined as: $k(x, y) = (\Phi(x).\Phi(y))$,where $x, y \in X$, X is the training dataset, and Φ is the feature mapping to a high-dimensional space $X \rightarrow F$. Note that SVMs are suitable for block-by-block incremental learning. As user behavior changes and new data is acquired, updating SVM models is straightforward and efficient. With each incremental step, prior data may be expunged and the support vectors computed from that data are retained and used to compute a new update model using the new data [Vapnik, 1999]. Syed at.al [Syed *et al.*, 1999] have shown that these preserved support vectors represent a 'succinct and sufficient set' for handling concept drift.

Also the use of a one-class modeling approach means that I do not need to define a priori what masquerader behavior looks like. I model normal user behavior only. I can preserve the privacy of the user when building user models, as I do not need to intermix data from multiple user for building models of normal and attacker behavior.

3.1.3 RUU Dataset

As I have noted, most prior masquerade attack detection techniques were tested using the Schonlau dataset, where 'intrusions' are not really intrusions, but rather random excerpts from other users' shell histories. Such simulation of intrusions does not allow us to test the conjecture that the intent of a malicious attacker will be manifested in the attacker's search behavior.

In order to address these shortcomings, I gathered user data and *simulated* masquerader data by conducting a user study under IRB approval [2]. I refer to this data as the RUU (Are You You?) dataset. To gather this data, a host sensor that could audit user activity and capture the data of interest was developed. In the following sections, I describe the user studies designed to collect the RUU dataset and the host sensor used to collect it.

3.2 User Study Methodology

The first step in designing a user study is to state the hypothesis as well as the null hypothesis. The user study is designed to explore the null hypothesis, and may lead to its rejection. I designed two human subject studies. The goal of the first study is to show that the intent of a masquerader can be manifested in his or her file system search behavior. The *experimental* hypothesis states that if the intent of the masquerader is *malicious*, then they

[2]Human subject studies of insider threat and masquerade detection are approved at Columbia University under Human Subjects protocol IRB-AAAC4240 presented in Appendix D.

will engage in a *significant* search activity on the victim's system. The *null hypothesis* states that the manipulation of the masquerader's intent does not have any significant effect on the masquerader's search behavior. In other words, the observed *significant* effect on search activity that gets observed during the experiment can be attributed to the manipulation of the masquerader's intent, and cannot be the result of pure chance.

3.2.1 Experimental Variables

Stating the experimental hypotheses also requires identifying the experimental variables: the independent variable, the dependent variable(s), and any confounding variables. The independent variable is the one variable that gets manipulated by the researcher, while all others are kept constant. A dependent variable is directly and tightly dependent on the independent variable. It is an observed behavioral feature to be measured by the researcher during the experiment.

I hypothesize that user search behavior is a behavioral feature that is impacted by the user's intent. If a masquerader is looking to steal information, his or her intent will be manifested in his or her search behavior through the volume of the search activities performed by the masquerader. The goal is to confirm this conjecture and to show that the attacker's search behavior is different from a normal user's search behavior, and that monitoring search behavior could be used for the detection of a masquerader's attack.

So the masquerader's *intent* constitutes the independent variable in our experiment, and the search behavior of the masquerader (his or her search volume in particular) is a dependent variable. Confounding variables are usually random variables that could affect the observed behavioral feature, namely *search*, such as problems with the experimental equipment or skill level. These variables are to be minimized or mitigated when designing the human subject study. I discuss the approach taken to limit the effect of confounding variables in subsections 3.2.3 and 3.2.4 .

The question then is how can the attacker's intent be manipulated in this user study? This is by no means a simple task. However, it can be achieved by crafting different and detailed scenario narratives that are handed to the participants in the experiment.

3.2.2 Scenario Narratives and Control Groups

When dealing with human experimental design for cyber-security studies, the scenario narratives should give the experiment participants detailed background information about the attack and the attacker's motives. This enables the participants to play the role of the attacker described in the experiment, and assume their intent.

I developed a very specific attack scenario that described the masquerader's motives and the surrounding conditions of the attack. The masquerade attack scenario had to be:

- **Representative of masquerade attacks,** *i.e.* **generalizable:** When conducting a cyber-security-related user study, it is very expensive to test all attack variants both in effort and time. Testing each attack variant requires recruiting an additional number of human subjects to participate in the experiment. Therefore, it is very important that the scenario narrative used in the study is descriptive and representative of the attack under study.

- **Conforming to the threat model:** Gathering quality data that can be effectively used for empirically testing the experimental hypothesis requires that the scenario narrative used in the human subject study accurately reflects the threat model.

- **Easily executable in a user study:** This means, for instance, that the execution of the masquerader scenario had to be time-limited. Not specifying a time limit for the attack adds a lot of uncontrolled variability to the experiments. Furthermore, it makes the experiments costly both in participant's and researcher's time.

- **Detailed:** The scenario narrative should be as detailed as possible. Answers to anticipated questions that could be posed by the participants should be included. Giving the answers to these questions to the participants in advance reduces the needs for asking such questions, and therefore limits the verbal communication between the researcher and the study participant. Furthermore, it ensures that all participants receive the same instructions, therefore minimizing the participant's bias.

In our masquerade attack scenario, the masquerader gets an opportunity to access a coworker's computer during a 15-minute lunch break, while the coworker leaves the office and stays logged in to his or her computer. I strove to ensure that the task of the user study participants was goal-oriented, thus revealing the malicious intent of the attacker.

One may argue that simulating a masquerade attack is not appropriate, and that it is hard for an innocent student to act as a masquerader. I argue that, if the scenario of the experiment is well-written, and with very clear instructions, the participants in the experiment will follow the instructions. To this extent, the reader is referred to the very well-known Milgram experiment, which shows how subjects generally obey an authority figure and blindly follow instructions, even when they contradict their own values and ethics [Milgram, 1974].

Despite Milgram's findings, I was concerned about the use of role-playing in this experiment. I wanted to ensure the validity of any experiment findings by making sure that the study participants took the scenarios seriously enough. I followed Caputo *et al.*'s approach [Caputo *et al.*, 2009a], and developed a post-study questionnaire, where I asked participants about their experiences during the experiment. I asked them whether the scenario narrative affected the way in which they performed their task. Eighty per cent of the malicious masqueraders answered positively, and 70% indicated that they acted very differently from their normal behavior. One participant indicated that he was extremely nervous while searching for a colleague's personal information. Another mentioned that she felt the urgency to perform the task quickly before her "colleague" showed up. A third participant indicated that he tried to hide the monitor with his body, so that no one can see what he was doing. Many cleared the browser's cache and/or shell command history in order to cover their activity. These are some of the pieces of evidence showing that the study participants took their tasks seriously.

Besides the 'malicious attacker' scenario, I developed a 'benign masquerader' scenario, and a 'neutral' scenario for control purposes. All three scenarios are described below.

Malicious Scenario: The participants in this first scenario were asked to perform a specific task, which consisted of finding any information that could be used for financial gain from a coworker's desktop computer. The participants had access to a coworker's computer for 15 minutes while he or she left out for lunch. An attacker can gain access to the victim's system in a different way, for instance remotely if they know the access credentials.

Regardless of the access method, I am interested in the attacker's behavior after they access the victim's computer. The scenario clearly described the financial difficulties that the user was going through and the personal problems he or she was having with the coworker. In particular, the malicious user believed that the coworker had been undeservingly promoted instead of him or her, making any PII information theft or financial damage to his or her colleague, that they might engage into, justifiable to him or her. The task was goal-specific in order to **capture the intent** of the users. The participants in this scenario knew that all of their actions were being monitored. While they were encouraged to find relevant information for their task, they were also urged to hide their masquerade activity. It is also important to mention that they **were not** specifically **asked to search** the file system in the scenario, *i.e.* some users could decide to look into the computer owner's e-mail, which constitutes another approach for information gathering, instead of searching files. After completing the task, the participants filled a questionnaire about their experience and behavior during the task, and how different it was from their own normal search behavior. Most participants indicated that they tried to leave the desktop in the same state that they accessed it in, including the same list of recently opened documents. Many avoided using desktop search tools and opted for manually exploring the contents of the file systems by traversing directories of interest. Some participants also cleared the browser's cache and history. Others interleaved search and information gathering actions with normal user actions that should not raise any suspicions, such as checking a news website.

Benign Scenario: Similar to the previous scenario, the participants in this scenario acted as employees in a specific organization. While their coworker left out for a 15-minute lunch break and stayed logged in to his or her computer, their own computer experienced a hard drive failure. Because they had to finish working on an urgent team project, which they had to provide an update on during a meeting occurring later in the afternoon, they did not hesitate to use the coworker's computer to finish working on the project.

Neutral Scenario: The participants in this scenario too had a coworker leave for 15 minutes to have lunch while staying logged in to his or her desktop computer. However, the participants in this scenario had no compelling reason to access the coworker's computer. They were left to freely choose whether they wanted to access their coworker's desktop. I observed the behaviors of the participants, and whether they decided to access the coworker's computer. In particular, I observed what they did if they decided to access it. The participants had also to describe what they did and explain their decision after completing the experiment.

These scenarios are the means to manipulate the intent of the attacker. Therefore, I strove to keep all variables constant including the duration of the experiment, the type of relationship between the attacker and the victim, etc.. I used each scenario to collect data for a control group against which I compare the results achieved using the 'malicious attacker' scenario. The choice of 15 minutes in all scenarios was driven by research findings from an insider threat study conducted in an actual commercial setting [Caputo *et al.*, 2009b; Caputo *et al.*, 2009a]. The researchers studied the differences between malicious and benign user behaviors and found that malicious users engaged in bursts of frantic behavior that were shorter than 15 minutes by copying large amounts of text indiscriminately for example.

Table 3.1 summarizes and compares the controlled experimental variables across all three scenario narratives.

Table 3.1: Comparison between Experimental Variables in all User Study Scenarios

Experimental Variable	**Value**	**Same/Different**
Scope	Local File System of Colleague's Computer	Same
Environmental Constraints	IDS Lab Computer	Same
Desktop Configuration	Same Recent Documents and Applications	Same
Relationship to Victim	Coworker	Same
Time Constraints	15 minutes	Same
Intent	**Malicious, Benign, or Neutral or Neutral**	**Different**

3.2.3 Sampling Procedures for Higher Experiment Sensitivity

In order to increase the sensitivity of our experiment, I must reduce uncontrolled variability. This in turn requires controlling user bias, which makes up the largest source of error variance in user study experiments [Keppel, 2004]. In behavioral sciences, there are three different techniques or sampling procedures used to reduce subject variability and user bias. The first and preferred technique is the use of the same subject in all 'treatment conditions' of the experiment, that is, in all three scenarios. This procedure cannot be used in our experiment as it undermines the assumption that masqueraders are not familiar with the file system under attack. Using the same subjects in different treatment conditions of the experiment means that they will be exposed to the file system more than once. This implies that, in the second and third treatment condition or scenario, the subjects have prior knowledge about the file system, which violates the assumptions made in the threat model. Recall that the threat model assumes that the masquerade attacker is not familiar with the victim's file system.

The second approach, and probably the most obvious approach, is to select a homogeneous group of subjects, *i.e.* subjects with similar characteristics that are relevant to the experiment, such as their familiarity with the use of computers, their ability to search for information in a file system, and their acuity or sense of cyber-security. Finally, the third approach for reducing subject variability is the use of several small subject sets with characteristics that are highly homogeneous within one set, but widely varying between sets.

I have chosen the second approach, and selected subjects who were all students at the Computer Science department of Columbia University, so that they have comparable skills. This should minimize the variability between subjects with respect to their familiarity with computer usage, and how to search a desktop in order to steal information, or how to perform a data theft attack without being detected, which in turn limits the confounds and bias in the results of this user study.

I was concerned, nonetheless, that there still could be some variety of ages, experience levels, and access to technology even within this set of participants. In order to evaluate the extent of this variety, I asked the participants in a post-study questionnaire about their familiarity with desktop search tools, with various operating systems, and with Linux shell commands. Their answers indicated that everyone was very familiar with the use of desktop search tools, although experience levels with user shell commands varied: Two participants, out of sixty, rarely used shell commands for search. I estimated that this lack of familiarity with shell commands would not significantly affect our results, as our experiments were conducted on a Windows system, and not on a Linux/Unix system, where typically certain shell commands are used for information gathering.

3.2.4 Reducing Confounds and Bias

Besides reducing subject variability, I strove to reduce the experimental treatment variability by presenting each user study participant with the same experiment conditions. In particular, I used the same desktop and file system in all experiments. I also ensured that the desktop accessed by the subjects looked the same to each participant. In particular, I cleaned up the list of recently accessed documents, and opened Microsoft Office documents before the beginning of each experiment, and automated the data collection and uploading to a file server, so that the user data collected for one study participant does not reside on the desktop used in the experiment and does not bias the results of the experiment. Finally, I strove to limit the number for unanalyzed control factors. For example, I ensured that all the experiments were run by the same research assistant.

The need to clean up and standardize the list of recently opened documents was revealed through the answers of study participants to the post-experiment questionnaire. When asked about their strategy for finding relevant information, a few participants indicated that they started by checking out the list of recent documents. This underlines the importance of running a pilot experiment before conducting the entire human subject study, as well as the importance of designing a questionnaire with the objective of identifying additional sources of variability and ensuring that the participants performed the experiment correctly. These questionnaires revealed an important detail that was missing in our scenario narratives, namely the name of the victim colleague. Study participants indicated that this piece of information would have helped them in their search for PII. This detail that was missing in the pilot experiment, was later added when conducting the full human subject study.

3.2.5 Power Analysis and Sample Size Estimation

Power analysis is an important step in designing a user study, which usually gets neglected by many researchers working on cyber-security user studies. An experiment's power is an indication of how statistically significant its results may be, and it varies normally between 0.5 and 0.9. The higher the power, the more statistically significant the results are. I have to determine the desired power of the experiment, in order to calculate the required number of samples, or human subjects, needed for each experimental condition of the user study. Obviously, reaching a higher power value requires a higher number of samples.

The adequate sample size for the experiment depends on several parameters:

- **Form of the experiment:** The number of independent variables manipulated in the experiment and the number experimental conditions drive the number of subjects needed for the user study. The more treatment conditions analyzed, the higher the number of participants needed in the experiment.

- **Hypothesis to be tested and the null hypothesis:** This requires identifying the desired effect size w^2 that the researcher wishes to detect. The effect-size measure is a measure of the size of an effect in the overall population, regardless of the specific details of the human subject study.

- **Desired power:** Achieving a higher power value for the experiment results requires a higher number of samples. A power of about 0.8 seems to be reasonable for human behavioral experiments [Keppel, 2004].

The sample size n needs to be large enough, so that the experiment can produce a reasonable accuracy, *i.e.* limit the sampling errors. Using a larger sample size may only add to the recruiting costs without adding more accuracy.

3.2.5.1 Calculating the Effect Size

There are several effect size measures such as Hedges' g, Cohen's f^2, and w^2 . Some of these measures estimate the effect size for the sample rather than the population. Others are biased and tend to overestimate the effect size. I use the w^2 effect size, which is considered a rather unbiased effect size measure for populations, and not for samples only.

I measure the population effect size w^2 of this feature by calculating the standardized difference between means of measured features within the populations of each scenario. The standardized difference takes into account the variability of the feature from one user to another.

The effect size is measured as follows:

$$w^2 = \frac{\mu_1 - \mu_2}{\sigma_{12}} \tag{3.1}$$

where μ_1 is the mean of a feature f in scenario 1 (*e.g.* the malicious scenario), μ_2 is the mean of feature f for users in scenario 2 (*e.g.* the benign scenario), and σ_{12} is the standard deviation based on both user populations of the two scenarios. Considering the sample sizes s_1 and s_2 of the two populations or groups, then σ_{12} can be defined:

$$\sigma_{12} = \sqrt{\frac{SS_1 + SS_2}{df_1 + df_2}} \tag{3.2}$$

where df_1 and df_2 are the degrees of freedom in both populations 1 and 2 respectively, i.e, $df_i = s_i - 1$ where $i \in \{1, 2\}$ and SS_i is defined as

$$SS_i = \sum_{j=1}^{s_i} y_{i,j}^2 \tag{3.3}$$

where $y_{i,j}$ is the value of feature f for user j in population i.

3.2.5.2 Estimating the Sample Size

Once the effect size has been estimated and the desired power value determined, the required sample size n can be calculated as follows:

$$n = \phi^2 \frac{1 - w^2}{w^2} \tag{3.4}$$

where ϕ is known as the non-centrality parameter.

The non-centrality parameter ϕ indicates to which extent the user study provides evidence for differences among the two population means. It can be extracted from the power function charts developed by Pearson and Hartley based on the desired power [Pearson and Hartley, 1951]. Using the right sample size is important for reaching the desired power of the experiment (usually between 0.5 and 0.9). However, increasing the sample size to reach very high power values beyond 0.9 may be very costly, as it becomes much harder to reach power values beyond that value.

3.3 Data Collection

After describing the human subject study methodology and the data collection planning phases, I discuss in this section how I conducted the user study, and present the RUU dataset that I collected during that process. I start by describing the host sensor developed to collect this dataset.

3.3.1 Host Sensor

We have developed a host sensor for Windows platforms that monitors all registry-based activity, process creation and destruction, window GUI and file accesses, as well as DLL libraries' activity. It gathers various process-related data items including process name and ID, the process path, the parent of the process, the type of process action (*e.g.* type of registry access, process creation, process destruction, window title change, etc.), the process command arguments, action flags (success or failure), and registry activity results. A time stamp was also recorded for each audit record. The Windows sensor uses a low-level system driver, DLL registration mechanisms, and a process table hook to monitor process activity.

3.3.2 Required Sample Size

It was hard to accurately predict the effect size of the different search-related features prior to conducting the human subject study, as there were no published results from similar studies. For instance, I could not predict how many more files would be touched by a masquerader as opposed to a user conducting his or her regular activities. So I made some assumptions in order to roughly estimate the required number of participants in the user study. It turned out that I needed more than 17.7 participants in order to achieve an 88% probability of achieving a significant result, assuming that the number of files touched by a masquerader would double on average (which was indeed validated by our experiments). Based on this guideline, I had eighteen students participate in the 'normal user' data collection exercise, and forty students participate in the 'capture-the-flag' exercise for masquerader data collection.

3.3.3 Collecting Normal User Data

Eighteen computer science students installed the Windows host sensor on their personal computers. The host sensor collected the data described in the previous subsection and uploaded it to a server, after the students had the chance to review the data and the upload. The students agreed to share their data with the research community. This unique dataset with a size of more than 10 GBytes is available for download after signing a usage license agreement. The data collected for each student spanned 4 days on average. An average of more than 500,000 records per user were collected over this time period.

3.3.4 Collecting Simulated Masquerader Data

To obtain masquerader data, I recorded the activity of forty students who posed as masqueraders by participating in a 'capture the flag' exercise and following the malicious attacker scenario of the human subject study described in Section 3.2.2. Recall that in order to ensure the validity of the experiment and the resulting data, I controlled the 'user's intent.' A total of sixty computer science students were randomly selected to participate in the exercise from a list of volunteers. The participants were randomly assigned to one of three groups. All participants had unlimited access to the same file system of a lab computer for 15 minutes each. None of the users had access to this file system before, which was designed to look very realistic and to include potentially interesting patent applications, personally identifiable information, as well as account credentials. The file system had more than 100,000 files indexed by desktop search tools installed on the system, and totaling a size of more than 70 GBytes. The files were copied from a modern Windows XP machine routinely used in a university research environment. They were created over a period of 5 years. The file system included at least 80 files containing personal information that could be used for identity theft or financial gain. The contents of certain personal files were sanitized, so that no personal information was leaked. I also installed applications that typical computer science students would have on their own machines, such as programming APIs, media players, etc., together with code projects, games, music, and video files. The goal was to make this machine look similar to the ones that the normal users in our experiment were using. Special care was taken to make sure that the desktop appeared in the same state to all participants in the experiment. The study participants were asked not to share any information about the experiment with others until the data collection exercise was completed. The objective was to limit user bias due to influence from other participants in the experiments. While simulating masquerader attacks in the lab is not ideal, it was the best available option. None of the students who shared their normal usage data were willing to lend their computers in order to run masquerade attack experiments on them.

3.4 User Study Experiment

The objective of this experiment is to explore the validity of the conjecture that a masquerader's intent has a significant effect on his or her search behavior. I extracted three features from the data collected in the user study after experimenting with several features such as the frequencies of different types of user actions and application events, the total size of touched files in bytes, the number of search windows and search window touches, etc.. The three selected features are:

1. The number of files touched during an epoch of two minutes
2. The number of automated search-related actions initiated by the masquerader within two minutes
3. The percentage of manual search actions during the same epoch

Automated search actions are search actions launched using a desktop search tool such as *Google Desktop Search*. Manual search actions are file system navigation or exploration activities. I display the distribution of these features for the malicious, benign, and neutral scenario participants of the user study in Figures 3.2, 3.3, and 3.4. The experiment demonstrates that the manipulation of the user intent has demonstrated a significant effect on user search behavior.

Figures 3.2, 3.3, and 3.4 are box-and-whisker plots where the horizontal line in the middle of each of the boxes in these plots corresponds to the median value of the displayed feature. Fifty per cent of the data falls within this box, while the top and bottom quartiles (25% of the data) of the data are represented by the whisker lines above and below this box. Data points whose value is above 1.5 times the upper quartile or lower than 1.5 times the lower quartile are considered outliers and are represented as small crosses. The short horizontal lines above and below the box represent the maximum and minimum data values excluding outliers.

Figure 3.2 depicts the distribution of the number of accesses to all files residing on the file system per a 2-minute epoch. It is clear that the average number of file touches amongst the malicious scenario group is much higher than in the other two groups. The z-test with means of 140, 40, and 35 decoy touches for the three respective groups rejects the null hypothesis at the 99% confidence level ($p \leq 0.01$).

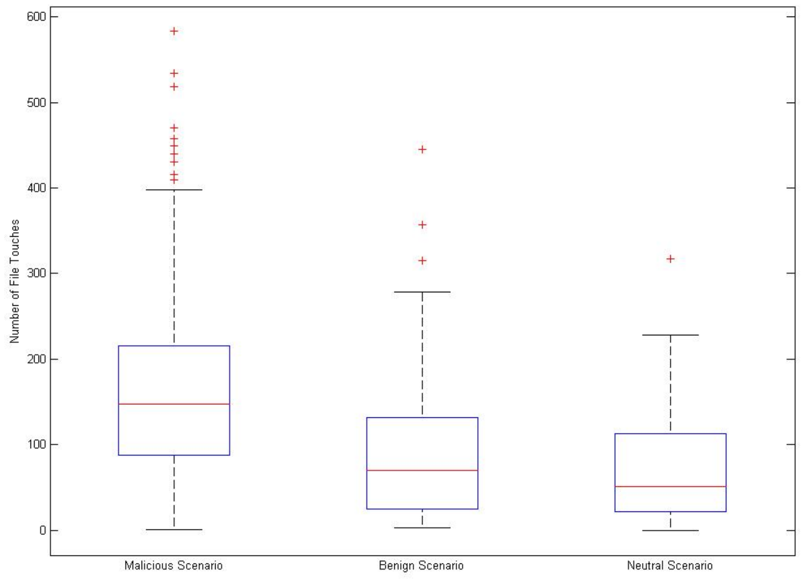

Figure 3.2: Distribution of File Touches across the three User Study Groups

Figure 3.3 shows the distribution of search-related queries to the registries and accesses to search-related DLLs and applications for the different groups in the human subject study. The average number of search-related records in the first group is comparable to that in the other groups, which might be unexpected. However, this could be explained by the fact that the participants in the first group were penalized if their illegal masquerade activities were discovered, which explains why most of them decided to refrain from using desktop search tools to find relevant information. However, Figure 3.4 reflects the extensive information exploration and gathering activities conducted by the participants in the first group.

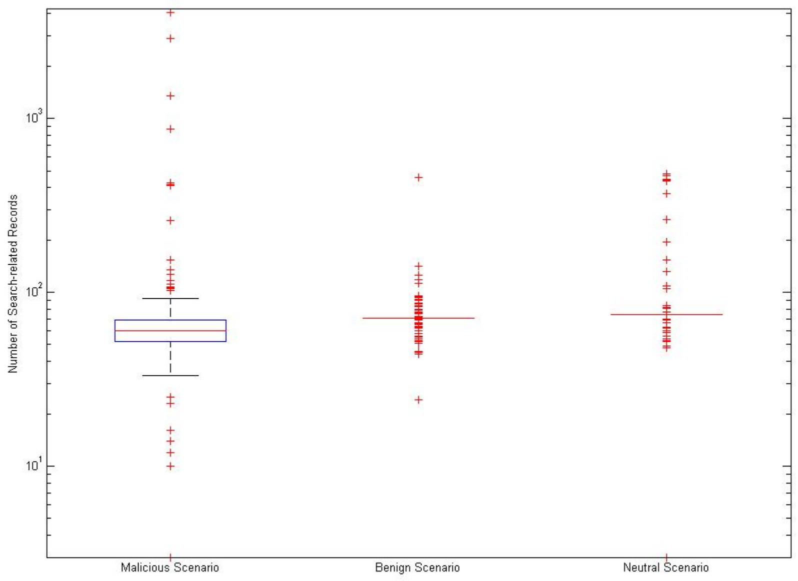

Figure 3.3: Distribution of Search-related Actions across the three User Study Groups

In the latter figure, one can clearly notice that the percentage of user actions related to navigating through the file system, in order to explore its contents, is much more significant in the first group. The participants in the second group did not have the intention to steal any information, which is why they did not engage in file system exploration activities. Most of them only tried to access the work file they had to review in order to finish working on their presentation. The percentage of file system navigation activities is minimal, except

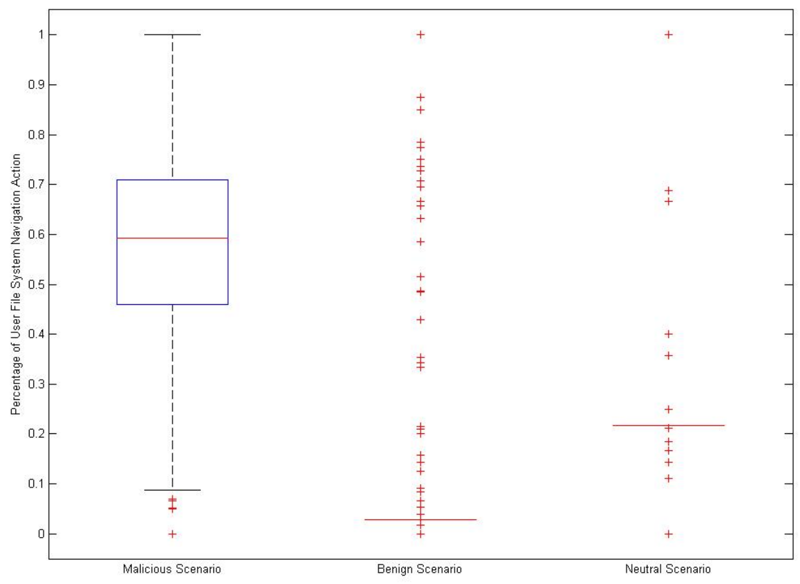

Figure 3.4: Distribution of the Percentage of File System Navigation User Actions across the three User Study Groups

for the outlier points, indicating that this group was focused on probably editing the work file and on the task to be completed. While most of the participants in the third scenario decided not to access the coworker's computer, some of them did urged by their curiosity, as indicated in the participants' answers to our post-experiment questionnaire. Figure 3.4 shows that for this group, the users explored the directories in the file system in order to satisfy their curiosity.

Finally, Figure 3.5 shows how the number of personal files accessed by masqueraders varies by user study scenario. The results of this user study provide evidence that search behavior is significantly affected by a masquerader's intent. Very few PII files were accessed by participants in the benign and neutral scenarios. The question that I attempt to answer next is: Can we model normal user search behavior and use it to detect malicious masqueraders?

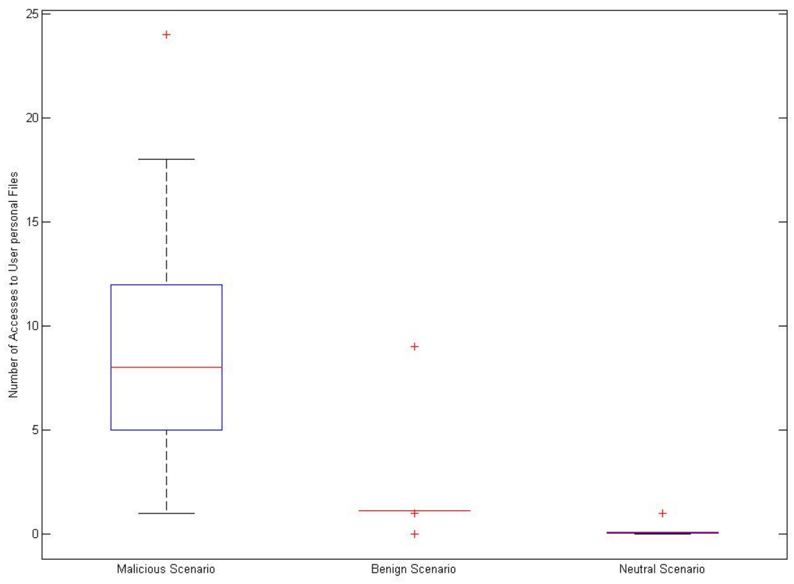

Figure 3.5: The personal files accessed by masqueraders

3.5 RUU Experiment

In order to evaluate our conjecture that search behavior modeling can provide a means for detecting malicious masqueraders, I use the normal user data to build user search behavior models. I then use the simulated masquerader data gathered for the participants in the 'malicious' scenario of our user study to test these user models. Here I describe the modeling approach, the experimental methodology, and the results achieved in this experiment.

3.5.1 Modeling

I devised a taxonomy of Windows applications and DLLs in order to identify and capture search and information gathering applications, as well as file system navigation user actions. The taxonomy can be used to identify other user behaviors that are interesting to monitor, such as networking-, communications-, or printing-related user activities. However, in the context of this chapter, I use it to identify search- and file system navigation-related activities only. I will discuss it in further details in Chapter 6. Monitoring other user behaviors will be the subject of future work. The use of the taxonomy abstracts the user actions and helps reveal the user's intent.

I grouped the data into 2-minute quanta of user activity, and I counted all events corresponding to each type of activity within each of the 2-minute epochs. I also explored other features such as the size of files touched and the number of processes running or launched during this epoch among other features. Eventually, a total of three features were selected for each of the 2-minute epochs. Each of the features is related to some aspect of the user's search or information gathering and information access behavior. The three features that provided the best accuracy results in our experiments are:

1. Number of **automated** search-related events: Specific sections of the Windows registry, specific DLL's, access to specific index files, and specific programs, particularly desktop search tools, are correlated with system searching. Within the 2-minute epoch, I model all search-related activity.

2. Number of file touches: Any file fetch, read, write, or copy action causes the requested file to be loaded into memory. I count the number of times files are touched and loaded into memory by any process within each 2-minute epoch.

3. Percentage of file system navigation user actions: Not all search is performed using a desktop search tool. Navigating through the file system to explore its contents is also a form of user search. I model all **manual search** or file system navigation user activity occurring during the 2-minute epoch.

To identify the automated and manual search applications and user activities, I referred to our Windows applications taxonomy. The chosen features are simple search features that characterize search volume and velocity to test our hypothesis. While no single feature could be used to achieve high detection rates, the combination of the three features could be very effective. More complex search features that describe user search patterns could be extracted. Such features include, but are not limited to search terms and specific directory traversals. Evaluation of these features is the subject of my future work.

3.5.2 Experimental Methodology

For each of the 18 normal users, the first 80% of their data was used for training a one-class SVM model. The user's test data and the masquerader data were kept separate. After the baseline models were computed, the same features used in the model were extracted for the test data after dividing them into 2-minute quanta of user activity. The models were tested against these features, and an empirically identified threshold was used to determine whether the user activity during the two-minute period was normal or abnormal. If the user activity was performed by the normal user, but was classified as abnormal by the ocSVM model, a false positive was recorded.

3.5.3 Detection Accuracy Evaluation

For evaluation purposes, I conducted two experiments. In the first one, I used one-class SVM models using the three features listed in Section 3.5.1. In the second experiment, I used the frequency of applications and processes within the 2-minute epoch as features for the ocSVM models. This is the modeling approach that achieved results comparable to those achieved by the naïve Bayes approach when applied to the Schonlau dataset [Wang and Stolfo, 2003], even though it is a one-class modeling approach, *i.e.* it uses less data for training the user models.

3.5.3.1 Accuracy Results

Using the search-behavior modeling approach, 100% of the two-minute quanta that included masquerader activity were detected as abnormal, while 1.1% of the ones with legitimate user activity were flagged as not conforming to the user's normal behavior. The results achieved are displayed in Table 3.2. The false positive (FP) rate is significantly reduced compared to the application frequency-based modeling approach, while a perfect detection rate is achieved. These results substantially outperform the results reported in prior work (see Chapter 2).

Monitoring file access and fetching patterns turned out to be the most effective feature in these models. Consider the case where a user types *'Notepad'* in the search field in order to launch that application. Such frequent user searches are typically cached and do not

Table 3.2: Experimental results of ocSVM modeling approaches using search-behavior related features and application frequency features

Method	**True Pos. (%)**	**False Pos. (%)**
Search-behavior ocSVM	100	1.1
App.-freq. ocSVM	90.2	42.1

require accessing many files on the system. Note that if the attacker follows a different strategy to steal information, and decides to copy whole directories in the file system to a USB drive for later investigation, instead of identifying files of interest during one user session, then the 'file touches' feature will reflect that behavior.

A typical means to visualize the performance of any classification algorithm is the Receiver Operating Characteristic (ROC) curve, which plots the *sensitivity* against *1- specificity.* The specificity is defined as $\frac{n_{TN}}{n_{TN}+n_{FP}}$ and the sensitivity is defined as $\frac{n_{TP}}{n_{TP}+n_{FN}}$ where n_{TN}, n_{FP}, n_{TP}, n_{FN} are the numbers of true negatives, false positives, true positives, and false negatives respectively. A true positive is a masquerade activity that has been correctly identified as so by the classifier. A false positive is a normal user's activity that was misclassified as a masquerader's. Similarly a true negative is a normal user's activity that the detector classifies as normal, and a false negative is a masquerade activity that the classifier fails to detect, the latter being perhaps the worst case of failure.

Since each user has his or her own model with his or her own detection threshold, it is not possible to build a single ROC curve for each modeling approach. However, we can compare the ROC curves for individual user models using the two modeling approaches investigated. One way to compare the ROC curves is to compare the Area Under Curve (AUC) values. The AUC, also known as the ROC score, is the integral of the ROC curve, *i.e.* it is a measure of the area under the ROC curve. It reflects the accuracy of the detection method or classifier used. The higher the AUC is, the better the overall accuracy of the classifier.

Figure 3.6 displays the AUC scores for all user models. The search behavior modeling approach outperforms the application frequency based modeling approach for each user model. The average AUC score achieved for all ROC curves when modeling search behavior is 0.98, whereas the average AUC score for the application frequency-based models is 0.63. The bad performance of the application frequency-based modeling approach can be explained by the high-dimensional feature vectors used in this modeling approach. This suggests that a lot more data may be needed for training.

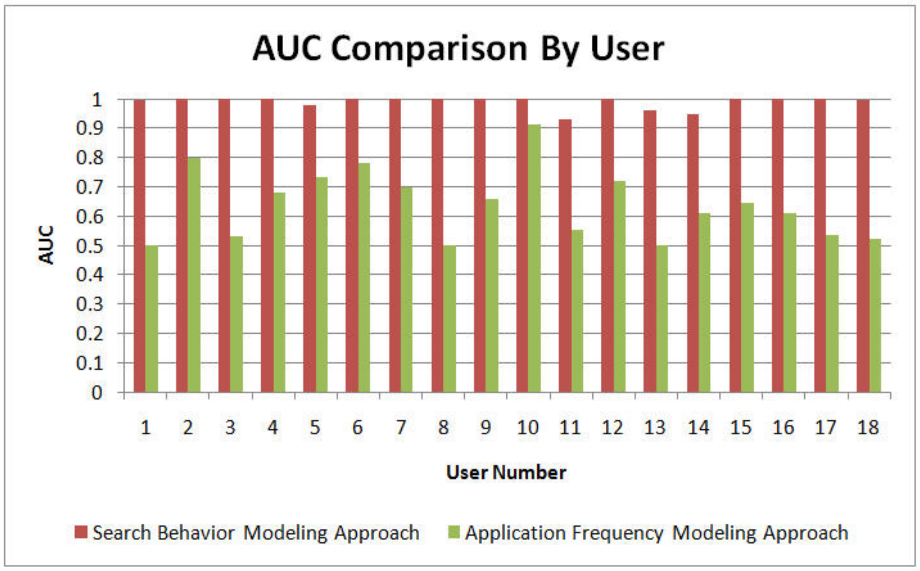

Figure 3.6: AUC Scores By User for the Search Behavior and Application Frequency-Based Modeling Approaches using one-class Support Vector Machines

Figure 3.7 depicts the number of ROC curves having AUC scores higher than a certain value for both modeling approaches. Note that for 12 user search behavior models, the AUC score is equal to 1 indicating a perfect detection rate and the absence of any false positives.

The RUU dataset consists of user data with varying amounts of data for different users. The amount of search behavior information varied from user to user. False positives were higher for users who contributed less data in general and less search-related data in particular, such as users 11 and 14, than for those for whom a large amount of such data was collected. For a 100% detection rate, the FP rate scored by these user models ranged between 11% and 15%, which proves the need for more training data for these users, in order to improve the performance of the classifiers.

In summary, the significant accuracy improvement achieved can be explained by the

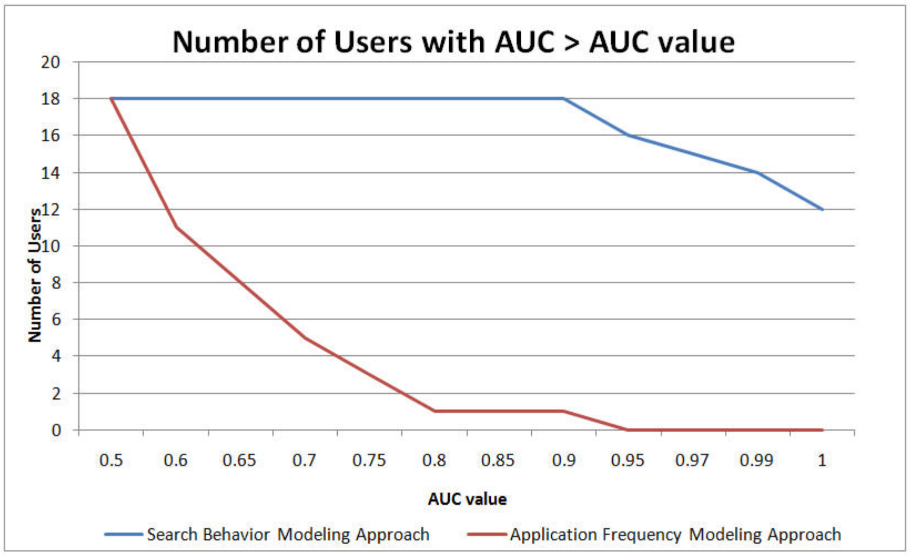

Figure 3.7: The number of user models with AUC values greater than the value displayed on the x-axis for the search behavior and the application frequency modeling approaches using one-class SVMs. (The upper-left point shows 18 user models with AUC scores greater than 0.5)

fact that features used for modeling are good discriminators between normal user behavior and fraudulent behavior. Masqueraders were focused on a clear objective, namely finding information that could be used for financial gain, and by the tight link between the masquerader's intent and his or her search behavior, as demonstrated through the user study described in section 3.4. Despite the simplicity of the search features used, which characterize search volume and velocity only, I was able to reliably detect malicious masqueraders trying to steal information. Note that many masqueraders indicated in the post-experiment questionnaires that their strategy for finding relevant information started by quickly scanning the most recently opened documents, or the list of bookmarks. However, they still engaged in a wider search activity eventually when these sources proved fruitless.

3.6 Schonlau Data Experiment

The results achieved by profiling user search behavior require careful thought when considering the prior results of techniques that model sequences of user commands from the Schonlau dataset. It is difficult to compare my results with the results presented in Tables 2.1 and 2.2 which were evaluated using the Schonlau dataset. Recall that the Schonlau dataset is not a 'true' masquerader dataset, since its 'intrusions' or 'masquerade' command blocks are just sequences of commands generated by randomly selected normal users. Moreover, information gathering and search activities of the users are not significant in this dataset as can be deduced from Figure 3.8. Furthermore, the Schonlau dataset does not include any timestamps, so temporal statistics cannot be extracted.

However, for completeness, I model specific user behaviors such as search, and test classifiers based on this modeling approach against the Schonlau dataset. To do so, I assign user commands to command categories, thus abstracting the user actions and identifying the specific user behaviors to be modeled. Therefore, I focus on the analysis of types or categories of user commands, rather than on simple user commands.

To accomplish the goal of accurately modeling user behavior I developed a taxonomy of Linux commands similar to the one I created for Windows applications and DLLs. The taxonomy is displayed in Figure 3.9. I conducted an experiment where I followed the methodology described in prior work of Schonlau et al. [Schonlau *et al.*, 2001] and Wang&Stolfo [Wang and Stolfo, 2003]. In this experiment, I measured the accuracy of one-class SVM models using frequencies of simple commands per command block as features, and I compared the performance of ocSVM models using frequencies of command categories or specific behaviors (per the command taxonomy) as features. I also used the same one-class modeling technique with binary feature vectors. The features indicate the presence or absence of a specific simple user command or command category within a 100-command block.

I used the first 5000 commands of a user as positives examples for training the model. No negative examples were used for training. Then I tested the classifier using the remaining 10,000 commands of the user, which may have injected command blocks from other users under a probability distribution as described in [Schonlau, 2001].

Table 3.3 summarizes the results achieved by the one-class SVM classifiers. The results

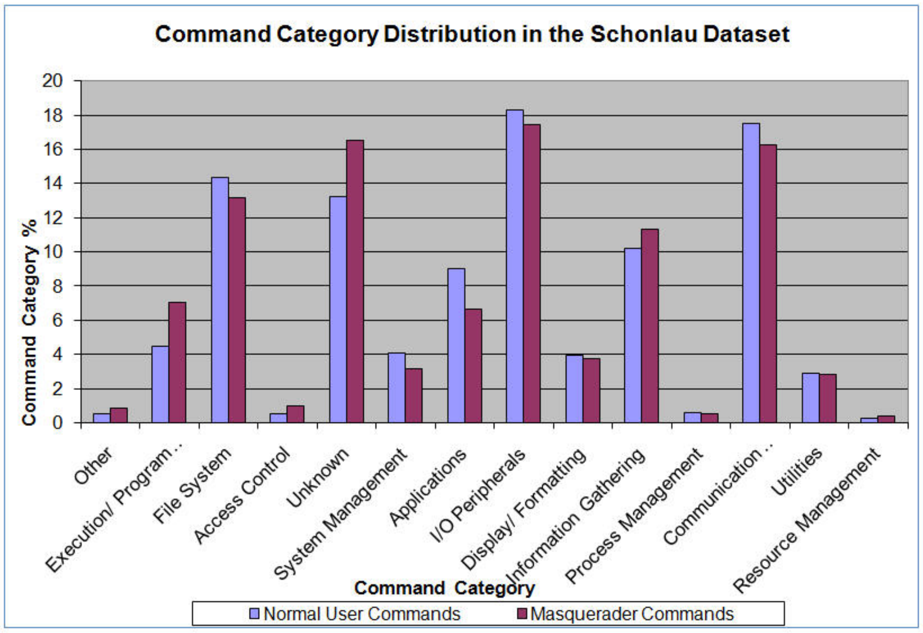

Figure 3.8: The Distribution of Commands across Various Categories in the Schonlau Dataset

show that the performance of one-class SVMs using command categories per the taxonomy is essentially the same as the performance of ocSVM that uses simple commands. This demonstrates that the information that is lost by compressing the different user shell commands into a few categories does not affect the masquerade detection ability significantly.

In section 3.7, I show how modeling search behavior by using the taxonomy of commands and applications reduces computational complexity, both for training and for testing the classifier. This is possible thanks to the smaller number of features used for modeling, which reduces the amount of sampled data required for training, as the data becomes less sparse in the new feature space.

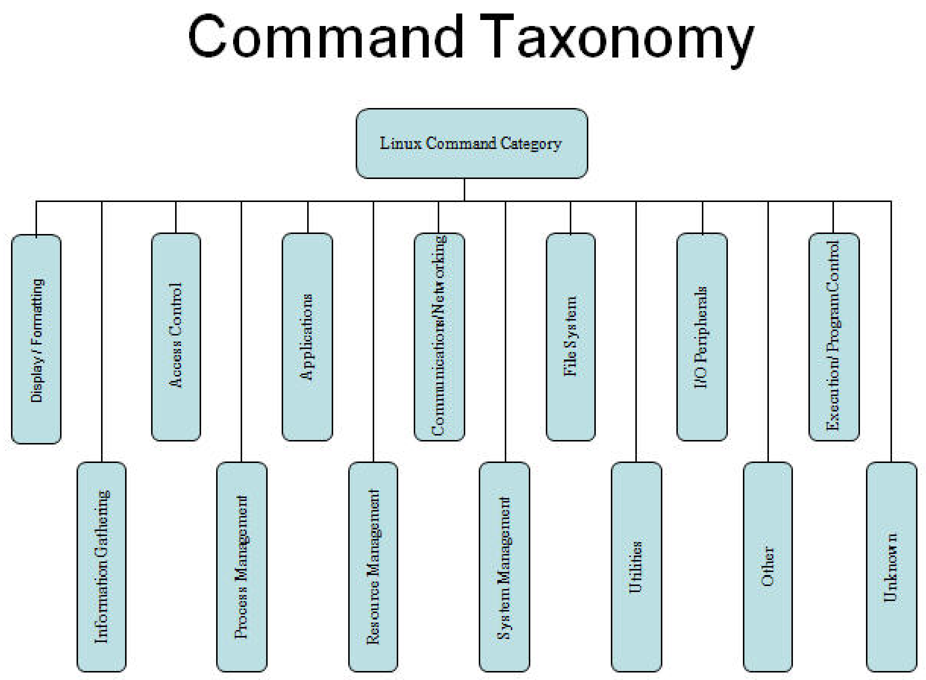

Figure 3.9: Taxonomy of Linux and Unix Commands

3.7 Performance Evaluation

3.7.1 Computational Complexity

Our experiment can be divided into four main steps that cover building and testing the classifiers:

1. Identifying the features to be used for modeling
2. Extracting the features to build the training and testing vectors
3. Building a ocSVM model for each normal user
4. Testing each user model against the test data

I discuss the computational complexity of each of these steps for one user model.

Let o be the total number of raw observations in the input data. I use this data to compute and output the training vectors $x_i \in R^n, i = 1, ..., l$ and testing vectors $x_j \in$

Table 3.3: ocSVM Schonlau Experimental Results

Method	**True Pos. (%)**	**False Pos. (%)**
ocSVM with simple commands (frequency-based model)	98.7	66.47
ocSVM with taxonomy (frequency-based model)	94.8	60.68
ocSVM with simple commands (binary model)	99.13	66.8
ocSVM with taxonomy (binary model)	86.58	56.9

$R^n, j = 1, ..., m$ for each user u, where n is the number of features used for modeling.

When using the application frequency features, this step requires reading all training data (about 0.8 of all observations o) in order to get the list of unique applications in the dataset. This step can be merged with the feature extraction step, but it would require more resources, as the feature vectors would have to remain in memory for updates and additions of more features. I chose to run this step in advance for simplicity. This step is not required for the search behavior profiling approach, as all features are known in advance.

In the feature extraction step, all input data is read once, grouping the observations that fall within the same epoch. n features are computed and output for each epoch. This operation has a time complexity of $O(o + n \times (l + m))$.

Chang and Lin [Chang and Lin, 2001] show that the computational complexity of the training step for one-class SVM model is $O(n \times l) \times \#$Iterations if most columns of Q are cached during the iterations required; Q is an $l \times l$ semi-definite matrix, $Q_{ij} \equiv y_i y_j K(x_i, x_j)$; $K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j)$ is the kernel; each kernel evaluation is $O(n)$; and the iterations referred to here are the iterations needed by the ocSVM algorithm to determine the optimal supporting vectors.

The computational complexity of the testing step is $O(n \times m)$ as the kernel evaluation for each testing vector y_j is $O(n)$. I experimentally validate the complexity analysis in the next section to determine whether the performance both in terms of accuracy and speed of detection has improved using the proposed search behavior modeling approach.

3.7.2 Performance Results

I ran the experiments on a regular desktop with a 2.66 GHz Intel Xeon Dual Core processor and 24 GB of memory on a Windows 7 platform. I measure the average running time of each step of the experiment over ten runs. The results are recorded in table 3.4. As I point out in the previous subsection, the very first step is not executed in the proposed search behavior modeling approach. This step takes more than 8 minutes when using the application frequency modeling approach. The running time of the feature extraction step shows that the number of raw observations in the raw data dominates the time complexity for this step. Note that the RUU dataset contains more than 10 million records of data.

The training and testing vectors are sparse, since only a limited number of the 1169 different applications could conceivably run simultaneously within a two-minute epoch. This explains why the 389.7 ratio of features does not apply to the running time of the training and testing steps, even though these running times depend on the number of features n. While one might argue that, in an operational system, testing time is more important than training time, I remind the reader that a model update has the same computational complexity as model training. For the latter, the use of a very small number of features as in our proposed approach clearly provides significant advantages.

All of these differences in running time culminate in a total performance gain of 74% when using the search behavior model versus the application frequency model typical of prior work. This computational performance gain coupled with improved accuracy could prove to be a critical advantage when deploying the sensor in an operational environment if a system design includes automated responses to limit damage caused by an attacker.

3.8 Conclusion

3.8.1 Chapter Summary

In this chapter, I showed that user search behavior can be used to reveal the malicious intent of a masquerader. I used a modeling approach that aims to capture the intent of a user

Table 3.4: Performance comparison of ocSVM modeling approaches using search behavior-related features and application frequency features

Step	**ocSVM app. freq.**	**ocSVM search-beh.**
Identifying Features (min)	8.5	0
Extracting Features (min)	48.2	17.2
Training (min)	9.5	0.5
Testing (min)	3.1	0.5
Total (min) (Rounded)	**69**	**18**

more accurately based on the insight that a masquerader is likely to perform untargeted and widespread search. Recall that I conjecture that user search behavior is a strong indicator of a user's true identity. I modeled search behavior of the legitimate user with three simple features, and detected anomalies deviating from that normal search behavior.

The use of search behavior profiling for masquerade attack detection permits limiting the range and scope of the profiles computed about a user. This limits potentially large sources of error in predicting user behavior that would be likely in a far more general setting. Prior work modeling user commands shows very high false positive rates with moderate true positive rates. User search behavior modeling produces far better accuracy. With the use of the RUU dataset [Ben-Salem, b], a more suitable dataset for the masquerade detection problem, I achieved the best results reported in literature to date: 100% masquerade detection rate with 1.1% of false positives only.

In an operational monitoring system, the use of a small set of features limits the system resources needed by the detector, and allows for real-time masquerade attack detection. Note that the average size of a user model is about 8 KB when the search-behavior modeling approach is used. That model size grows to more than 3 MB if an application and command frequency modeling approach is used. Furthermore, it can be easily deployed as profiling in a low-dimensional space reduces the amount of sampling required: An average of four days of training data was enough to train the models and build effective detectors.

3.8.2 Future Research

In my future work, I will explore more complex search features that describe user search patterns. Such features include, but are not limited to search query contents, parameters used, and specific directory traversals that could improve accuracy results and extend them to other masquerade attack scenarios. Other potential features to model include the use of bookmarks and most recently opened documents, which could also be used by masquerade attackers as a starting point for their search. The models reported here are primarily volumetric statistics characterizing search volume and velocity.

My focus in this work was on monitoring a user's search behavior in real time to determine whether current user actions are consistent with the user's historical behavior. Note that, while the list of search applications and commands may have to be updated occasionally (just like an Anti-Virus needs periodic signature updates) for best detection results, most of the search-related activity would be manifested in accesses to search index files and regular user files on the system.

Monitoring other user behaviors, such as the ones discussed in Section 3.1.1 will be the subject of future work. A masquerader could choose to copy data to a USB drive for later examination. They may choose to access the victim computer remotely and ex-filtrate data over the network. They could even try to evade the monitoring system by renaming DLLs and applications so that they are assigned to a different category per our applications taxonomy, other than the search or information gathering category. I could easily use the application taxonomy to monitor these specific behaviors in case the attacker resorts to such strategies. As noted in section 3.5.3.1, the 'file touches' feature already captures some aspect of this behavior. The applications taxonomy could be used to extract 'Networking'-, 'Communications'- and I/O-related features to be included in the user model, so that such masquerade behavior gets detected easily.

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Chapter 4

Evaluation of Decoy Document Properties

In the previous chapter, I investigated how user search behavior profiling can be used for masquerade detection. Another approach for detecting masqueraders is the use of baits such as honeynets and honeypots. Honeypots are information system resources designed to attract malicious users. They have been widely deployed in DMZs to trap attempts by external attackers to penetrate an organization's network. Some researchers proposed the use of honeyfiles, a type of honeypot, to detect malicious insider activity [Bowen *et al.*, 2009b]. They introduced the concept of *perfectly believable decoys* and proposed several properties to guide the design and deployment of decoys, namely:

1. Believability: The attacker will not use the bait information if it does not appear authentic to the attacker.

2. Enticingness: No attack detection will be possible if the attacker does not access the bait information because it does not look attractive enough.

3. Conspicuousness: Decoys should be easily located or retrieved in order to maximize the likelihood that an attacker takes the bait.

4. Detectability: If the access to the bait asset is not detectable than the deployment of the decoys is useless.

5. Variability: Decoys should not be easily identifiable to an attacker due to some shared invariant.

6. Non-interference: Decoys should not interfere with the legitimate user's normal activity. Non-interference is defined as the likelihood that legitimate users access the real documents after decoys are introduced [Bowen *et al.*, 2009b].

7. Differentiability: Legitimate users should be able to easily distinguish decoy documents from authentic documents, which has a direct effect on non-interference.

8. Shelf-life: Decoys may have a limited time period during which they are effective.

While all of the above are important decoy properties, it can be difficult to design and deploy decoy documents that would optimize these properties, which in turn would assure effective detection of a masquerade attack. One has to find the right trade-offs between these properties in order to use them effectively. Such trade-offs may vary depending on the type of attack.

For example, while believability is a very important property of decoys when used for detecting insider attacks that aim to exfiltrate sensitive information, it becomes of a lesser importance when the decoys are aimed at detecting masquerade attacks. In the case of an insider attack, the attacker already has legitimate access to the system where the sensitive information assets are located. Access to such assets does not necessarily constitute evidence of malicious intent or activity. However, subsequent exfiltration and use of such information does. If the attacker identifies the decoy document as bogus, then they would not use the information contained in that document, which is why the *believability* of the decoy document is important. In the case of a masquerade attack, the mere access to the decoy document does constitute evidence of an attack as the masquerader is not a legitimate user of the system, and therefore should not be accessing any assets residing on that system. Whether the masquerader finds the decoy document believable or not, after having accessed it, is irrelevant to the detection of the attack, since the evidence of the malicious activity has been already established [1].

[1] This work was published in [Ben-Salem and Stolfo, 2011a].

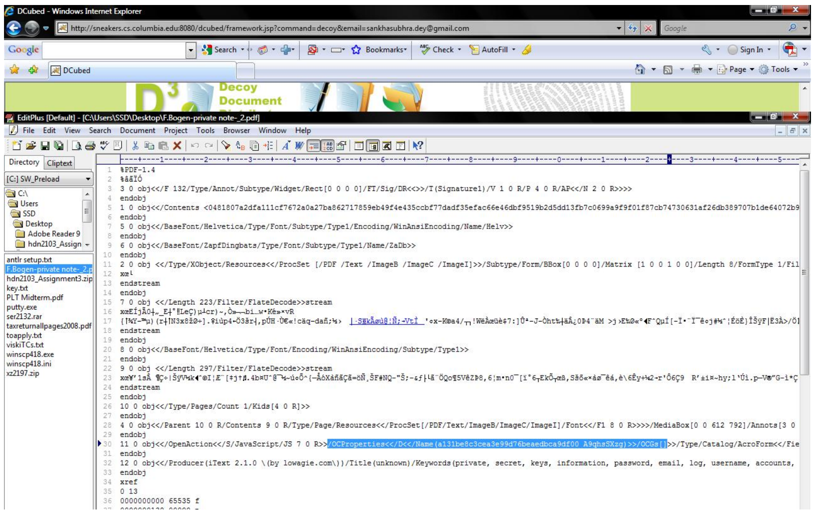
4.1 Trap-based Masquerader Detection Approach

4.1.1 Trap-based Decoys

The trap-based technique used by our sensor relies on trap-based decoys [Bowen *et al.*, 2009b] that contain 'bait information' such as online banking logins, social security numbers, and web-based email account credentials. Users can download such decoy files from the Decoy Document Distributor (D^3) [Bowen and Hershkop, 2009], an automated service that offers several types of decoy documents such as tax return forms, medical records, credit card statements, e-bay receipts, etc. The decoy documents carry a keyed-Hash Message Authentication Code (HMAC) [Krawczyk *et al.*, 1997] embedded in the header section of the document, and visible if the document is opened using a hex editor only. The HMAC is computed over a file's contents using a key unique to the user, and is hidden in the header section of the file. For instance, the use of the full version of the SHA1 cryptographic function in combination with a secret key to tag the decoy documents with an HMAC tag prevents the attacker from distinguishing the embedded HMAC from a random function [Kim *et al.*, 2006]. It is this marker or HMAC tag that our sensor uses to detect access to a decoy document. An example of a decoy document with an embedded HMAC is shown in Figure 4.1. In the next section, I describe how the sensor makes use of this marker.

Besides the embedded HMAC tag, the decoy files carry a visible marker that is used to prove data leakage through screen-capture in case the masquerader manages to exfiltrate data without being detected. This marker is a string generated from a regular expression that is unique to the legitimate user. They also have a beacon that signals a remote website upon the opening of the decoy document. This can be disabled if we suspect that the attacker might notice that the beacon document is phoning this remote website. Noticing this informs the attacker that his or her activity has been discovered.

We have architected a Decoy Documents Access (DDA) sensor and designed decoy documents in such a way that a sophisticated attacker with more knowledge and higher capabilities, in particular an inside attacker, would not be able to escape detection if they touched a decoy document. A sophisticated attacker with wide resources would not be able to distinguish the HMAC tags of decoy documents from random functions. Both types of attackers, *i.e.* the sophisticated outsider or the malicious insider, would have to know that the system under attack is baited. The detection of this class of attack is beyond the scope of this thesis. Here, I devise user studies for attackers, who have no knowledge whether the system is baited or not, with the objective of investigating the decoy deployment properties.



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6 0 obj<</BaseFont/ZapfDingbats/Type/Font/Subtype/Type1/Name/ZaDb>>
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Figure 4.1: HMAC Embedded in the OCP Properties Section of a PDF Document

4.1.2 Decoy Documents Access Sensor

The DDA sensor detects malicious activity by monitoring user actions directed at HMAC-embedded decoy documents, since any action directed towards a decoy document is suggestive of malicious activity [Ben-Salem, a]. When a decoy document is accessed by any application or process, the host sensor initiates a verification function. This function is responsible for distinguishing between decoys and normal documents by computing a HMAC for that document and comparing it to the one embedded within the document. If the two HMACs match, the document is deemed a decoy and an alert is triggered; otherwise, the document is deemed normal and no action is taken. The DDA sensor alerts when decoy documents are being read, copied, or zipped. The sensor was built for the Windows XP platform and relies on hooks placed in the Windows Service Table. The hooking is performed by injecting code into the address space of the processes, and by replacing the address of the *file open* system call which is present in the kernel (.dll) library of windows. This code injection guarantees that our code will be executed first, and post processing it will call the actual system call. This approach also enables the configuration of the list of processes that should be hooked into or should be excluded from hooking into.

4.2 Human Subject Study 1

4.2.1 Experiment Design

My first human subject study aims to measure decoy document accesses performed by the legitimate users of the system, which can be considered as false positives. I seek to answer two questions through this study:

1. Does the number of decoy files planted in a file system have an impact on their non-interference with the legitimate user's normal activities?

2. What are the best locations for planting decoys on a file system, so as to minimize their non-interference?

To answer these questions, I designed an experiment where I controlled the number of decoy documents n planted in a file system. I followed the same prescription outlined in Section 3.2. I postulate that non-interference is a variable that is dependent on the number of decoy documents n. I do not measure non-interference as a probability. However, I measure the average number of decoy accesses per one week of computer usage. To that extent, I asked four user groups of thirteen computer science students each, to plant ten, twenty, thirty, or forty decoy documents generated by D^3 on their own file systems. The fifty-two students downloaded a total of 1300 decoy documents from D^3. I encouraged the participants in the user study to carefully consider where to place the decoy files and how to name them by taking into account the desired properties of such documents, particularly enticingness, conspicuousness and non-interference [Bowen *et al.*, 2009b]. Recall that the objective, when placing such decoy files, is to maximize the likelihood that a potential masquerader will get detected when he or she illegitimately accesses the victim's computer, while minimizing the likelihood that the legitimate user accidentally accesses these documents due to confusion or interference with his or her normal activity. For instance, the user can choose file names that are easily recognizable as decoy by him or her, while remaining enticing to the adversary. The file name could, for example, include the name of a person who is outside the social network of the user. For instance, one participant renamed a decoy file to *TaxReturnSylvia.pdf*, while he did not file any tax returns jointly with *Sylvia*, nor did he know anyone with that name. Carefully selecting the file names would make the file easily recognizable as a decoy file by the legitimate user, but could make it intriguing for the attacker.

The participants in the user study, who installed the DDA sensor before downloading the decoy documents, agreed to share their data. The experiment lasted for about seven days on average, during which access to decoy files was monitored. The data collected by the DDA sensor was uploaded to a central server for analysis.

4.2.2 Experiment Findings

At the end of the human subject study, the participants reported the directories under which they placed the downloaded decoy files. I have summarized the results of these reports and selected the 40 directories with the highest number of placed decoys. These directories are shown in a directory tree in Figure 4.4. The ranking of these file locations is shown in Appendix C. Subdirectories under the *My Documents* and *Desktop* directories seemed to be the most popular choices by the participants. In the following, I summarize the main findings of this study.

4.2.2.1 Interference Increases Super-Linearly with More Decoy Files:

Recall that non-interference is defined as the likelihood of the legitimate user accessing the authentic files after installing the decoy files. Decoy files planted on a file system for masquerade detection are not supposed to be accessed by the legitimate user. They are placed there in order to entice attackers to open and use them. Any accidental accesses to decoy files by the legitimate user of the system, *i.e.* accesses that are not caused by an attacker gaining access to the file system, are considered false positives. I have ignored all alerts issued within the first hour of the students installing the decoy documents on their systems. This gives the participants an opportunity to decide where to place the decoy documents and how to rename them, based on the recommendations given to them in the user study description. Table 4.1 presents the number of false positives and shows that it grows super-linearly with the number of decoy files planted in the file system. The higher the number of decoy files placed in the file system, the higher the likelihood of a legitimate user accidentally accessing one of these decoy files, thus, the lower the non-interference of these decoy files with the normal activities of the legitimate user. While a more longitudinal study is needed to investigate the relationship between the number of decoys planted and their impact on non-interference, our preliminary results show that interference increases super-linearly with the number of decoys planted.

Table 4.1: Number of Decoys and Decoy Touches

Number of Placed Decoys	**Number of Participants in Experiment**	**Number of Decoy Accesses**
10	13	2
20	13	6
30	13	9
40	13	24

4.2.2.2 Distribution of False Positives:

Figure 4.2 is a box-and-whisker plot of the decoy file accesses by the legitimate users for the four different values of decoys planted in the file system. The figure shows that for the case of ten decoys, only one false positive was recorded for any single user, whereas that number reaches up to nine false positives-point when 40 decoys are placed in the file system. Although the "'nine false positives"' data point is considered an outlier in this figure, more than 50% of the users who placed 40 decoy documents in their file systems did accidentally access at least one decoy file and experienced some level of interference with their normal activities. As the figure shows, not only does the likelihood of interference for each user grow with the number of decoy documents placed in the file system, but the amount of interference for each affected user increases super-linearly as well.

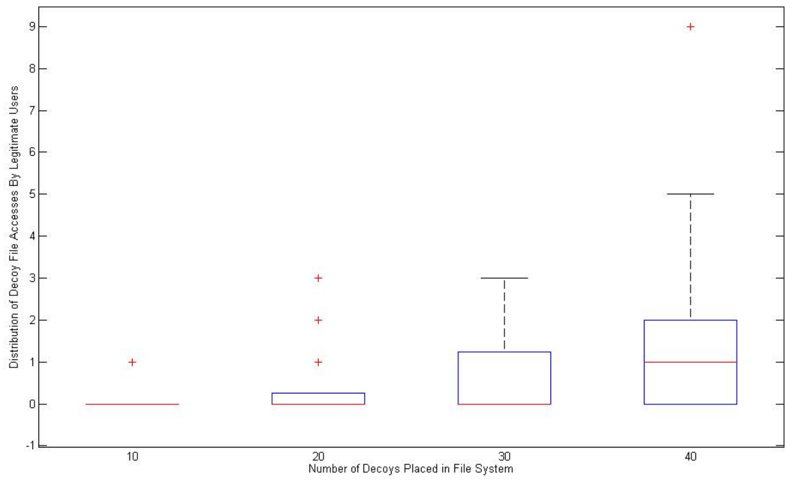


Figure 4.2: Distribution of the Number of Decoy Document Accesses by Legitimate Users

4.2.2.3 Placement of Decoy Files:

Figure 4.3 shows the number of false positives by decoy location. The specific directory locations are listed in Appendix C.

The number of false positives varies widely by decoy document path or location. It is noteworthy that fifteen of the top 40 decoy file locations only were accidentally accessed by the legitimate users. Many decoy files were never accessed by these users, demonstrating that non-interference of the decoy documents varies by the chosen decoy placement in the file system. While the ideal decoy placement that minimizes interference should be customized by the user based on his or her file system access habits, it seems that certain locations should be avoided such as the *high traffic* locations or locations that get automatically scanned by applications installed on the system.

The highest number of false positives are due to accesses to decoy files placed in location number 14, *i.e.* under the *Downloads* directory. While eight of the nine false positives in this location were triggered by a single user, the results show that decoy files in this location can introduce a high level of interference. This is not surprising knowing that most browsers save downloaded files in the *Downloads* directory by default, thus forcing a lot of user activity and *traffic* on files in this directory.

4.2.2.4 Differentiability to the User is not Enough:

The second decoy file location that exhibited a high number of false positives according to Figure 4.3 is the *My Music* directory. These false positives can be accidentally triggered by the legitimate users when manually browsing the directory, but they are more likely to be triggered by media players that are scanning the directory in order to discover recently added music files. Even though this scanning for media files is initiated by the user who knows exactly which files are decoy files, the media player or application performing a thorough scan cannot identify these decoy files, and therefore will access them in an attempt to identify whether they are indeed music or video files.

I will further investigate the decoy placement strategies in the next section, where I will show that decoy placement, and consequently decoy conspicuousness, is also tightly linked with the ability to detect masqueraders.

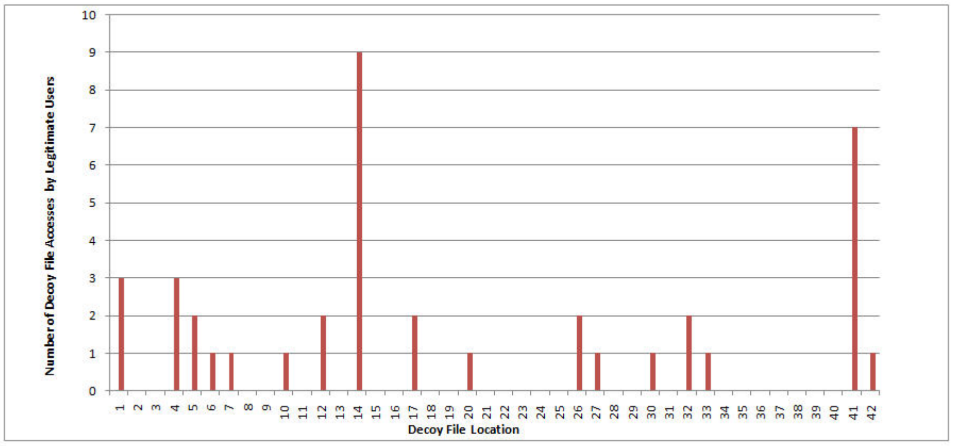


Figure 4.3: Accidental False Positive Decoy Document Accessed by Legitimate Users by Decoy Location

4.3 User Study 2

4.3.1 Experiment Design

In this experiment, I investigate two decoy deployment-related properties, namely enticingness and conspicuousness. Evaluating the design-related properties such as believability, particularly as it pertains to the contents of the decoy document, is not very relevant to the masquerade attack problem. Recall that I detect access to the decoy files before the attacker sees the contents of the file. I ensure variability by tagging all files on the system with a pseudo-random HMAC tag. Detectability can be ensured through the use of the DDA sensor, by the protection of the sensor, and the protection of the HMAC key (used to compute the HMAC tags of the decoy files) from any tampering attempts. Note that any attempt to modify the HMAC tag by the attacker requires access to the decoy file and its loading into memory, which triggers an alert by the DDA sensor.

I seek to answer the following questions through this experiment:

1. How many decoy documents are needed to detect, with a high probability, masqueraders looking to steal information?

2. Where are decoy documents most likely to trap masquerade attackers, *i.e.* in which directories should one place the decoys in order to maximize the likelihood of catching a masquerader, while not interfering with the legitimate user's normal activities?

3. What is the number of decoy documents that leads to the best trade-off between masquerade detection while not interfering with the legitimate user's activities?

4. To what extent do decoy file accesses reveal a masquerader's *malicious* intent?

4.3.2 Experimental Set-Up

I conducted a set of experiments where I simulated masquerader attacks, as described in Section 3.3.4. I installed the DDA sensor on the lab computer used in the human subject study, and planted n decoy files in the local file system. I monitored when and where the masqueraders accessed these decoy files. Table 4.2 shows how I varied the number of decoy documents n for the four experiments. Each experiment involved ten participants acting as masqueraders.

In order to reduce experimenter bias when placing these decoy documents, I have surveyed 52 computer science students as to where they would place decoy documents on their file systems. The directory trees, shown in Figures 4.4, 4.5, 4.6 and 4.7, indicate where I placed the decoy documents for each experiment. Recall that these decoy locations have been selected based on the reports collected from the fifty-two student participants in the first human subject study.

The number of decoy documents n is the independent variable that I control in this user study. The number of decoy file touches is the dependent variable on the number of decoys n planted in the file system.

The file system used in our lab had more than 100,000 files indexed by desktop search tools installed on the system, and totaling a size of more than 70 GBytes. The file system included at least eighty files containing personal information that could be used for identity theft or financial gain. The contents of certain personal files were sanitized, so that no personal information was leaked.

Table 4.2: Total Number of Decoy Alerts by Experiment

Experiment	**Number of Placed Decoys**	**Number of Decoy Alerts**
1	40	96
2	30	90
3	20	71
4	10	56

Before conducting the experiments, I ensured that all non-decoy documents on the file system were tagged with a random tag, that is indistinguishable from the HMAC tag of the decoy documents. This was done so that a more knowledgeable attacker cannot distinguish the decoy files from the normal files by editing them through a hex editor and looking for the HMAC tag within the document. This ensures the fifth desirable property of decoy documents, namely that they are not easily distinguishable as decoys to the attacker.

Besides tagging the real *non-decoy* files, I have indexed all the decoy files using the available desktop search tools on the system. Recall that the DDA sensor issues an alert if the contents of the decoy file are read or if the file gets loaded into memory. Therefore, indexing the decoy files during the deployment phase can reduce potential false positive alerts that might be issued by the DDA sensor during the experiments. The goal is to have more reliable and accurate results, where the sensor alerts are truly caused by the masquerader's activity, and not by desktop search tools suddenly scanning the decoy files.

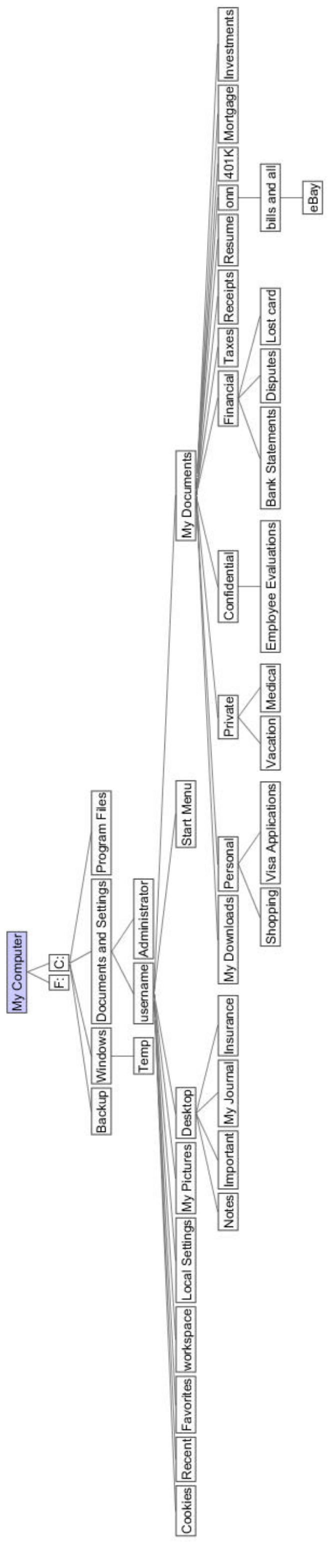


Figure 4.4: Placement of 40 decoy files in Experiment 1

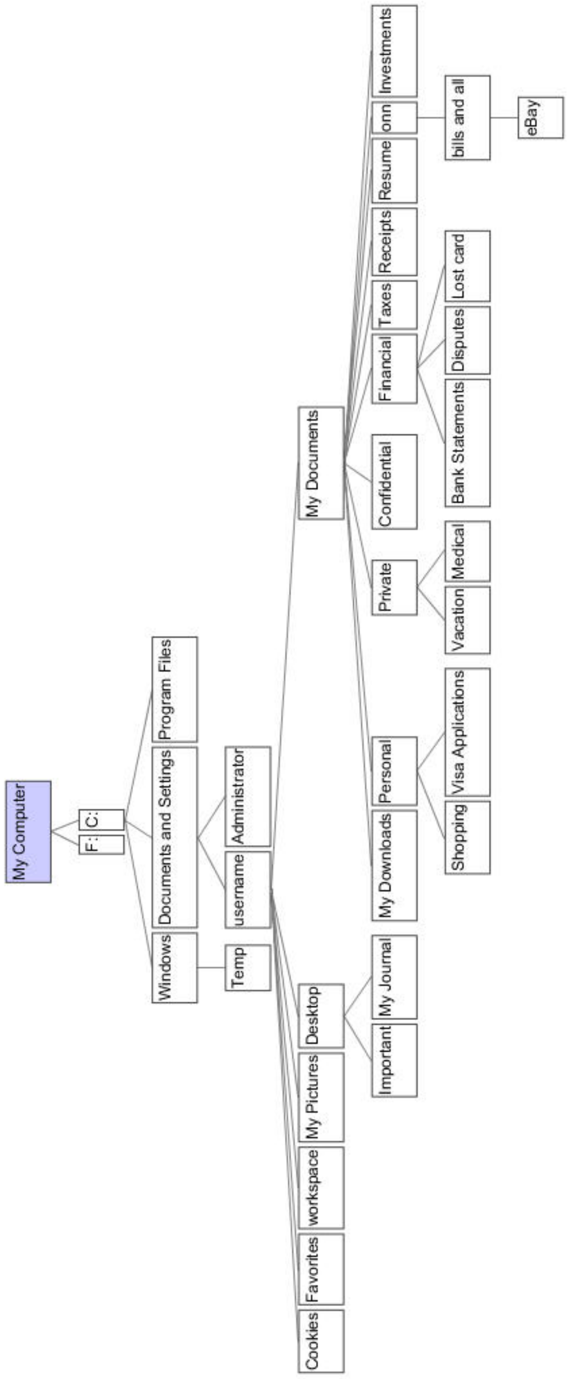


Figure 4.5: Placement of 30 decoy files in Experiment 2

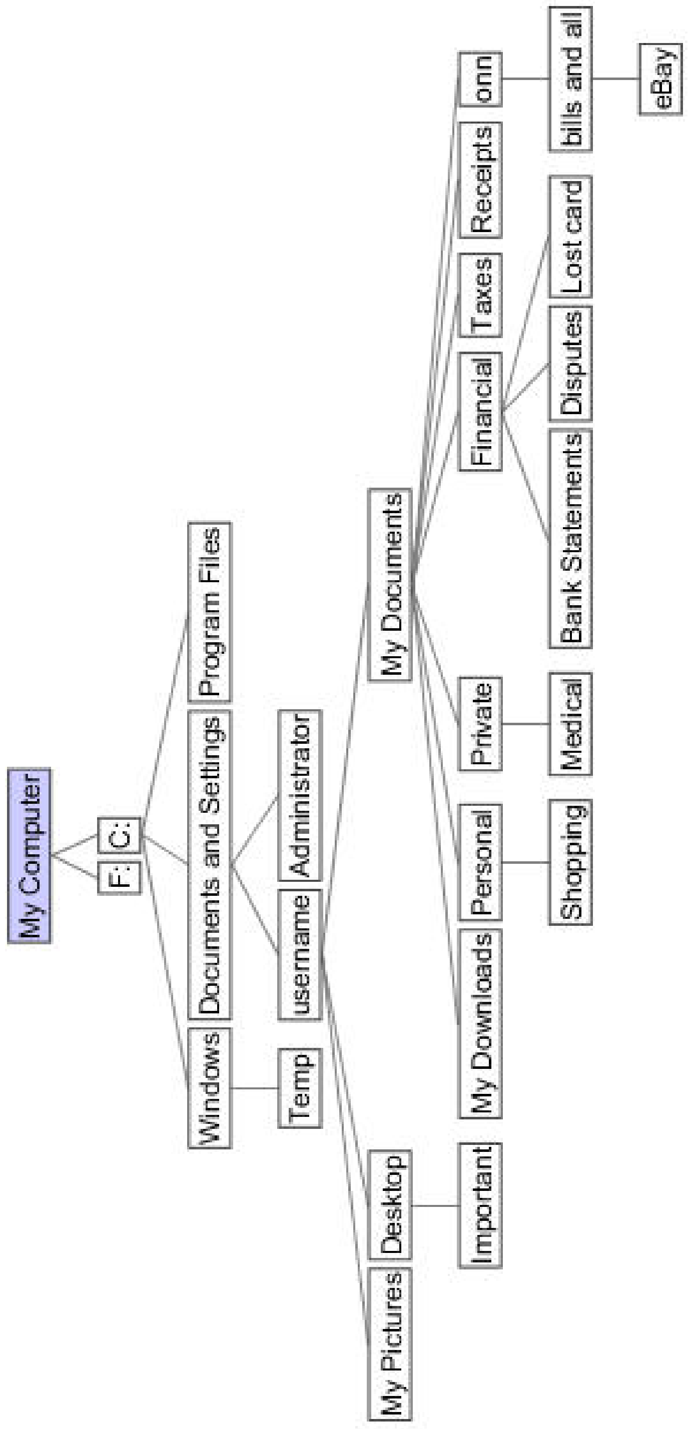


Figure 4.6: Placement of 20 decoy files in Experiment 3

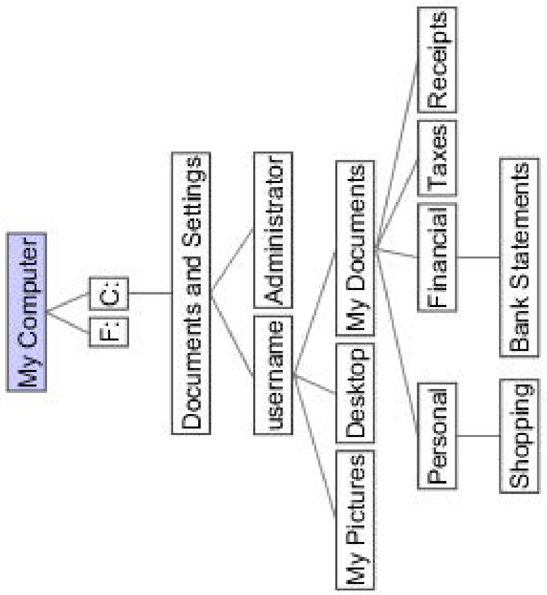


Figure 4.7: Placement of 10 decoy files in Experiment 4

4.3.3 Experiment Findings

In the following section, I list the major findings of this human subject study.

4.3.3.1 The Use of Decoys is Effective:

The main purpose of the use of decoy files is to detect masquerade attacks. While non-interference with legitimate users' activities is desirable, decoys would be useless if they fail to attract masqueraders by being enticing and conspicuous. The results displayed in Figure 4.8 suggest that at least one access to a decoy document was detected by the DDA sensor for every masquerader, regardless of the number of decoys planted in the file system. This finding shows that well-placed decoys can be very effective for masquerade detection. When combined with other intrusion detection techniques, they could potentially provide even more effective and accurate detectors.

4.3.3.2 Recommended Number of Decoys:

Figure 4.8 shows the distribution of the number of decoy file accesses by attackers in the four experiments by the number of decoy files placed in the file system. One could clearly see that the average number of touched decoys (horizontal line within each box) is comparable in the case of 20, 30, and 40 decoys. Whereas it is slightly lower (5.6 touches) when 10 decoys are planted in the file system. Considering Figures 4.2 and 4.8 then, one can conclude that the use of twenty decoy documents provides the best trade-off between detection capability and non-interference. Although the minimum number of touched decoys jumps from 1 or 2 to 5 in the case of 40 planted decoys, this high number could be attributed to the location of the planted decoys and not merely to the higher number of decoys. This can be clearly seen in Figures 4.12 and 4.13 which show the conspicuousness of decoy files 33 and 37 for instance. I will elaborate on this point in the following subsection.

4.3.3.3 High Number of Decoy Accesses is Indicative of Attacker's Malicious Intent:

The question is how many of these decoy file accesses are caused by the masquerader's malicious activity. To answer this question, I conducted an experiment with three groups

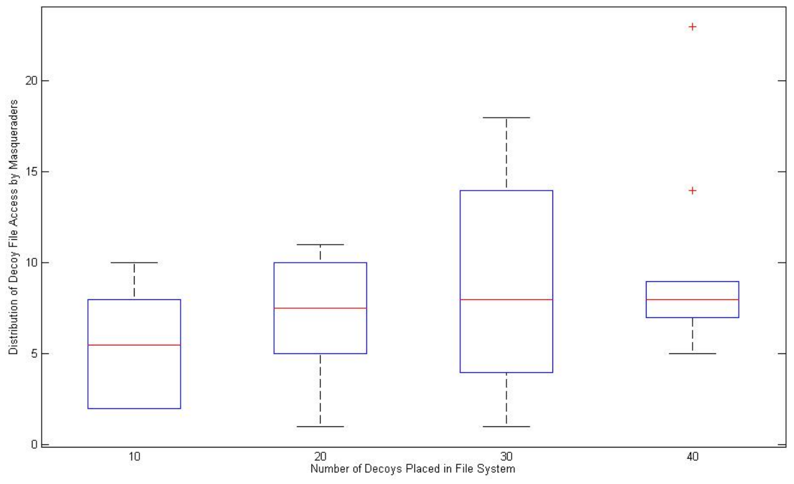


Figure 4.8: Distribution of the Number of Decoy Document Accesses

of ten participants each. Each group was given a different scenario to execute: a 'malicious attacker' scenario, a 'benign masquerader' scenario, or a 'neutral' scenario. The scenarios are described in Appendix A. In all three scenarios, I placed 30 decoys in the file system of the lab computer that served as the participant's coworker's computer. The benign and malicious scenarios can provide a baseline to compare the decoy touches of a malicious masquerader to. Figure 4.9 shows the distribution of decoy touches by scenario. One can clearly see that the number of decoy touches is very low in the benign and neutral scenarios when compared to the malicious scenario. For the following mean decoy touch values, the p-value of the statistical z-test is lower than p=0.001: 9 decoy touches in the malicious case, 0.05 touches in the benign case and 0 touches in the neutral case).

4.3.3.4 The Use of Decoys is Efficient:

According to the results shown in Figure 4.10, seventeen attackers were detected during the first minute of their masquerade activity, while another ten were detected during the second minute after accessing the victim's computer. All masqueraders were detected within ten minutes of their accessing the system under attack. Figure 4.10 also shows that for attackers 31-40, who participated in experiment 4 with 10 planted decoy documents only, the average

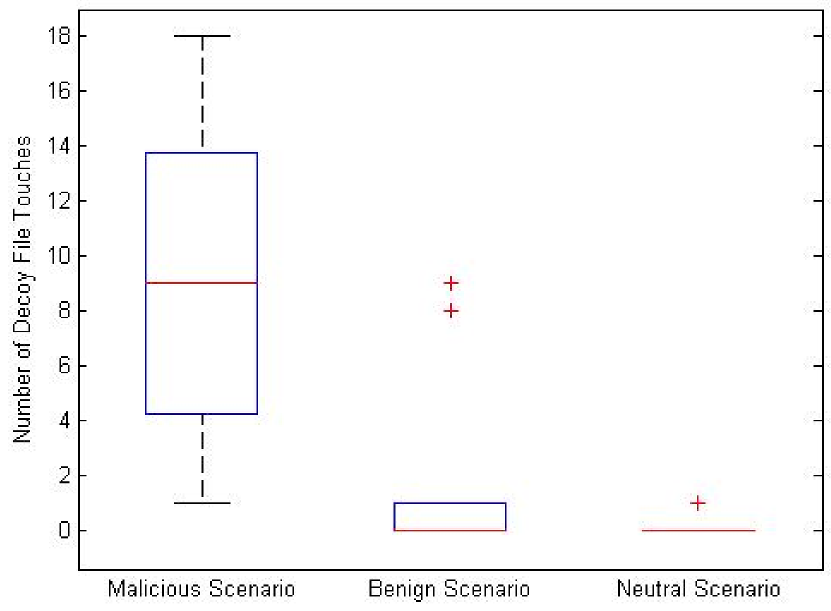


Figure 4.9: Distribution of the Number of Decoy Document Accesses by Scenario

period of undetected masquerade activity (3.6 minutes) is much longer, than for attackers 1-10 (1.3 minutes), 11-20 (1.6 minutes), and 21-30 (1.2 minutes).

Attackers 1 and 14 recorded the longest times of undetected masquerade activity. These attackers had a different strategy for finding personal information. One attacker was mostly after information related to the victim's online banking activity, rather than after information that existed locally on the file system. The attacker, therefore did not navigate or search the *My Documents* directory, where most decoys were located. Not surprisingly, the first decoy that the masquerader hit was decoy number 16, located under Internet Explorer's *Favorites* directory. Attacker 14, on the other hand, suspected that no important information would be stored under the user's file system, but rather under the administrator's file system, which is why he or she hit a single decoy document, namely decoy number 8 (see Appendix C for the exact decoy location). Note that attacker 1 took part in the first experiment where 40 decoys were planted, and attacker 14 participated in experiment 2, where 30 decoys were used. So even with a larger number of decoys, the attackers managed to escape detection for 10 minutes, which suggests the need for a well thought-out placement of decoys that covers all potential attacker strategies for locating and stealing information.

Consider the null hypothesis that all masquerade activity within a 10-minute time window gets missed with at least 10% probability. Based on the observed results, we can reject this hypothesis at the 2% significance level with a p-value=0.0148. In other words, we can claim that with a 98% probability, the probability of detecting a masquerader within 10 minutes of his or her activity on the victim's system is at least 90%.

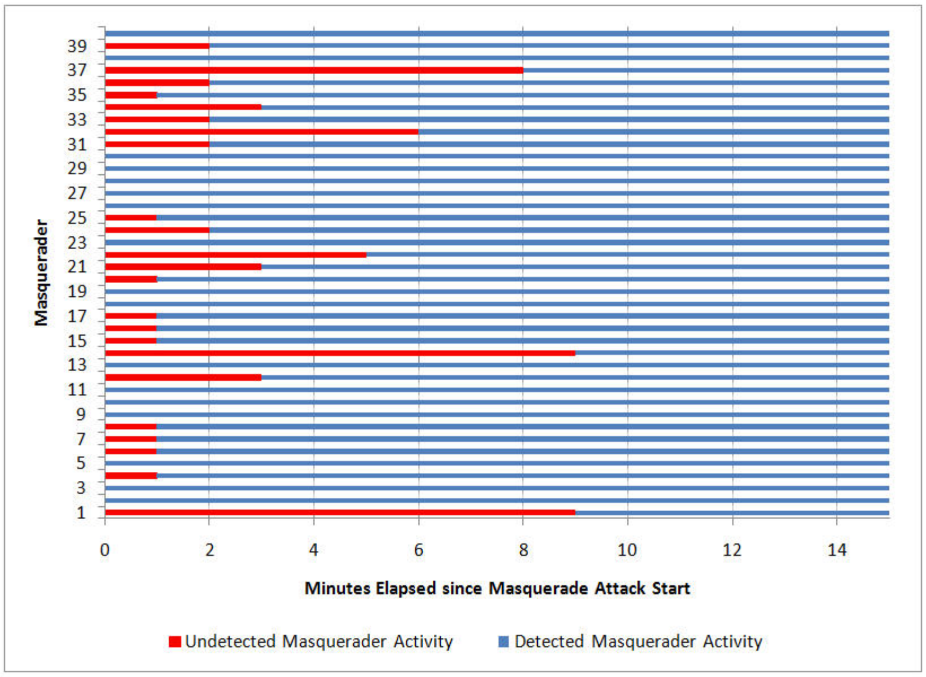


Figure 4.10: Detection Time by User

4.3.3.5 Decoy Placement is Important:

The objective is to identify the decoy document locations that would be less interfering with the normal activity of the legitimate user, while being conspicuous to potential attackers. While the experiments have not been conducted on the same system, and the decoy file locations vary by normal user (customized for his or her own non-interfering use of the system), I argue that the cumulative results do provide ground for comparison, as I have

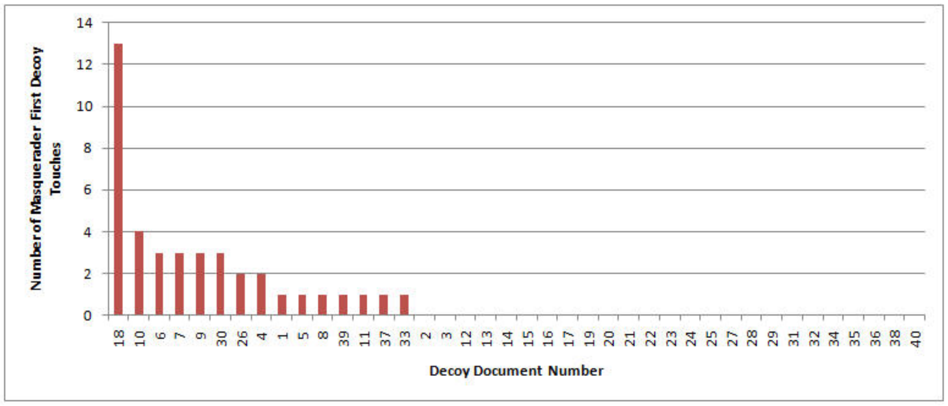


Figure 4.11: Decoy File First Touches

monitored the use for about seven days on average for each user, for a total of 52 users.

Figure 4.12 shows the number of accesses to each decoy file by experiment. Note that the first ten decoy documents were present during all four experiments, whereas the decoys 31-40, for instance were in place during the last experiment only. This explains the falling blue line in Figure 4.12, which depicts the maximum number of potential attackers accessing these decoys, knowing that there were ten masqueraders in each experiment.

The number of decoy file accesses varies widely by file location. Again, the file locations are available in Appendix C. Some files were accessed more than 25 times, while others, namely nine out of the forty decoy files, have never been touched by any attacker. This underlines the importance of decoy placement in highly conspicuous locations.

Considering figures 4.12 and 4.2 for instance, one can notice that the decoy placed in location 18 was touched by 28 masqueraders. Decoys placed in the same location by the participants in the first user study were not touched by the legitimate users and did not trigger any false positives. On the other hand, decoys placed in locations 19, 23, 25, and 31 for instance caused several false positives without catching any masquerader. The two figures clearly show that the location of the decoy document plays an important role in its detection capability and non-interference with normal user activities. While the locations that yield the least interference depend on the legitimate user's file system access patterns, there is clearly room for placing decoys under directories, so that high detection rates can be achieved with very low interference rates.

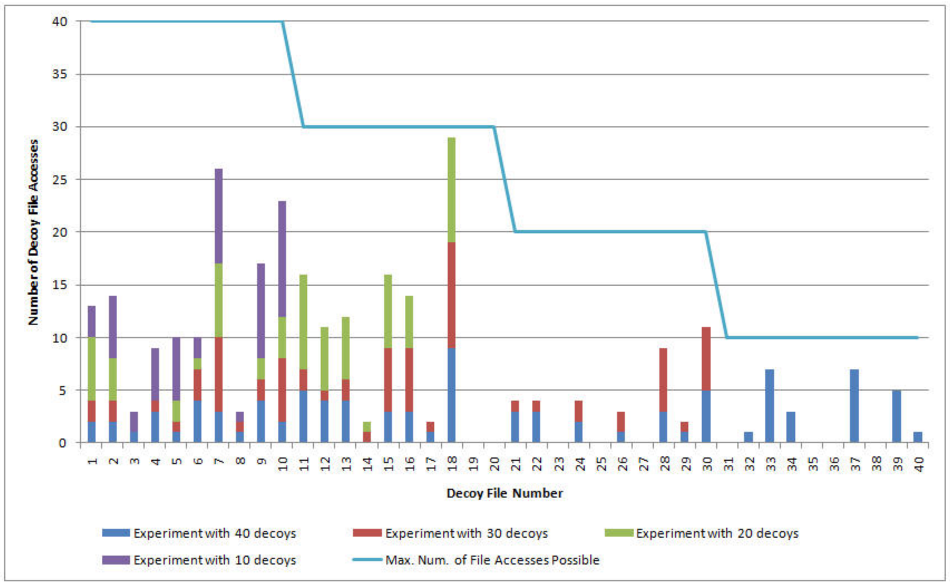


Figure 4.12: Number of Decoy Document Accesses

4.3.3.6 Conspicuousness Comes First:

In order to understand how effective each decoy file was in catching masqueraders, I have ranked the decoy files based on the probability of an attacker accessing them in Figure 4.13. Recall that an access in this case refers to viewing, editing, copying, zipping, or moving the decoy file. Considering Figure 4.13 and the table in Appendix C, the top three decoy files that are most likely to be accessed by an attacker reside on the *Desktop*. These three files reside respectively in the *Important*, *Notes* and *Insurance* directories. The first file is a payment receipt. The second file includes a budget plan, and the third file is a copy of test results from a medical lab. Other decoys with contents similar to the contents of decoy 18, such as decoys 4 and 5 which constitute payment receipts also, did not achieve the same detection capability as decoy 37. This leads us to the conclusion, that conspicuousness is more important than enticingness. Although the attackers were mostly after information with financial value, they were more likely to access files with health-related information, which were highly conspicuous (located on the desktop), than other decoys with more relevant information to their objective, *i.e.* finance-related information.

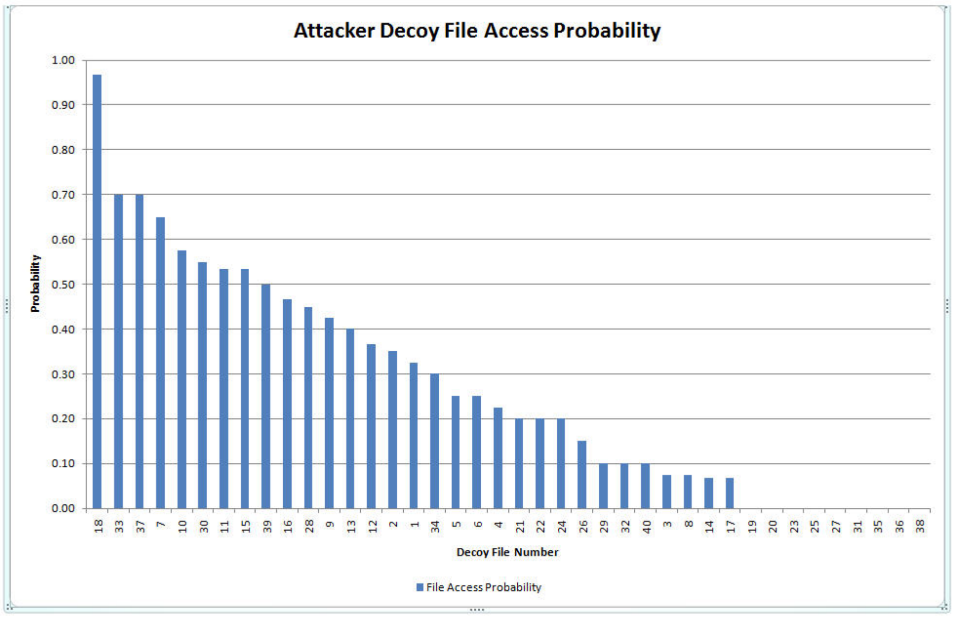


Figure 4.13: Probability of an Attacker Opening a Decoy File

4.4 Discussion and Recommendations

We have shown in Chapter 3, that the masqueraders in our human subject study tended to search the file system manually, *i.e.* by navigating the file system, rather than automatically through the use of a desktop search tool. Figure 4.14 depicts the distribution of decoy document accessed by the search method. It shows that about 88% of decoy document touches resulted from a manual search of the file system that led the masquerader to come across the decoy and take the bait by accessing it. Only 12% of the decoy touches were the result of a search query submitted by the masquerader to a desktop search tool. Although this finding is somewhat not expected, it reinforces the importance of the conspicuousness of decoy files.

Although different users may have different patterns of accesses to *authentic* files depending on what they use their computer for, they are not expected to access decoys differently. For instance, a novelist or a technical writer may have a different file access pattern than

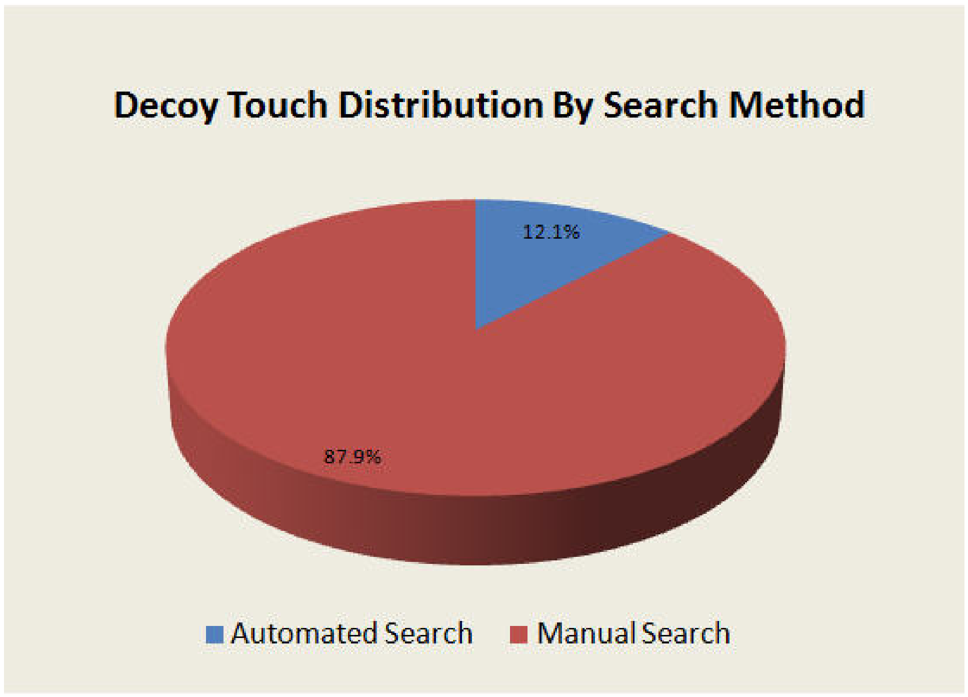


Figure 4.14: Decoy File Touch Distribution By Search Method

someone who writes music, makes videos, or runs large statistical analyses. However, these users are not necessarily more or less likely to access self-planted decoys than others. The results are not expected to vary based on the user's file access pattern as long as the decoys are strategically placed by the user according to the guidelines and best practices described in this chapter. However, I note that the threat model I considered focused on attackers looking to steal PII information. If a computer is used for business for instance, it may contain intellectual property information or other highly confidential files, besides PII information. The optimal number of decoys required in this case may slightly change in order to effectively cover the various types of files and directories that a masquerader might be interested in stealing information from.

Below, I list a few recommendations related to the deployment of decoy documents for effective masquerade attack detection based on the findings of the human subject studies.

4.4.1 Recommendation 1

While, the detectability property of the decoy documents is the most important property, the second user study has shown how important the *conspicuousness* property is. The latter is even more important than the *enticingness* property, as revealed by the user study.

I recommend considering the following ranking of decoy properties when designing and deploying decoy documents for masquerade attack detection. The ranking is based on decreasing importance of the decoy properties.

1. Detectability

2. Conspicuousness

3. Enticingness

4. Non-Interference and Differentiability

5. Believability

The importance of the *variability* property varies by attacker sophistication. Similarly, the importance of the *decoy shelf-life* depends on the deployment environment.

4.4.2 Recommendation 2

While the number of false positives varies widely by user and by decoy document location, overall less than 1 false positive per user per week was recorded on average. This is a very encouraging number, but it could be reduced even further with more intelligent placement of the decoy documents. For example, the decoy files placed under the *My Pictures* and *My Music* directories could be accessed by applications scanning the file system for picture or music files respectively. Such accesses are not deliberate accesses by the legitimate user and could be avoided, if the decoy files were placed under directories that do not get scanned by such applications by default.

4.5 Conclusion

4.5.1 Chapter Summary

In this chapter, I presented an experimental evaluation of the different deployment-related properties of decoy documents. I also made a few recommendations based on the findings from my experiments. These recommendations should guide the deployment of decoy documents for effective masquerade attack detection. By way of summary, I presented:

- a host-sensor that detects access to decoy documents when loaded in memory using stealthy HMACs embedded in the decoy documents,
- a measurement of how effective decoys can be in detecting masquerade activity,
- an investigation of the trade-offs between deployment properties of decoy documents when applied to the masquerade attack detection problem through human subject studies, and
- a set of recommendations for the effective use of decoy documents for masquerade attack detection.

4.5.2 Future Work

In my future work, I will repeat the human subject studies in different environments other than universities, in order to determine to what extent my results are generalizable.

I will also evaluate other decoy document properties, including the *believability* of documents. Furthermore, I will investigate the decoy document properties for masquerade attacks perpetrated through the installation of rootkits and malware such as *Torpig*. Finally, I will study how attacker behavior changes based on the attacker's knowledge about the monitoring mechanisms running on the victim's system and the perception of risk and expected financial gain.

Chapter 5

Diversifying Detection Approaches

In this chapter, I investigate the combination of search behavior anomaly detection with the monitoring of trap-based decoy files. I evaluate the effect of the combined detection approach on detection accuracy. I postulate that this provides stronger evidence of malfeasance, and therefore improves the detector's accuracy. Not only would a masquerader not know the file system, they would also not know the detailed contents of that file system especially if there are well placed traps that they cannot avoid. I conjecture that detecting abnormal search operations performed prior to an unsuspecting user opening a decoy file will corroborate the suspicion that the user is indeed impersonating another victim user. Furthermore, an accidental opening of a decoy file by a legitimate user might be recognized as an accident if the search behavior is not deemed abnormal. In other words, detecting abnormal search and decoy traps together may make a very effective masquerade detection system [1].

5.1 Introduction

In the previous chapter, I studied the placement of decoy files in order to maximize the detection probability and speed of fraudulent activity on a local file system. Monitoring decoy files alone however, may not provide enough evidence for fraudulent activity. A legitimate user may accidentally access a decoy file, or a masquerader may be able to

[1]Portions of this chapter were published in [Bowen *et al.*, 2009a].

escape detection if the decoy files are not well-placed on the file system. Several measures can be taken to maximize the likelihood that an adversary stumbles upon the decoy file, such as increasing the conspicuousness and enticingness of the file [Bowen *et al.*, 2009b; Ben-Salem and Stolfo, 2011a]. However, the risk that an intrusion goes unnoticed or does not get detected quickly enough still exists. Moreover, if the adversary knows that the system is baited, he or she may be more careful with accessing decoy files. For these reasons, I propose to supplement monitoring access to decoy files on a host with profiling user behavior in order to get more coverage for suspicious activity that could be indicative of a masquerade attack.

On the other hand, anomaly detectors suffer from low accuracy, and particularly from high false positive rates. Combining several base classifiers into one ensemble classifier should aid in overcoming this shortcoming. Each classifier uses a different modeling algorithm to profile user behavior. Base models can be aggregated by learning from labeled data or by achieving consensus among the individual models. The ensemble methods output collectively one classification label that reflects the meta-learning from these models or the consensus amongst them.

Techniques for creating ensemble classifiers using multiple diverse classifiers have been studied extensively [Chawla *et al.*, 2001; Dzeroski and Zenko, 2002; Dietterich, 2000; Domingos, 2000]. The objective of using such ensemble methods is to improve robustness and classification accuracy over single-model methods. Improvement in classification accuracy, however, can be achieved only if the base models are mutually independent. This conditional independence assumption may not always hold true though.

In the absence of the independence condition, how effective are these ensemble anomaly detectors, *i.e.* how effective is *model diversity*? Tan and Maxion studied the effects of using diverse anomaly detection algorithms on detector performance [Tan and Maxion, 2005]. They investigated how various sequence-based anomaly detectors dealt with a specific anomaly, namely a 'foreign' sequence, *i.e.* a sequence that has never been seen during the training phase of the detection algorithm. Their results showed that limited performance/anomaly coverage gains can be achieved by combining various anomaly detection algorithms. The anomaly coverage gains are mostly seen at the edges of the anomaly space.

This indicates that such gains are highly dependent on the characteristics of the detected anomaly and on the parameter settings of the anomaly detector. Furthermore, these limited gains may not justify the additional classifier training and deployment cost and performance overhead that are likely introduced through the combination of different classifiers.

Moreover, if the anomaly space of various classifiers is mostly overlapping, the ensemble method does not offer any additional protection mechanism against evasion attacks. Note that anomaly detectors are subject to mimicry attacks, where the attacker tries to mimic the legitimate user's behavior. In this case, the attacker's activities will not be detected as abnormal, and consequently the attacker can escape detection. If the different classifiers have highly overlapping anomaly spaces, then, when mimicking normal user behavior to successfully evade detection by one classifier, an attacker is likely to escape detection by the other classifiers. Combining different classifiers in this case does not constitute a defense mechanism against mimicry attacks.

To overcome the limitations of model diversity, I propose diversifying the detection techniques. I combine the following two detection techniques for the purpose of detecting masquerade attacks: (1) the **user search behavior profiling technique** presented in Chapter 3, and (2) the **baiting technique** presented in Chapter 4, where access to decoy documents is monitored. Decoys files are strategically placed by the legitimate user in his or her own file system. The user is not supposed to touch these files after installing them on his or her system. Any access to these decoy documents is then considered indicative of masquerade activity and triggers an alert.

The two detection techniques are **orthogonal**. Recall that I conjectured that, if a masquerade attack takes place, it can be manifested in both data streams that are monitored and modeled by the individual detection techniques, namely user search behavior on the victim's system, and touches to decoy documents. Despite this, the two data streams remain relatively independent in the absence of masquerade attacks. Based on this conjecture, I show that combining the two techniques can be used to improve the accuracy results of a masquerade attack detector. The search behavior profiling approach alone achieved a 100% detection rate with a 1.12% FP rate [Ben-Salem and Stolfo, 2011b]. My objective is to substantially reduce this FP rate, without significanlty affecting the true positive or detection rate. I also show that the combination of the two techniques can be used as a defense mechanism against evasion attacks targeted at any user behavior anomaly detector.

5.2 Motivation and Approach

In systems, the concept of diversity is applied to system design, process, as well as argument diversity. Similarly, in anomaly detection, diversity can be applied along different dimensions listed below:

1. Diversity in the design of IDSs, thus providing reliability when sensors are subject to the same software/system attack.
2. Diversity in modeling algorithms, as some algorithms are more suitable for certain user profiles and behaviors than others. For example, support vector machines, while making very effective classifiers in the general case, may not make the best classifier in the case of a user whose behavior is closest to the 'average' user behavior as has been demonstrated in our prior work [Ben-Salem and Stolfo, 2010].
3. Diversity of features used by one modeling algorithm in order to accurately model the unique and distinct user behavior.
4. Diversity of data streams and events used for modeling by the anomaly detector.

'Algorithmic diversity' does not necessarily improve detection accuracy due to the highly overlapping anomaly spaces [Tan and Maxion, 2005]. However, combining diverse and orthogonal detection technique may provide such improvements.

5.2.1 Detection Approach

A sensor was developed to detect data theft attempts performed by masqueraders on single-user systems. The sensor may be expanded to detect 'need-to-know' policy violations perpetrated by traitors on multi-user systems, such as file servers. We refer to this sensor as the RUU (Are You You?) sensor. The RUU sensor is composed of two sensors. The first sensor is the User Search Behavior (USB) sensor which uses the modeling approach described in

Chapter 3. As its name indicates, this sensor profiles user search behavior, and detects any abnormal search activity. The second sensor is the Decoy Documents Access (DDA) sensor described in Chapter 4, which monitors any access to the decoy documents embedded in the file system. It acts as an oracle to the USB sensor. The sensor also includes a monitoring infrastructure, which I describe in Section 5.5.1. The monitoring infrastructure ensures that the sensor does not get tampered with.

The integrated RUU sensor provides three mitigation strategies when it suspects malicious masquerade activity. These strategies can be selectively implemented depending on the confidence level of the sensor that malicious activity is taking place:

1. Sending an alert message to a remote server
2. Displaying a set of challenge-response questions that the user must correctly respond to: The answers to these questions are given by the owner of the system during the installation of the sensor.
3. Stealthily recording audio and taking a picture, if a webcam is available: The data will be kept on the system and could be used as evidence against the malefactor if a masquerade attack did indeed take place.

Here I describe how each component of the RUU sensor works, and how the USB and DDA sensors are integrated in order to detect masquerade attacks.

5.2.1.1 USB Sensor

The USB sensor implements the modeling and detection approaches described in Chapter 3. It detects abnormal user search behavior after profiling user actions and forming a baseline of *search* behavior. Then, it detects abnormal search behaviors that exhibit large deviations from the baseline. Such deviations signal a potential masquerade attack.

The sensor builds a one-class Support Vector Machine model that profiles the user's search behavior. Vectors with three search-related features are extracted for each two minute quantum of user activity. Recall that the three search behavior-related features described in Section 3.5.1 are:

1. The number of **automated** search-related events
2. The number of file touches
3. The percentage of file system navigation user actions

I identify two thresholds per user model which I use to classify the observed user search activity as normal, abnormal, or non-identifiable. The first threshold thr_1 is determined empirically, so that the miss rate or false negative rate is minimized. A second threshold thr_2 is also set to minimize the FP rate. During the detection phase, I continuously monitor user search activity, and extract a feature vector v every two minutes. I measure the deviation d between current user behavior (as capture in vector v) and the historical user behavior as defined by the user model u. The distance d is compared to thr_1 and to thr_2 in order to determine whether there is enough evidence for masquerade activity. Further details are given in Section 5.2.1.3 .

5.2.1.2 Monitoring Access to Decoy Documents

I use the decoy documents described in Section 4.1.1 and downloaded from the Decoy Document Distributor (D^3) [Bowen and Hershkop, 2009] to bait the masquerader. Recall that the DDA sensor detects when decoy documents are being read, copied, or zipped by validating the HMAC tag embedded in the header section of the file.

During the deployment of the decoy documents, the user can take certain actions to increase the conspicuousness and the enticingness of these decoys. For instance, the user can strategically place them in the file system so that they are easy to spot. Furthermore, the user can protect them using passwords to increase their enticement. They can also carefully choose the file names so that they are easily recognizable as decoys for him or her, while remaining enticing for the adversary. For instance, the file name could include the name of a person who is outside the social network of the user. This would make the file easily recognizable as a decoy file for the user, but could make it intriguing for the attacker. Also, during deployment, the user tags all non-decoy documents on the file with a random tag, that is indistinguishable from the HMAC tag of the decoy document. This is done so that a more knowledgeable attacker cannot distinguish the decoy files from the normal files by editing them using a hex editor and looking for the HMAC tag within the document. Moreover, file indexing during the deployment phase can reduce potential false positive alerts. False positives may arise when the user submits search requests that would require indexing processes to access the decoy files.

Other actions can also be taken to reduce the interference of these decoys with the user's normal activities and to minimize false alerts by the sensor that are not related to masquerade activities. I already presented some recommendations and best practices for maximizing the effectiveness of decoy documents in detecting masquerade activity based on the human subject studies presented in the previous chapter.

5.2.1.3 Integrated Masquerade Detection Approach

I use the DDA sensor as an oracle for the USB sensor. I explained in Section 5.2.1.1 that two detection thresholds are defined for each user search model thr_1 and thr_2. Recall that thr_1 is set, so as to minimize the miss rate or false negative rate. If the user behavior captured in feature vector v is similar enough to the user model u which captures the user's historical behavior, then the user behavior should be deemed normal. In other words, if the distance d between the v and user model u is smaller than thr_1, then no masquerade activity is suspected, and no alert is generated. If, on the other hand, feature vector u exhibits a highly abnormal search, *i.e.* if $d > thr_2$, then an alert is generated. However, if $thr_1 < d \leq thr_2$, then the USB sensor checks whether any excessive access to decoy documents has been recorded by the DDA sensor. If so, then an alert is generated and the right mitigation strategy is initiated. Otherwise, the user search activity is not deemed suspicious enough. Figure 5.1 describes the overall decision process related to masquerade alert generation using the two sensors.

5.3 Experimental Evaluation

5.3.1 Dataset

Recall that I use the RUU dataset which consists of both normal user data and simulated masquerader data. The normal user data has been collected for 18 users over a period of one

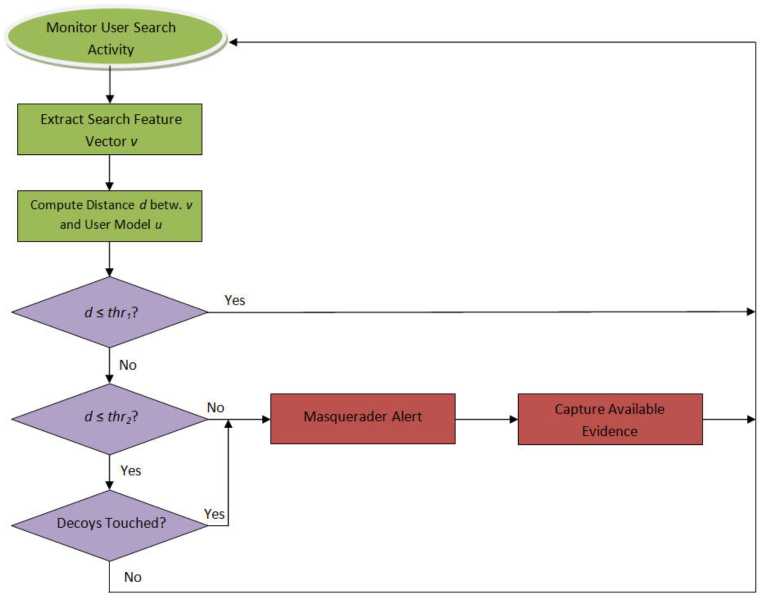

Monitor User Search Activity
Extract Search Feature Vector v
Compute Distance d betw. v and User Model u
$d \leq thr_1$?
Yes
No
$d \leq thr_2$?
No
Masquerader Alert
Capture Available Evidence
Yes
Decoys Touched?
Yes
No

Figure 5.1: Alert Generation Decision Process

week on average, while simulated masquerader data has been collected for 40 masqueraders. To gather the latter dataset, I ran four experiments as detailed in Chapters 3 and 4. I started with 40 decoy files in the first experiment and randomly selected 10 participants from the volunteers to act as masqueraders. In the second experiment, I reduced the number of decoy files to 30, all located in the top 30 most popular locations selected by the normal user population. Similarly, the third and fourth experiments included 20 and 10 decoy files respectively.

5.3.2 Experimental Setup

I use 80% of the data to train one-class SVM models using the three search-related features. I used the LibSVM tool kit to build the models [Chang and Lin,]. I build a linear decoy access classifier for each user, which checks the history of accidental accesses of the user to the decoy documents on his or her file system. Based on this historical behavior, I select a threshold, beyond which access to decoy documents is considered excessive or suspicious, in other words indicative of masquerade acivity. These models are also developed for each individual user by using 80% of the decoy access data. The remainder of the user data, as well as the simulated masquerader data, are used for testing the user models.

5.3.3 Detection Accuracy

I ran an experiment where I supplemented the one-class user search behavior models with a linear classifier based on decoy file accesses, as described in Section 5.2.1.3 and Figure 5.1. Table 5.1 shows that using this combined or integrated approach achieves a 99.94% detection rate or TP rate with a 0.77% FP rate. The TP rate is almost equivalent to that achieved by the search profiling approach only, while the FP rate is 36% lower. The FP rate translates to one false positive every 260 minutes, or every 4 hours and 20 minutes, as opposed to one false positive every 180 minutes or 3 hours.

Table 5.1: Experimental Results of the Search Profiling and Integrated Modeling Approaches using **2-minute** Quanta for Feature Vector Extraction

Method	**True Pos. (%)**	**False Pos. (%)**
Search Profiling	100	1.12
Combined Approach	99.94	0.77

I can further reduce the frequency of false positives to one every $5\frac{1}{2}$ hours approximately (338 minutes), if I use the same modeling approach over 5-minute quanta. This is derived from the 1.48 false positives recorded every 5*100=500 minutes, as reported in Table 5.2. While this is still a relatively high frequency of false positives, it can be even further reduced if I increase the look-ahead time window where I check for decoy accesses. Recall that I postulated that detecting a high-volume search followed by a decoy file access corroborates the suspicion that the user is impersonating another victim user. In the current modeling scheme using 2-minute (or 5-minute) time epochs, I account for decoy accesses that happen simultaneously with abnormal search actions only. If I use a lookahead window to check for potentially imminent decoy file accesses, I can improve the accuracy performance even further.

To compare the individual classifiers for each user using the two detection schemes, I build a ROC curve for each classifier and calculate the corresponding AUC score for each.

Table 5.2: Experimental Results of the Search Profiling and Integrated Modeling Approaches using **5-minute** Quanta for Feature Vector Extraction

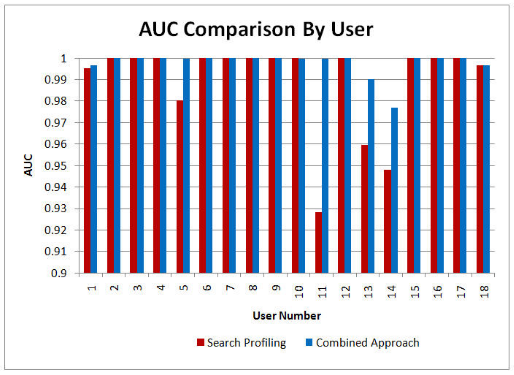
Method	**True Pos. (%)**	**False Pos. (%)**
Search Profiling	100	2.38
Combined Approach	100	1.48

Figure 5.2 displays the AUC scores achieved by both detection approaches by user model. The results show that each user model using the combined detection approach achieves a higher or equal AUC score, *i.e.* equal or better accuracy results than the user model based on the search profiling approach alone. The best accuracy improvements are achieved for users 5, 11, 13 and 14. These user models scored the top four FP rates amongst all user models based on search profiling alone. For these specific users, the FP reduction rates ranged between 33% and 67% when using the combined detection approach. This confirms the efficacy of using this combined approach to limit the number of false positives and improve the accuracy of the masquerade attack detector.

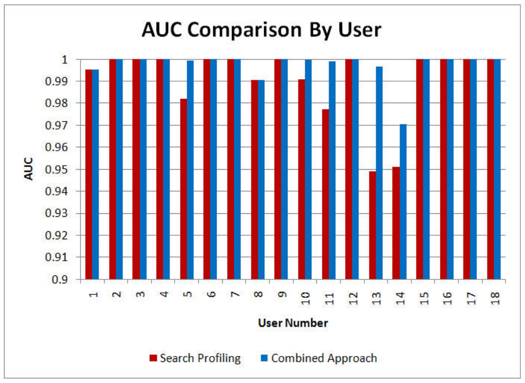
Figure 5.3 depicts the relationship between the frequency of the occurrence of false alerts and the length of the modeling epoch. The figure shows that the longer the modeling epoch, the lower the frequency of false alerts issued by the masquerade detector for 100% detection rates.

5.4 Defending Against Evasion Attacks

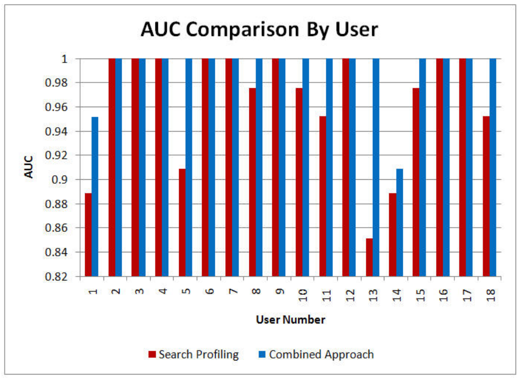
Any anomaly-based intrusion detection system (AIDS) is subject to mimicry attacks. Tan *et al.* [Tan *et al.*, 2002] identified two mechanisms for performing mimicry attacks: (1) contaminating the learning and/or model update process by inserting attack data into normal user data, and (2) intertwining attacks with normal user activity so that the attacks go undetected, which is also known as an evasion attack. I assume that the classifier training process has not been subject to a poisoning or data contamination attack, and focus the analysis here on evasion attacks. Wagner and Soto listed six types of evasion attacks against host-based intrusion detection systems using a malicious sequence of user



(a) Modeling Using Feature Vectors per 2-minute Quanta



(b) Modeling Using Feature Vectors per 5-minute Quanta



(c) Modeling Using Feature Vectors per 15-minute Quanta

Figure 5.2: AUC Comparison By User Model for the Search Profiling and Integrated Detection Approaches

commands or system calls as previously noted in Section 2.5. Most of these attacks do not apply to the RUU sensor, as I model only frequencies of user activities and not sequences of user commands. Below I discuss whether the RUU sensor is vulnerable to these attacks.

1. The *lip under the radar* attack: The attacker avoids causing any change to the observable behavior of the application, *i.e.* he or she does not launch any processes that the legitimate user would not normally run. The attacker uses already running processes only, and at the same rate, as the victim user. This is equivalent to the *'slow-and-low'*

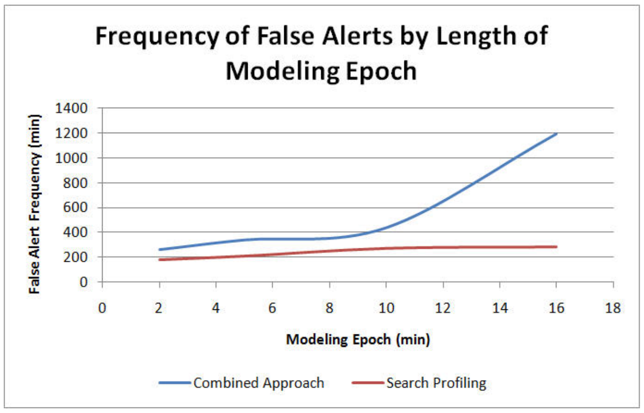


Figure 5.3: False Alert Frequency By Modeling Epoch Length

attack. When trying to evade the RUU sensor, the attacker would then have to refrain from engaging in any large-scale search activities. He or she would also have to access files at a slow rate, so that his or her activity goes undetected. Consequently, it would take them longer to find any interesting or relevant information that could be stolen. Although masquerade activity in this case would take much longer, the adversary is still very likely to access decoy files. Based on the human subject studies described in Chapter 4, every attacker who accessed the victim's system was detected within 10 minutes, regardless of his or her search behavior. The user study results demonstrated that 90% of masqueraders could be detected by monitoing decoy files accesses alone with 98% confidence as noted in Chapter 4.

2. The *be patient* attack: The attacker waits for the time when the malicious sequence is accepted. The RUU sensor does not implement sequence-based modeling, and, therefore, is not vulnerable to this type of attack.

3. The *be patient, but make your own luck* attack: The same argument applied to the previous attack is valid also for this attack.

4. The *replace system call parameters* attack: This is also not applicable to the RUU sensor as the detection approach does not rely on monitoring system calls.

5. The *insert no-ops* attack: Since the features used by the USB sensor are based on frequencies of certain user-initiated activities and processes rather than on modeling sequences of system calls, inserting does not have a significant impact on the RUU sensor, and can potentially only slow down user activities. An extreme case of this could turn into a *slow-and-low attack*, which I discussed under the first type of evasion attacks.

6. The *generate equivalent attacks* attack: An attacker might decide to load the entire search index file at once into memory and directly read it instead of searching for files using the desktop search tool user interface. This would reduce the number of user search actions detected by the RUU sensor, and may impact its ability to detect the attacker's fraudulent activity if relying on modeling search behavior only. Again in this case, monitoring accesses to decoy files becomes more significant in detecting the attacker's activity.

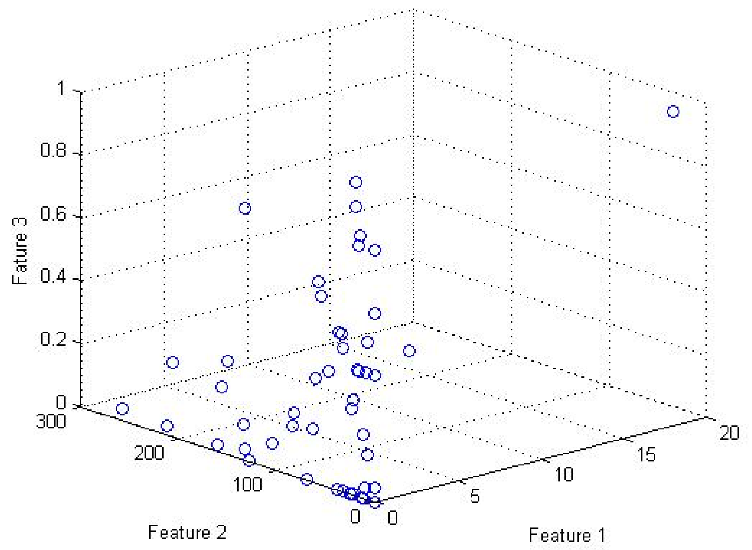
I conjectured that combining the baiting technique with the user search behavior profiling technique serves as a defense mechanism against mimicry attacks, or evasion attacks in particular. I assume that user models and training data were not contaminated with masquerader data during the model training or update phases. In order to validate my conjecture, one would ideally have a masquerader mimic a legitimate user's behavior. However, when simulating masquerade attacks as described in the 'capture-the-flag' exercise, it was extremely difficult to make the volunteers participating in the user study mimic the behavior of a specific user. To evaluate my conjecture though, I reviewed all search behavior models and identified the user who had the most similar search behavior to that exhibited by masquerade attackers. To identify this user, I measured the similarity between the legitimate user behavior and masquerade behavior by applying the probability product kernel to the distribution of their feature vectors [Jebara *et al.*, 2004]. User 13 showed the closest behavior to that of masqueraders as can be seen from Figure 5.4. This figure depicts the distribution of the three search-related features for user 13, and for all masqueraders combined. I can support my conjecture by reviewing the results achieved by this user's model in Figure 5.2, which are indeed significantly better than the results achieved using the search behavior modeling technique alone, particularly when I extend the monitoring and modeling window to 15 minutes.

Figure 5.2(c) clearly shows how all attacks are detected for user 13 when using the combined detection approach, while a high number of false positives are still recorded if only the search profiling approach is used.

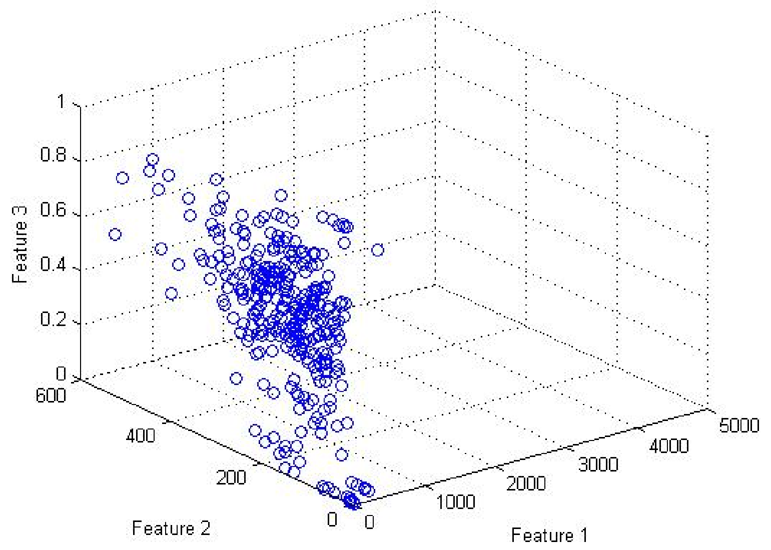
One might expect that hardening the detector against mimicry attacks could drive higher FP rates. The experimental results show the opposite effect. Figure 5.5 helps in understanding how this can be achieved. When using the search profiling approach only, the circular point above the threshold line in Figure 5.5(a) triggers a false positive. If I use a lower threshold beyond which search behavior is considered suspicious as in Figure 5.5(b), I can widen the anomaly space for the detector. This in turn means that the adversary has to work harder in order to faithfully mimic the legitimate user's behavior. However, this alone may introduce false positives. By combining search profiling with the baiting technique, I can use a second threshold for the highly abnormal search behavior, beyond which a 100% TP rate is achieved. For points that fall in the 'ambiguous' space between the two thresholds, the access to decoy information can be used to inform the classification decision. The key to this process is the use of decoy documents that are strategically placed, highly-enticing and conspicuous in the file system, so that the attacker is very likely to touch them. The 'capture the-flag' exercise showed that all masqueraders did indeed touch at least one of the placed decoy files as reported in Figure 4.10.

5.5 Sensor Architecture

In Sections 5.2 and 5.3 of this chapter, I discussed how I combine the USB and DDA sensors into one classifier, the RUU sensor, which makes a single classification decision. In this Section, I present the remaining components of the RUU sensor. The full host sensor is shown in Figure 5.6. Besides the USB and DDA sensors, one of the main components of the RUU sensor is its integrated monitoring infrastructure,which serves for the detection of any tampering attempts.

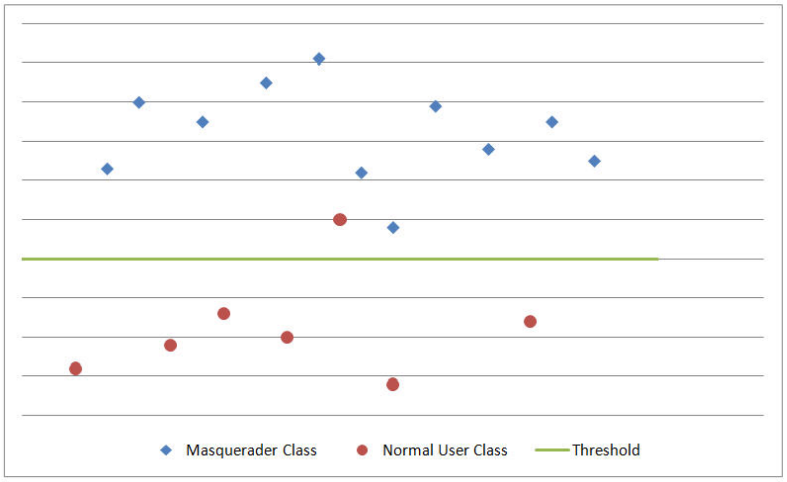


(a) Feature Vectors for User 13

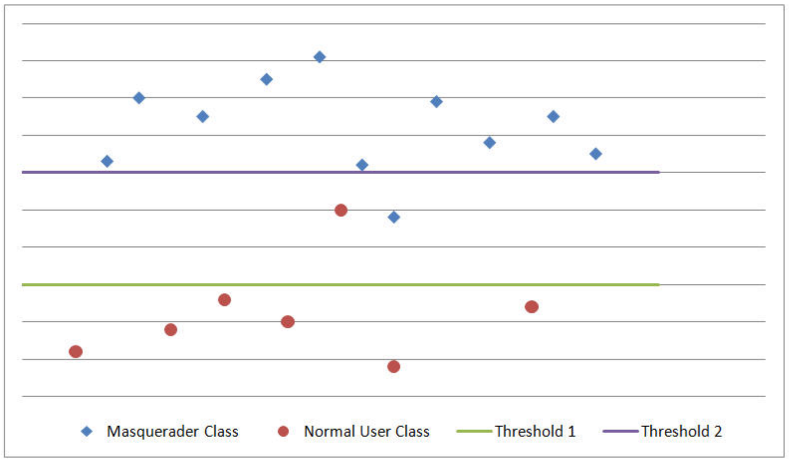


(b) Feature Vectors for Masquerade Attackers

Figure 5.4: Feature Vectors for User 13 and Masquerade Attackers



(a) Search Profiling Classifier Example



(b) Search Profiling and Baiting Classifier Example

Figure 5.5: Anomaly Space for the Search Profiling and the Combined Approach Classifiers

5.5.1 Sensor Monitoring Infrastructure

Research shows that host sensors are increasingly being disabled by malware [Llet, February 9 2005], and could similarly be disabled by masqueraders. In order to prevent, or at least detect any tampering attempts directed against the RUU sensor, I implemented a set of self-monitoring monitors that monitor the critical processes of both sensors. The monitors can be shutdown only using a unique random sequence that is accessible only to the legitimate

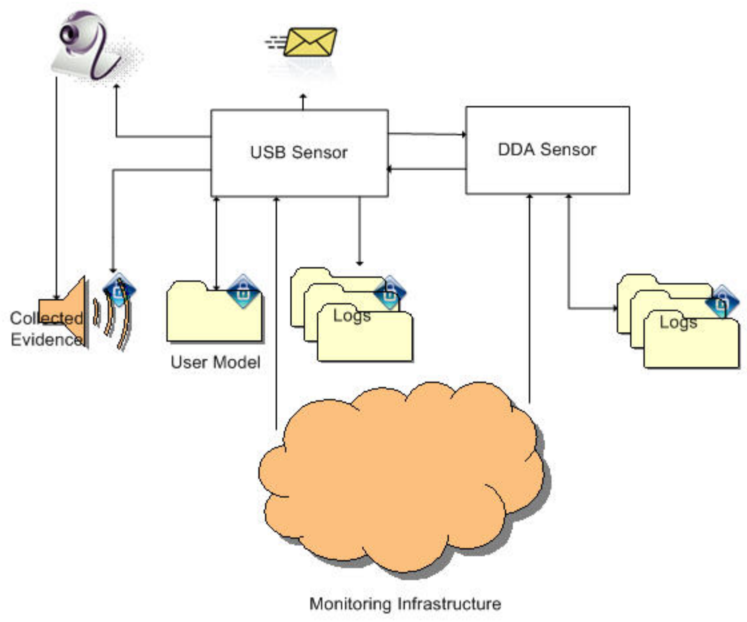


Figure 5.6: Architecture of the RUU Masquerade Attack Sensor

user of the system, on which the host sensor is running. Any attempt to shutdown the sensor or one of the monitors not according to the right shutdown sequence results in an alert and is highly indicative of potential malicious activity on the system.

Several solutions for tamper-proofing software exist as noted in Section 2.6. They are designed to prevent the unauthorized use of software, but they could presumably be easily modified to detect unauthorized attempts to disable or shutdown the software. However, they all require the presence of a third party that can execute code for verification. Moreover, they are computationally expensive, and if used with the RUU sensor, they could significantly slow it down to the point where it becomes vulnerable to overload attacks. In my work, I seek to protect the sensor from being illegitimately disabled, without necessarily having to rely on a third party for monitoring. To that extent, I use a novel approach based on a set of self-monitoring monitors and inspired by the mechanisms used in safety devices for nuclear weapons [Laboratories, 1992; Plummer and Greenwood, 1998], which were designed to prevent the unauthorized launch of such weapons.

Given that adversaries may be aware of system monitoring, special care must be taken to prevent the sensor from being shut down or to detect when it gets shut down. To that extent, a random directed cycle of n monitors, x_1 through x_n protects the RUU sensor as proposed by Chinchani et al. [Chinchani and Upadhyaya, 2003] and Stolfo et al. [Stolfo *et al.*, 2009]. The directed cycle of monitors is created based on a seed known only to the owner of the system. It defines a **unique** shutdown sequence that must be followed in order to shut down the sensor without any alerts.

Let x_i be the monitor watching the critical process of the sensor, where $1 \leq i \leq n$. If an attacker attempts to shut down the critical process, x_i will issue an alert. Monitor x_i is itself monitored by x_j as defined by the directed cycle of monitors, where $1 \leq j \leq n$, and $i \neq j$. So if x_i is shutdown by the attacker, x_j issues an alert. Therefore the attacker has to know the entire shutdown sequence in order to be able to shutdown the sensor and all monitors without getting detected. The attacker has a $\frac{1}{n!}$ probability of guessing the right shutdown sequence. So the higher the number of monitors n, the less likely the sensor may be shutdown without any alert.

In order to prevent an attacker from identifying the right shutdown sequence by observing inter-process traffic, each monitor pings all other $n-1$ monitors periodically. Moreover, all monitors 'monitor' the sensor's critical processes as shown in Figure 5.7, while only one would actually issue an alert if the sensor is shut down. The threat model assumes that the time span between process pings is less than the time needed by the attacker to shut down two processes. In my future work, I will extend the monitoring infrastructure in order to protect the sensor's logs, the user behavior model, and the files containing collected evidence. More important, this monitoring infrastructure should be pushed down to the hardware level in order to prevent any highly-privileged user from shutting down all monitoring processes at once.

5.6 Sensor Operational Costs

The host sensor performs tasks similar to anti-virus programs. In evaluating the performance of the sensor, I use overhead comparisons of anti-virus programs as a benchmark, since the task of comparing an HMAC code is not substantially different from testing for

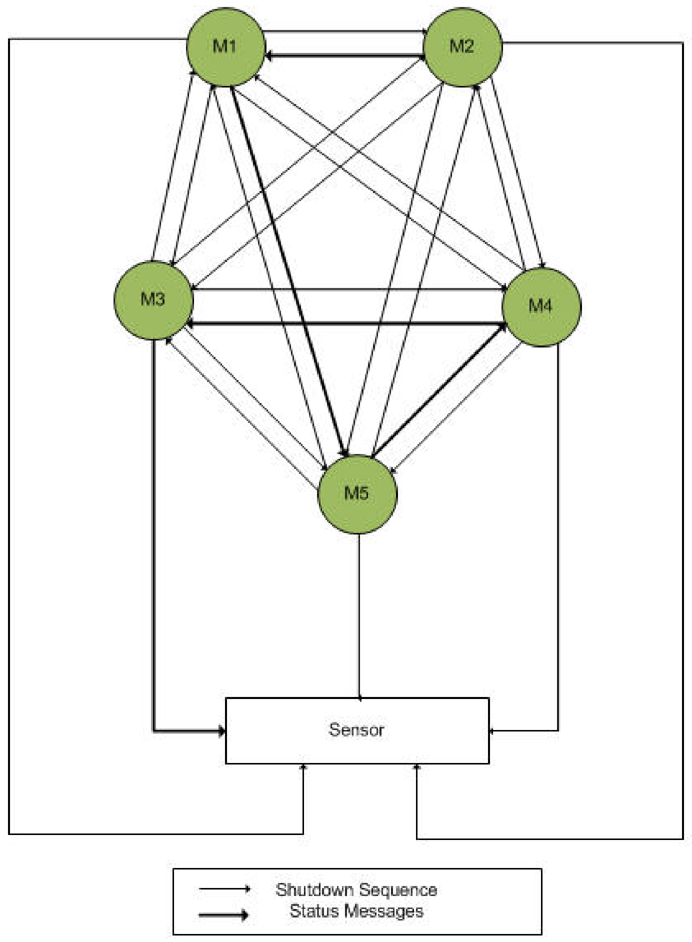


Figure 5.7: Sensor Monitoring Infrastructure

an embedded virus signature. With regard to the resource consumption of the sensor, the components of the sensor use an average 40 KB of memory during testing, a negligible amount compared to Symantec's anti-virus. The additional file access time introduced by the sensor is unnoticeable when opening or writing document files. It averages 26 ms per file. Based on these numbers, I assert that the sensor has a negligible performance impact to the system and user experience.

This overhead can be further reduced. Note that there is a fundamental difference between the task of detecting malware and that of detecting decoy activity. Anti-virus programs are designed to quarantine and prevent the execution of malicious software whenever any process is initiated. In decoy detection, the objective is merely to trigger an alert when a decoy file is loaded into memory. Thus, the decoy detection does not need to serialize execution. For example, it may be executed asynchronously and in parallel by running on multiple cores, which would reduce the file access delay even further.

5.7 Characteristics of the RUU Sensor

The architectural decisions made during the design phase of the sensor enabled certain properties and characteristics.

1. **High Accuracy, Fast Training, and Low Operational Costs:** The use of a limited number of features by focusing on *search behavior* helps in constraining the problem and thus improving detection rates. It also induces a lower runtime overhead, requires limited system resources, and allows for real-time detection. Furthermore, it speeds up deployment as profiling in a low-dimensional space reduces the amount of sampling required to train the detector.

2. **Efficient Model Updates to handle Concept Drift:** SVMs are suitable for block-by-block incremental learning. With the advent of new data and the potential need for updating the model in order to deal with concept drift, SVMs do not have to be retrained with the whole set of new and old data. Instead, it is sufficient to use the most recent data for re-training in addition to the support vectors identified in the old SVM model [Vapnik, 1999; Syed *et al.*, 1999]. This in turn makes the use of meta-learning techniques using several models easier. The use of such techniques may be necessary for handling concept drift. Therefore, the choice of SVMs for building user models helps in satisfying both the low operational costs and the adjustment to new behavior requirements. Moreover, they enable one-class modeling, another critical feature of the sensor.

3. **Privacy-Preservation:** The use of data from multiple users to train classifiers for masquerade attack detection is complicated and introduces potential privacy threats.

Furthermore, requiring the mixture of data from multiple users necessitates substantial retraining of classifiers as users join and leave an organization. The application of one-class modeling avoids such problems and preserves user privacy, besides reducing training time.

4. **High Accuracy and Protection Against Mimicry Attacks:** The perfect detection rate with a very low FP rate can be attributed to the combination of two complementary detection techniques. The motivation for user behavior profiling comes from the fact that user behavior is not readily available for stealing and use (assuming the historical information profiled is kept secret). The use of an anomaly detector applied to user behavior, however, may trigger a large amount of false positives, something that most anomaly detectors suffer from. On the other hand, trap-based techniques are known for their very low false positive rates. The correlation of search behavior anomaly detection with trap-based decoy files provides stronger evidence of malfeasance, and therefore improves the detector's accuracy. Furthermore, this combination of two orthogonal techniques hardens the sensor against mimicry attacks.

5. **Tamper-Resistance:** The implementation of the self-monitoring monitors protects the sensor from being disabled by issuing an alert to a remote system or several systems. It can also protect the collected evidence in case of masquerade attacks as well as the logs and the user model.

5.8 Conclusion

5.8.1 Chapter Summary

In this chapter, I presented a privacy-preserving sensor for effective and efficient masquerade attack detection. The sensor has a very high accuracy with very low operational costs, and was able to detect all masquerade attacks at their onset. It implements a user search profiling technique with a baiting technique that uses decoy documents embedded in the victim's file system. By combining these two orthogonal detection techniques, false positives were reduced by 36% over the search profiling approach alone. A 99.94% masquerade detection rate was achieved with only 0.77% of false positives, the best results ever reported in the literature.

5.8.2 Future Work

In my future work, I will extend the monitoring infrastructure of the sensor in order to protect the sensor's logs, the user behavior model, and the files containing collected evidence. Protecting the user model is extremely important, and the lack thereof exposes the user behavior to the threat of being stolen just like other credentials can be. If an attacker steals a user model, they could craft a mimicry attack against the sensor by poisoning and contaminating the model.

Another improvement to the sensor involves running the HMAC validation function of the sensor when opening files in parallel with other code, so that delays are minimized for the user.

Finally, I also plan on upgrading the sensor, so that it makes use of user feedback for user model updates. Abnormal user search events, especially those that culminate in an access to a decoy document, are a cause for concern. A challenge to the user, such as asking one or a number of personalized questions, may establish whether a masquerade attack is occurring. If the user answers the challenge questions, the sensor will assume that the abnormal user search events are indicative of a user behavior change, and will update the user model accordingly.

Chapter 6

Personalized Diversified User Models

User behavior profiling has been the preferred approach taken in most prior work for detecting masquerade attacks. Various techniques have been used to build user models that reflect that behavior. However, despite the increasing recognition of the value of diversity in intrusion and anomaly detection, this concept has not been applied to user models, to our knowledge, yet. The same modeling technique and the same features are generally used to build user models. Even detection thresholds may not be user-dependent in many user models.

User behavior naturally varies for each user. I conjecture that each user has a very personal way of using his or her computer, and believe that no single model can capture the inherent vagaries of human behavior. I also posit that diversity in user models through the selection of different features for different users, not only could enable modeling the unique behavior of specific users, but could also bring additional detection accuracy gains to the anomaly detector. I aim to automatically learn a distinct user's behavior, much like a credit card customer's distinct buying patterns. To achieve this goal, I propose diversifying the features used to build user models. Furthermore, I propose personalizing these features and customizing them to the behavior of the user in order to accurately model **individual** and **unique** user behavior.

To that extent, I propose an approach to profile a user's behavior based on the 'taxonomy' of Windows applications and user commands presented in Section 3.1.1. Recall that the taxonomy abstracts the audit data and enriches the meaning of a user's profile, thus reflecting the type of activity that the user is performing on the computer. User commands and applications that perform similar types of actions are grouped together in one category making profiled user actions more abstract and meaningful. Commands are thus assigned a type or a class, and classes of user activity are modeled rather than individual user actions.

Furthermore, I use a maximum entropy discrimination approach to determine the classes of user activity that should be monitored for each user. This approach, which I describe in the following Section, provides a formal basis for comparing user models and for identifying the best 'separating' or discriminative features to diversify user models.

6.1 Modeling Approach

I postulate that each computer user has their personal way of using his or her computer. For instance, the activities that the user performs on his or her computer, such as programming, editing a file, or playing a game, and how frequently he or she engages in those activities, may be tightly related to his or her job description, or his or her personal preferences. Moreover, the frequency and speed at which the user emits commands or uses certain applications may be related to his or her proficiency with those commands or programs. Furthermore, he or she may have certain habits such as checking e-mail at the beginning of a user session or checking the online news early in the morning or late in the evening for example.

I use the Windows applications taxonomy to profile user behaviors, since it can readily identify and model specific computer user activities. The user activity abstraction enabled by the taxonomy also reduces the number of features extracted to profile user activities, and therefore decreases computational complexity.

I am interested in all different classes of user activity, and particularly those that reveal the user's computer usage habits. For instance, one interesting behavior that I monitor is user search behavior, as already presented in Chapter 3. Other examples of user behaviors that I monitor include browsing behavior, networking, and remote access behavior. Again the taxonomy allows a system to automatically audit and model a whole class of commands and application functions corresponding to a specific type of user activity.

Note that modeling classes of user activities, in lieu of modeling the use of specific applications, eliminates the artificats of the dataset, caused by the collection of data from different systems. Suppose user A has the *Firefox* browser installed on their computer, while user B installed *Google Chrome*. If I model the use of each browser, then the resulting classifier can easily identify that the presented data belongs to a different user. Therefore, it is imperative to model the **type** of user activity, rather than the **application** used, in order to build reliable user models for masquerade detection.

In the following subsection, I describe the feature vectors used for training the user models.

6.1.1 Feature Vectors

I audit and model the volume and frequency of user activities within epochs or time quanta of fixed length, assuming that other users will exhibit a different behavior from the legitimate user. A total of 22 features, displayed in Table 6.1 are therefore extracted for each epoch. I hypothesize that this could characterize certain users, as some users might start their session with checking their e-mails, others might prefer to check their online newspaper, while yet others may prefer to plunge into work as soon as they power their computers on.

6.1.2 Diversified User Behavior Profiling

In the general case of feature selection, select the best predictive features for a classifier serves two purposes: (1) improving the accuracy of the classifier, and (2) reducing the computational cost caused by the high-dimensionality of the original feature space. Maxion pointed out that most prior profiling approaches apply the same features to all user models [Maxion, 2005]. I posit that diversifying features by selecting the best features for a specific user model independently from all other user models improves the overall aggregated accuracy of all classifiers. Furthermore, diversifying the model features also hardens the classifier against mimicry attacks. Now, an adversary has to identify the specific features modeled for the individual victim before being able to launch a mimicry attack successfully.

Feature Number	**Feature Description**
1	Browsing
2	Communications
3	Database Access
4	Desktop Configuration
5	Development
6	Editing
7	File Compression
8	File System Management
9	Games
10	Installation
11	IO Peripherals
12	Learning
13	Media
14	Modeling
15	Networking
16	Organization
17	Other
18	Search
19	Security
20	Software Management
21	System Management
22	Web Hosting

Table 6.1: Features Extracted for Building User Models

I therefore increase the costs of launching such attacks against a wide set of users.

I apply this concept of diversified modeling to support vector machines (SVMs), which have been shown to achieve the best accuracy results when used for user behavior profiling [Seo and Cha, 2007; Ben-Salem *et al.*, 2008]. The choice of SVMs was suitable for online learning due to their adequacy for block-by-block incremental learning: With the advent of new data and the potential need for updating the model in order to deal with concept drift, SVMs do not have to be retrained with the whole set of new and old data. Instead, it is sufficient to use the most recent data for re-training in addition to the support vectors identified in the old SVM model [Vapnik, 1999; Syed *et al.*, 1999].

To implement the concept of diversified modeling, I use the maximum entropy discrimination framework. In the following subsections, I briefly introduce this framework, and explain how I use it to apply the diversified modeling approach.

6.1.2.1 Maximum Entropy Discrimination Framework

Jebara and Jaakola developed a Maximum Entropy Discrimination (MED) framework for support vector machines and large-margin linear classifiers, which they later extended to sparse SVMs and to multi-task SVMs [Jebara and Jaakkola, 2000].

Solving a regular quadratic convex problem returns a SVM model $\Theta = \{\theta, b\}$. The MED framework can be used to return a distribution of parameter models $P(\theta)$ in lieu of a single parameter value θ, such that the expected value of the discriminant under this distribution matches the labeling of the feature vectors [Jebara, 2004]. The framework can therefore be considered as a generalization of support vector machines.

As the developers of the framework note, one can augment the discriminant with a feature selection switch vector s, which becomes a part of the more complex model $\Theta = \{\theta, b, s\}$ [Jebara, 2004]. The switch vector represents weights corresponding to the features used to train the model. If the weight is equal to zero, then the corresponding feature is not included in the model and can be discarded from the input data. I use these augmented models to select the best features for the user models. This is done for each user model **independently** from the remainder of user models.

The model returned by the MED framework can be further augmented to include joint densities over parameters of several classifiers and feature and kernel selection configurations, rather than parameters of a single classifier only [Jebara, 2011]. This constitutes the **multi-task learning** variant of the framework. Instead of learning each classifier or task independently, one can *pool* all tasks and corresponding data together to form one global prediction problem and learn a single classifier for all of them.

Although the models are conditionally independent given the data, the model representation used makes them dependent otherwise. Observing the data with the latent shared parameter s introduces such dependencies among the multiple tasks or classifiers. For example, in the simple case of multi-task learning with two models ($\Theta_1 \rightarrow D_1 \rightarrow s \leftarrow D_2 \leftarrow \Theta_2$), observing the data D_1 and D_2 links the two user models Θ_1 and Θ_1 unless the shared feature binary switch s is also observed. This shared classifiers or shared models setup may be particularly beneficial in the case of a limited number of training examples for each task.

6.1.2.2 Feature Selection

I use the MED framework in order to select the best features for the user models. I apply the MED's feature selection capability in two different ways. The first is to select the best features for individual user models independently. I call this the **independent learning** technique, which results in the **diversified modeling** approach, as the selected features for each classifier vary from one user model to another. In the second approach, I present the MED framework with training data from all the users, *i.e.* for all classifiers or tasks, and use it to select the best features for all user models. The MED framework returns one global solution for all user models where the same features get selected for all classifiers. I call this the **multi-task learning**, or more accurately in this case, the **meta-learning** approach, since no additional samples are made available to the learner. Meta-learning improves accuracy through the inter-dependencies between the binary tasks, and not through additional data samples.

To apply the MED framework, I build a Gram matrix G, whose entries are given by the kernel function evaluated over all pairs of data points $G\left(x,\bar{x}\right) = \sum_{d=1}^{D} \hat{s}\left(d\right) k_d\left(x,\bar{x}\right)$, where $k_d\left(x,\bar{x}\right) = x\left(d\right) * \bar{x}\left(d\right)$ is the scalar product of the d'th dimension of the input data needed for feature selection. The MED framework will return the optimal weighted combination of features $\hat{s}$.

6.1.3 Personalized User Behavior Profiling

As explained above, I count the frequencies of user actions corresponding to certain classes of user activity, within a time window w of fixed length. The average length of a user session varies from one user to another, and the speed at which they emit user commands and work with applications also varies.

Therefore, an epoch or time window w of length l may be appropriate for user A, but could yield poor results when used in building a model for user B, whose average session is much longer than that of user A for example. In order to improve the accuracy of the user models, I define a user-specific epoch length. The selected features using the diversified profiling approach are then extracted within these epochs of length w_u for each user u. I call this the **personalized modeling** approach, as w_u is personalized or customized for each user.

I use a metric called the Mahalanobis distance to determine the epoch length w_u. The distance is defined as $MD(x) = \sqrt{(x - m_x)' C_x^{-1} (x - m_x)}$ where x is the feature vector whose elements are the frequencies of commands and applications with the time window. The vector m_x is the mean vector of frequencies of commands for all the training set. C_x is the covariance matrix for x. The metric is used to measure the similarity between an unknown sample set and a target distribution. It takes into account the correlations of the data set, as opposed to the Euclidean distance. The distance is computed for consecutive windows using window sizes of various lengths. The best window size w_u is selected for each user u, such that the mean of all distances is minimized after five-fold cross-validation.

6.2 Experimental Setup

To evaluate personalized diversified modeling, I use the portion of the RUU dataset that was collected for normal computer usage behavior profiling. I implement the MED framework in Matlab. I follow the approach taken by the authors of the framework, and solve the MED problem by exploiting a convenient upper bound on logistic-quadratic functions. This effectively turns them into regular quadratic functions, which in turn allows for the application of standard quadratic programming to solve the MED problem. I used the Mosek software package to solve the convex quadratic optimization problem and find the best MED solution [MOSEK, 2009]. I also interleave bounding the logistic-quadratic function with finding the support vector machine solution, thus iteratively maximizing the objective function.To initialize my program, I use white Gaussian priors with zero mean and identity covariance for user models, and I initialize the binary feature switch vector with Bernoulli priors. The algorithm used is described in detail in [Jebara, 2011] together with all the optimizations used.

I start by setting the regularizers $\alpha = 0$ and $C = 1$, then I increase both parameters iteratively until the error is minimized on a cross validation set. C is the regularizer that bounds the Lagrange multipliers from above in the non-separable classification case, while α is a regularizer that corresponds to the level of sparsity, and where higher values of α indicate sparser feature selection. I explore multiple values of C for the independent learner and multiple values of C and α for the multi-task learner. The final values of C and α were determined by five-fold cross-validation on held out data and then tested against a previously unseen data set. To speedup my algorithm, I warm-start each iteration and seed the SVM solver with a solution from the previous iteration, or from a previous final solution of the algorithm that converged for a smaller setting of C or α.

6.2.1 Experimental Methodology

I ran three experiments to evaluate the diversified personalized modeling approach. For each of the eighteen users, I build three user models. For the first user model, parameters and features were selected for each user model independently from all other models. For the second user model, I pooled all data for all users to select the best features and model parameters for all users. In this multi-task feature selection exercise, I converted the problem (and dataset) into eighteen binary 'one-versus-all-others' classification problems. Here, instead of training SVMs on each binary classification, I estimate a feature selection configuration for the aggregate dataset and have all eighteen SVM models share the same configuration. This turns the task into a meta-learning problem. All resulting models share a common feature selection vector s. Therefore the same features are selected and have the same weights for all user models. Finally, in the third model, I use independent model training and feature selection, however with personalized epoch lengths for feature extraction, as explained in the previous section.

Once the baseline models were computed, they were tested on previously unseen data, and a threshold was used to determine whether the user activity was deemed as *self* or *non-self*, *i.e.* performed by a different user. If the user activity was performed by the normal user, but was classified as performed by some other user by the SVM model, a false positive was recorded.

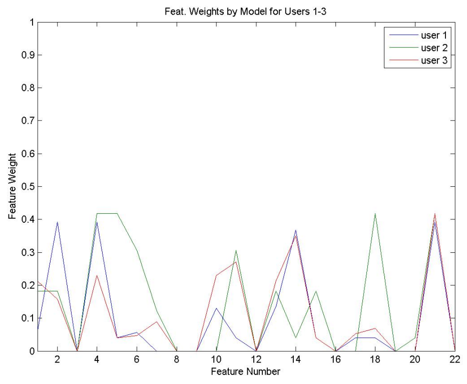
6.3 Experimental Results

6.3.1 Diversified Modeling Results

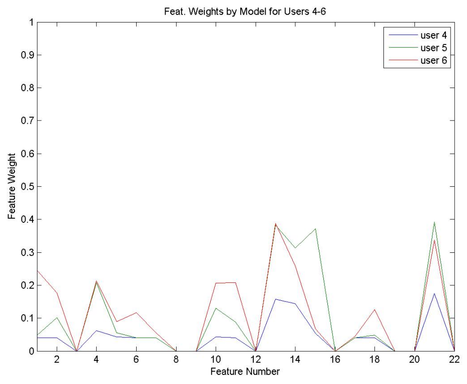
In Figure 6.1, I plot the weights of the twenty-two features (extracted for 10-minute epochs) in the resulting user models for the feature selection SVMs with $\alpha = 24$ and after optimizing over the regularization parameter C for all eighteen user models. As can be seen in the figure, many feature weights are equal to 0, making the corresponding features ineffective when classifying user activity as *self*, or *non-self*. Most importantly, one can clearly see that user models for different users emphasize different features. This shows that user activities vary by user. For example, for user 7, one can conclude that their use of *Media* applications makes them relatively distinguishable from other users, while for user 8, their *Networking* behavior seems to provide that advantage more than any other behavior.

One can also notice that some features are consistently not good predictors of user behavior, such as features 3, 8, 12, 16, 19, 20 and 22. These features correspond to the *Database Access*, *File System Management*, *Learning*, *Organization*, *Security*, *Software Management*, and *Web Hosting* activities respectively. Note also that the *Games* feature weight is maximized for user 8 and nullified for all other users, confirming my conjecture that different users use their computers for different purposes, even though the dataset was collected from a **homogeneous** group of graduate computer science students.

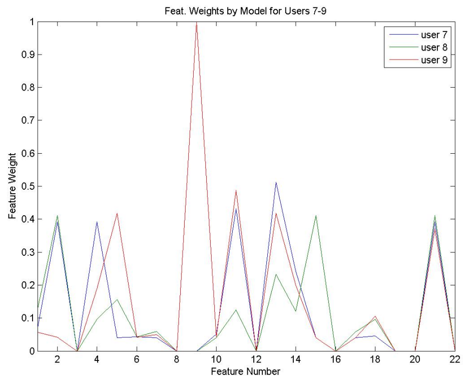
The feature weights optimized for the multi-task learning approach with a common feature configuration for all SVM user models are displayed in Figure 6.2. Recall, that this feature selection method chooses a sparse subset of the twenty-two features that are



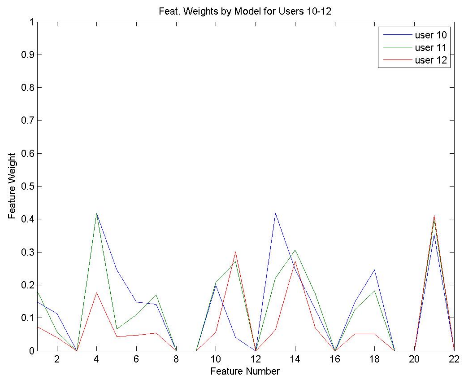
(a) Feature Weights for User Models 1-3



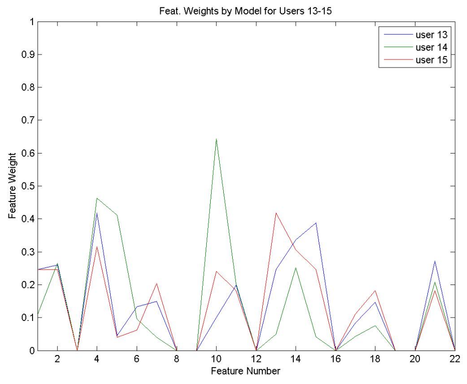
(b) Feature Weights for User Models 4-6



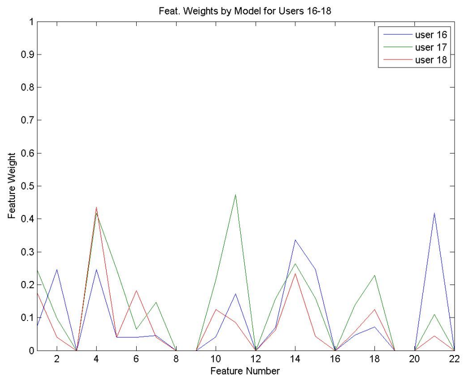
(c) Feature Weights for User Models 7-9



(d) Feature Weights for User Models 10-12



(e) Feature Weights for User Models 13-15



(f) Feature Weights for User Models 16-18

Figure 6.1: Feature Weights by User Model for α=24 and 10-minute long Epochs Using the Independent Learning Approach

consistently good at predicting the label for the 18 different tasks or classes. One can notice that features 3, 8, 12, 16, 19, 20, and 22 are discarded, while the remainder of the features are retained with different weights.

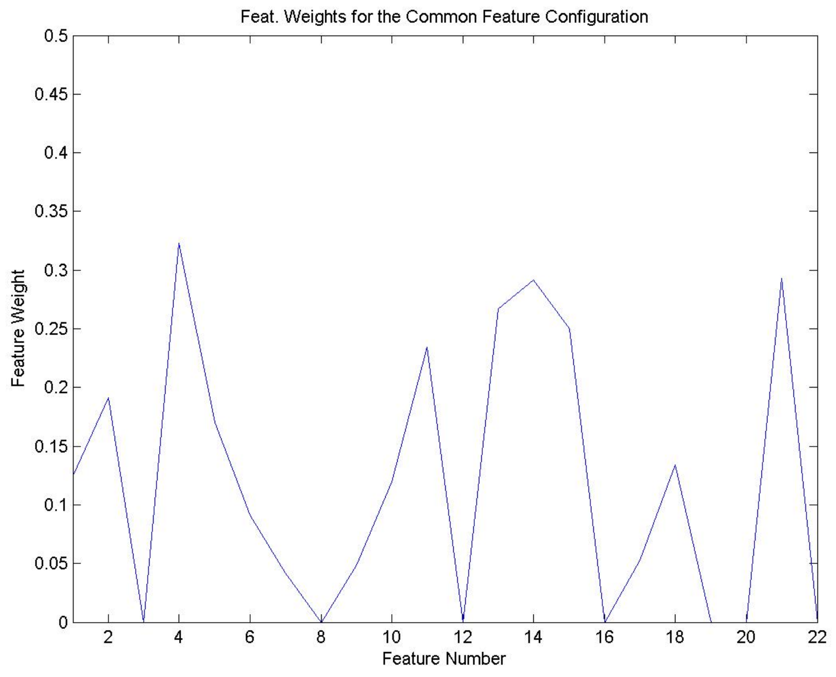
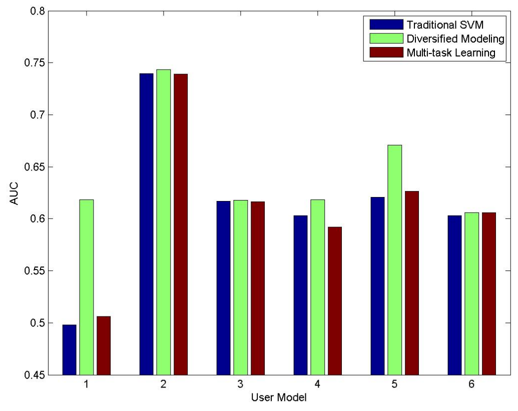


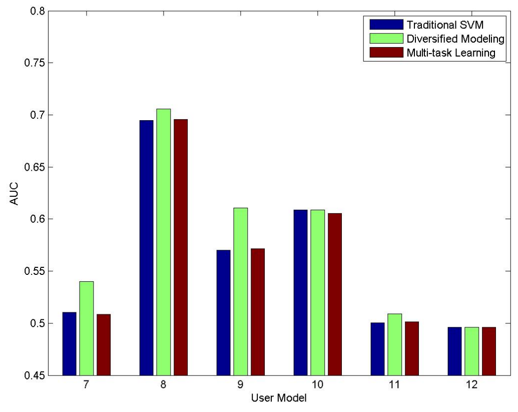
Figure 6.2: Feature Weights for Multi-Task Learning Approach

Figure 6.3 depicts the AUC scores for the diversified modeling approach optimized over the feature selection level α. The figure also shows the AUC scores for the traditional SVM approach, *i.e.* with no feature selection, and for the meta-learning (or multi-task learning) with a common feature weight configuration as displayed in Figure 6.2.

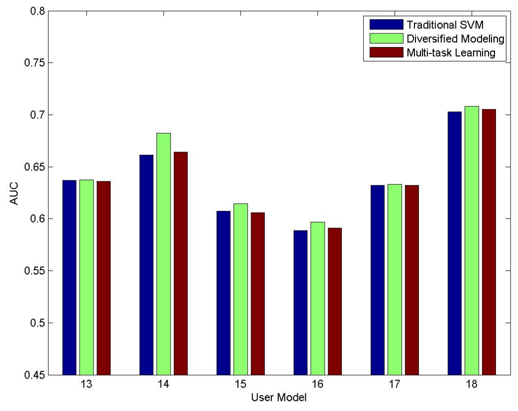
The results show that diversifying the features per user model improves the accuracy of the resulting classifier, when compared to the multi-task learning approach and the traditional SVMs. While the classification accuracy of these models is not very high, I stress that I only use a very limited set of features. The user models are also simple and only based on user activity volumetrics. I do not model any sequences of activities, nor do I take timing information into account. However, regardless of the overall accuracy of these models, the results do demonstrate that diversifying the features per user model achieves



(a) AUC Scores for User Models 1-6



(b) AUC Scores for User Models 7-12



(c) AUC Scores for User Models 13-18

Figure 6.3: AUC Scores by User Model for the Traditional, Diversified and Multitask Modeling Approaches

better classification accuracy overall.

In my future experiments, I will use a more extensive set of features. In particular, I will extract features that measure user activities in a more detailed manner by using the subcategories of Windows applications, in lieu of the higher-level categories. Furthermore, I will use timing information to model when certain activities are performed by users. I expect the use of these features to improve the accuracy of the models overall, regardless of the machine learning approach used, while confirming the advantage of the diversified modeling approach. In the following subsection, I investigate whether the results of the diversified modeling approach can be improved upon by customizing the epoch length, which is used for extracting feature vectors, to individual user activity patterns.

6.3.2 Personalized Modeling Results

Diversified modeling achieves even better accuracy results when the epoch length, for which I extract feature vectors, is customized by user. I measure the variability of user activities for various epoch lengths: 5, 10, 20, and 30 minutes, and select the epoch length that yields the smallest average Mahalanobis distance computed per Section 6.1.3. I use that epoch length for extracting feature vectors to build the model for the corresponding user. Once the feature vectors are extracted, I apply the diversified modeling approach and test the user models using the same feature weights determined in Section 6.3.1. I call this approach **personalized diversified** modeling. Figure 6.4 demonstrates that personalizing the epoch length improves the accuracy of the resulting classifier. Note that for users 5, 14, and 18, the diversified model and personalized diversified model achieve the same accuracy, since a 10-minute epoch length was determined as most appropriate for these users. Recall that the diversified user models presented in Section 6.3.1 are built based on 10-minute long epochs.

6.4 Conclusion

6.4.1 Chapter Summary

In this chapter, I present a new approach for diversifying and personalizing computer user models, with the objective of profiling unique and personal user behavior. I hypothesize

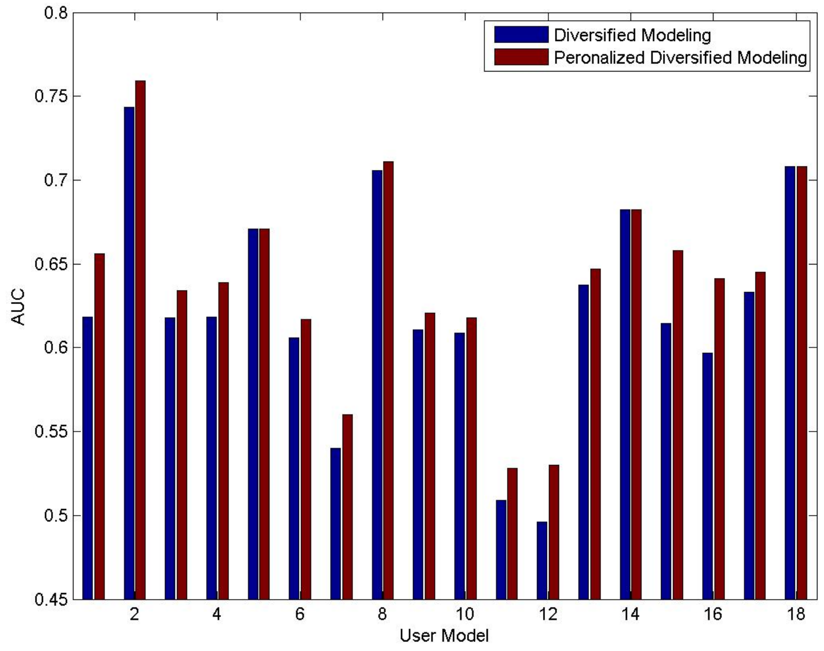


Figure 6.4: AUC Scores by User Model for the Diversified and Personalized Diversified Modeling Approaches

that each user has a unique way of using their computer, a footprint, that is distinguishable from the behavior of any other computer user. I present a modeling approach that aims to profile this personal user behavior using a taxonomy of Windows applications, DLLs, and MS-DOS commands. The taxonomy captures the types of activities that a user performs on a computer, abstracts them, and enriches the meaning of user activities performed on the host system. More importantly, the use of the taxonomy significantly **reduces the dimensionality of the feature space**, and thereby reduces the complexity of the computation.

I use the maximum entropy discrimination framework to identify the best discriminative features for each model, thus diversifying the user models. I further personalize these models based on the lengths of user sessions and the speed at which users emit commands. The results show that the personalized diversified modeling approach improves classifier accuracy. Furthermore, by diversifying the features used and personalizing the user models, I make the anomaly detector based on these models less vulnerable to mimicry attacks. The adversary is now less likely to know the exact features being modeled for the victim user. While the models I use are built using a very small set of simple features which limits the accuracy of the resulting classifier, I expect these results to improve when I expand the set of features and model user activities in more granularity. My plan for further improvements is briefly explained in the following subsection.

6.4.2 Future Work

My ultimate objective is to build more secure and dependable systems that (de)-authenticate legitimate users by their behavior, rather than exclusively by their possibly stolen credentials. In my future work, I will continue exploring new features that could be used for profiling user behavior, so that user models can reflect a user's *truly unique* behavior. In particular, I will account for the time of the day and the time elapsed since the start of a user session when a user action is performed. Including this information, when building a user model, helps in capturing individual user habits, such as checking e-mail at the beginning of a user session, etc. I will also refine the user models by adding more granularity to the classes of user activities. The taxonomy of Windows applications can be further leveraged in this regard, so that I model user command sub-categories or sub-classes instead of modeling the command high-level categories.

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Chapter 7

Conclusion

Masquerade attacks resulting in identity theft are a serious computer security problem. This dissertation introduced a novel approach for detecting masquerade attacks that are motivated by data theft. As the focus of this thesis has been on effective and efficient masquerade attack detection, there are several interesting directions for future work. In the following sections, I review the results, contributions, and limitations of this work, and propose several directions for future work.

7.1 Thesis Summary

In this thesis, I presented a set of light-weight effective sensors for masquerade attack detection. In doing so, I introduced new ideas and approaches for maximizing the efficiency and effectiveness of the sensors. I demonstrated that masquerade attacks that are motivated by data theft can be detected reliably, efficiently, and with very low latency. Prior work on masquerade detection focused on profiling sequences of user commands. Sequence-based modeling of user command data may not be very scalable considering the potentially unbounded number of possible commands or applications to be modeled especially in Windows-based environments. Scalability becomes a challenge particularly in multi-user environments or computationally limited devices.

Access control mechanisms failed in preventing masquerade attacks. Consequently, user behavior profiling becomes important in detecting these attacks. One advantage of using this approach for masquerade attack detection is the fact that behavior is not readily available for stealing and use, unlike any user credentials, assuming that the historical information profiled is kept secret.

I presented an efficient search-behavior modeling technique specifically developed for masquerade attack detection. I showed that search volume is correlated with masquerade activity. A legitimate user of a system should be familiar with the files on the system and where they are located. Any search for specific files is likely to be targeted and limited. Whereas, a masquerader, who gets access to the victim's system illegitimately, and who is not familiar with that environment, is likely to engage in widespread and untargeted search and in an information gathering exercise before launching any attack.

While I did not conduct a human psychological study to show that the real intent could be established by profiling user behavior, I approximated this kind of user study by conducting a set of user experiments following an established scientific protocol to provide evidence that monitoring search behavior works well in identifying malicious masqueraders. My results showed that user search behavior profiling can detect masquerade attacks reliably with low FP rates and a very low latency. The question of whether the true intent of a user is established is beyond the scope of this work.

I developed an anomaly-based intrusion detection system using one-class SVM models trained with vectors using three search-related features to profile users' search behaviors. Modeling specific classes of commands and user-initiated events, as opposed to modeling all classes of commands and events, provided significant operational improvements in detection performance over prior work. Moreover, reducing feature space dimensionality allowed for building accurate classifiers, with four days-worth of training data only, thanks to the limited amount of sampling required. In an operational monitoring system, this also minimizes the system resources needed by the detector, and allows for real-time masquerade attack detection. Furthermore, it improves the generalizability of the classifier and enables its quick deployment, besides reducing its operational costs and footprint. Recall that the average user model size is about 8 KB when the search-behavior modeling approach is used. That model size grows to more than 3 MB if an application and command frequency modeling approach is used.

One of the important strengths of this approach is that detection happens within two minutes of the malicious activity, thus limiting the harm that the attacker can do. The victim can immediately take steps to limit the damage when the attack is detected, by changing his or her online banking passwords or canceling his or her credit cards. If the attack remains undetected for a long time, it is more likely that information gets compromised and potentially used for monetary gain by the attacker.

My approach is generalizable as it does not specify what bad behavior looks like. Instead, I model normal behavior only and detect deviations from that behavior. The use of one-class modeling approach preserves the privacy of the users. A sensor that monitors user's actions and violates user privacy would probably not be widely adopted. A masquerade attack detector has to be able to build and apply user models without sharing any data collected about the user. This can be achieved using one-class modeling techniques, so no data sharing is required.

The user search profiling approach achieved a 100% detection rate and with a 1.12% FP rate, *i.e.* one false positive every three hours on average. In order to reduce the frequency of false positives and improve the user experience, wihout negatively affecting the detection capability of the masquerade detector, I monitored accesses to decoy files that are strategically placed by the user on his or her own file system. Once the decoys containing 'bait information' are in place, the legitimate users of the system are supposed to avoid any access to the decoys. Any decoy file access, then, suggests that a masquerader is trying to access highly enticing information. I note that using this approach alone, I was able to detect all masqueraders within 10 minutes of launching their attacks. Thirty-five per cent of masqueraders were detected during the very first minute of their frauduent activity.

I used the access patterns to decoy files as an oracle to validate the alerts issued by the search behavior profiling sensor, since the correlation of abnormal search behavior with decoy file touches should provide stronger evidence of malfeasance, and therefore improve the detector's accuracy.

Besides detecting masqueraders, placing monitorable decoy files on the system has a deterrence effect that may not be easily measurable, but that definitely plays a role in preventing potential masquerade activity by risk-averse attackers.

Combining the two orthogonal techniques also serves as a defense mechanism against mimicry attacks. Anomaly detection-based techniques are vulnerable to evasion attacks. If a sophisticated adversary attempts to evade the search behavior sensor by mimicking the victim's behavior, he or she is likely to get trapped, as he or she does not know where the decoys were placed.

I proposed a masquerade attack sensor that integrates the two complementary and orthogonal techniques that aim to detect evasive adversaries. The diversity of detection techniques can increase the likelihood of detection of malicious activity and dramatically reduces the number of false positives associated with a malicious event, typically a challenge for any anomaly detection system. My results confirmed the improvement in detection accuracy: the overall FP rate was reduced to 0.77%, while all masquerade attacks were being detected.

The sensor has a negligible performance overhead. Empirical tests show that the sensor uses 40 KB of memory only, a negligible overhead compared to Anti-Virus tools for instance. The detection capabilities of this light-weight host sensor can be further leveraged when combined with other network-level sensors to cover other insider threat models [Bowen *et al.*, 2009a].

7.2 Contributions

In summary, the main contributions of this dissertation include the following:

- Taxonomies of Windows applications, DLLs and Linux/Unix user commands that elicit classes of user activities on information systems. These classes of user activities can be used to accurately model user behavior, characterize fraudulent behavior, and tease out the intent of malicious users. Abstracting the user commands and actions and modeling the classes of user behaviors (as opposed to modeling simple user commands) enables the reduction of features used for user behavior profiling, and introduces significant gains in computational complexity.

- A set of search-related features whose limited number reduces the amount of sampling required to collect training data. Reducing the set of features required for profiling user behavior enables improved detector accuracy and significant performance gains over prior user profiling techniques.

- A **set of guidelines for conducting user studies** applied to cyber-security that assists researchers in designing and executing generalizable and powerful computer security-related experiments involving human subjects.

- A real-world Windows dataset made available to the research community for the study and evaluation of novel masquerade attack detection approaches. The dataset consists of normal user data collected from a homogeneous user group of 18 individuals and simulated masquerader data from 40 different individuals. The dataset is the first publicly available dataset for masquerade attack detection since the Schonlau dataset. The Schonlau dataset, unlike the RUU dataset, does not include any masquerader data, and was rather used for the study of author identification problems.

- A set of guidelines, best practices, and recommendations related to the strategic deployment of decoy documents on local file systems for an effective detection of masquerade attacks, based on an empirical evaluation of how effective decoys can be in detecting masquerade attacks.

- A privacy-preserving masquerade attack detection approach based on the integration of two orthogonal detection techniques: user search behavior profiling and monitoring access to highly-crafted and well-placed decoy documents used to bait attackers. The approach improves detection accuracy over prior techniques, is less vulnerable to mimicry attacks, and provides stronger evidence of fraudulent activity.

- A light-weight, privacy-preserving, tamper-resistant host-sensor that detects the onset of masquerade attacks within two minutes of fraudulent activity. The host sensor implements the two orthogonal detection techniques and collects potential evidence that could be used to identify the attacker. The sensor reliably detects masquerade attacks with a very low false positive rate, a very small footprint, and low operational costs.

- A diversified and personalized user behavior profiling approach for improved classifier accuracy and higher user model generalizabiliy.

7.3 Limitations

While the proposed masquerade attack detector offers high accuracy and low detection latency, we recognize a few limitations for certain attack scenarios. For instance, the sensor, just like any anomaly-based IDS is subject to a *training data poisoning attack*, albeit to a much more limited extent. A training data poisoning attack is an attack whereby the adversary injects malicious data into the dataset that is used for training the classifier and building the user model. It leads the machine learning or statistical algorithm used to learn the wrong model, therefore, eventually classifying potentially fraudulent activity as normal, and failing to detect masquerade attacks.

The user search behavior profiling sensor is vulnerable to such an attack if the adversary manages to induce high-volume search activity into the data that is used to train the sensor. When the detector is deployed, the search behavior profiling sensor may fail to properly classify extensive file system search by the attacker as abnormal. However, the attacker is still very likely to access decoy documents, which will be detected by the DDA sensor. This makes the masquerade attack detector less vulnerable to training data poisoning attacks, but not completely immune to them.

In Section 5.2.1 I mentioned the possibility of enhancing the detector and adapting it to multi-user environments. Consider a file server within an enterprise's network. The detector can develop user models for all users that have access to the file server, and use them to detect need-to-know policy violations. In this setting, if an adversary gets access to several user credentials belonging to different users of the file server, then he or she can impersonate many users when conducting their attack. He or she can 'divide' their fraudulent activity between different sessions for various victims. By doing so, the attacker may manage to stay *under the radar* during each user session by limiting his or her information gathering activity to normal user search activity levels. However, by aggregating all the information gathered during the different user sessions, the adversary may be successful in his or her attack. The same result may be achieved if the masquerader colludes with several malicious insiders.

7.4 Future Work

7.4.1 Immediate Future Work

In the concluding section of each chapter, I presented several short-term and medium-term extensions to the masquerade attack detector presented in this work. Here I review some of the main extensions discussed in the previous chapters.

In most cases, the attacker's objective is to steal data that could be used for financial gain from home users or enterprise users, such as financial credentials or intellectual property.

When developing and evaluating the sensor, the objective was to detect masquerade attacks with the purpose of stealing sensitive and confidential data perpetrated by individuals illegitimately. Many of these attacks resulted in fraud incidents, which affected 11.2 million consumers in the United States in 2009 according to a Forbes report, causing $54 billion in ID fraud costs [Greenberg, 2010].

However, many identity theft incidents are caused by malware installed on the victim's computer systems. In 2009, researchers, who have monitored the Torpig botnet, affirmed that within the span of 10 days only, Torpig obtained the credentials of 8,310 accounts at 410 different institutions [Stone-Gross *et al.*, 2009]. Enterprise users have also been targeted by different malware such as Confickr/Downadup [Higgins, 2009]. I expect the sensor proposed here to detect data theft attacks caused by such malware, based on the malware's file touch, file system navigation, and decoy access patterns, just like human masqueraders get detected. However, this has to be validated with a new set of experiments, including human subject studies to study the strategic decoy placement for such threat models.

An interesting problem to study is how to calibrate the modeling and detection frequency to reduce the detector's false positive rate with its false negative rate. False negatives in this context, *i.e.* an undetected masquerader, are far more dangerous than an annoying false positive. A thorough evaluation of the right model checking and alerting frequency in light of average search times on a file system *inter alia,* is the subject of my future research.

One critical enhancement is the protection of the user model from unauthorized changes. The user model on the user's system has to be adequately secured and monitored, just like the sensor itself, in order to prevent the attacker from modifying the user model and launching a mimicry attack based on the new model.

Another important enhancement to the sensor, is the integration of user feedback in model update operations. User feedback is important for distinguishing whether any surge in false alerts is the result of a real attack or merely a consequence of a change in normal user behavior.

Finally, I seek to generalize the detection techniques used in this sensor to other computing platforms such as Mac OS.

7.4.2 Long-term Future Work

In the long-run, I envision several directions that my research work can take. In this work, my objective is to detect data theft attempts performed by masqueraders on single-user systems. One interesting direction, it to enhance the sensor to detect 'need-to-know' policy violations perpetrated by traitors on multi-user systems.

In the threat model, I assumed that the attacker has no knowledge whether the victim's system is baited or not. One interesting line of work is the study of attacker behavior and his or her perception of risk and expected gain if the adversary knows that the system under attack is baited.

The development of adaptive behavioral sensors that could be generated online when fraudulent behavior is suspected, based on abnormal search patterns, will also be the subject of future work. One could adaptively change the location of the decoy files based on the file system navigation patterns of the attacker, or change the results that get returned by a desktop search tool to include decoys generated in real-time.

I pointed out in Chapter 1 that the observables at the network level are more distant from a distinct user, as attributing a network level event to a distinct user is hard. Detecting masqueraders from network-level data alone remains a challenge. However, network-level events are valuable in detecting malicious or unusual activities such as massive downloading of information that an insider does not have a need to know, or the dissemination of information outside the organization's network. Integrating the RUU host sensor with network-level sensors may allow for more accurate detection and a wider coverage of attacks.

Finally, I plan on extending the combined detection approach from a local file system setting to a Cloud setting. The Cloud is intended to be as transparent to the user as a local file system, and experimental results suggest that the approach proposed here may allow for the detection of illegal data accesses and industrial espionage attacks from insiders in the Cloud as well.

Ultimately, I hope the that work presented in this thesis eventually enables the development of highly accurate masquerade attack detectors for human masqueraders and rootkits as well, potentially integrated with anti-virus engines. I also hope that it will eventually help in the adoption of behavioral models as another factor in user authentication, in order to harden existing access control mechanisms.

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Part I

Appendices

Appendix A

User Study Scenarios

A.1 Malicious Scenario

You have been going through rough financial times lately. You have lost all of your investments in the stock market, after going through loss after loss. You had an accident two months ago and your brand new car has been totaled. That car has not even been paid for. You have only put a small down-payment. You have been charging up your credit cards just to pay your monthly bills. Debts have been accumulating and your monthly salary hardly covers 70% of your living expenses and monthly bills. You really have to do something, or otherwise you will be facing bankruptcy.

You have been sharing your office with your co-worker 'John Smith' for the last three months. John has been getting on your nerves for the last several months. Although you know that you have been working harder than him, he has received a better appraisal than yours, and has been promoted recently. He's your supervisor's favorite even though he does not deserve it.

You do recall that your office-mate once mentioned that he can't remember all of his user IDs and passwords, whether they are for e-mail accounts or for online-banking accounts, etc. That is why he stores them all on his computer. You know also that he uses his work laptop for personal business. He takes care of his personal business during work hours anyway. So you have been recently thinking that, if you can get the passwords to his financial accounts, you can get yourself some money. You may also find some valuable

PII information (Personally Identifiable Information) that could be very valuable. This can solve all of your financial problems. After all, your officemate is in a much better financial position. Stealing a few thousand dollars from his bank account is not going to make him bankrupt. But if you don't do that, you will be facing bankruptcy.

Yesterday, and after reviewing your bills and notices for payment, you have made your decision. You will give this a try. Today, during lunch hour, your office mate left the office during and left his laptop on. He is driving to a near-by fast food restaurant to buy lunch. So you know that he will not be back before at least 15 minutes. It may take him even longer. This is really your chance. Your financial problems will be soon over, and you can start enjoying your life again, if you manage not to get caught. You just need to make sure that your unauthorized access does not get detected.

P.S.: All of your actions will be monitored for later investigation.

A.2 Benign Scenario

You have been working for company ABC for one year. You have been sharing your office with your co-worker 'John Smith' for the last three months. Today, during lunch hour, 'John' left the office and left his laptop on. He is driving to a near-by fast food restaurant to buy lunch. So you know that he will not be back before at least 15 minutes. It may take him even longer than that.

Your machine has suddenly stopped working. You have a meeting this afternoon with representatives of an important client and you need to give them an update on the yield improvement project, which you have been working on with John. The report that you will be presenting to the client reps is not ready yet. Now you can get access to your colleague's machine for 15 minutes. Think about what you will do and do it. Please indicate your choice. If you decide to take a look at his laptop, please describe what you did, (e.g. just browsing, sending e-mail, searching for specific information), and for how long you did it. In 15 minutes, you will answer a questionnaire, and describe exactly what you did.

P.S.: All of your actions will be monitored for later investigation.

A.3 Neutral Scenario

You have been working for company ABC for one year. You have been sharing your office with your co-worker 'John Smith' for the last three months. Today, during lunch hour, your office mate left the office and left his laptop on. He is driving to a near-by fast food restaurant to buy lunch. So you know that he will not be back before at least 15 minutes. It may take him even longer than that.

You have the option of using his laptop for whatever purpose, or you can decide to do something else.

If you decide to take a look at his laptop, please note what you did. In 15 minutes, you will answer a questionnaire, and describe exactly what you did.

P.S.: All of your actions will be monitored for later investigation.

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Appendix B

Post-Experiment Questionnaire

1. Which scenario have you been given (Please circle the right choice)?

    a) Scenario 1

    b) Scenario 2

    c) Scenario 3

2. Please indicate date and time of the experiment.

3. Please describe what you did during the 15 minutes:

4. Please indicate why you did so:

5. Please list relevant documents (with respect to the task performed) that you were able to find:

Filename	**Path**

6. What's you major?

7. What program are you in?

   a) Undergraduate

   b) Masters

   c) PhD

   d) Other. Please specify: .

8. How would you rate your knowledge of Linux?

   a) No Knowledge

   b) Basic knowledge

   c) Moderate knowledge

   d) Deep knowledge

   e) Expert

9. Which operating system do you have running on your personal computer(s)? (Select all that apply)

   a) Linux .. Please specify:

   b) Windows XP

   c) Windows Vista

   d) Mac OS

   e) Other .. Please specify:

10. How familiar are you with Linux commands?

    a) Unfamiliar

    b) Somewhat unfamiliar

    c) Neutral

    d) Familiar

    e) Very familiar

11. How many years/months of experience do you have using Linux/Unix commands? (Years or months)

12. How many years/months of experience do you have using MS-DOS commands? (Years or months)

13. How often do you use user commands to search for information in a Linux environment?

    a) Never
    b) Rarely
    c) Monthly
    d) Weekly
    e) Daily

14. How often do you use Google Desktop Search on your personal computer?

    a) Never
    b) Rarely
    c) Monthly
    d) Weekly
    e) Daily

15. How often do you use other Desktop Search tools on your personal computer?

    a) Never
    b) Rarely
    c) Monthly
    d) Weekly
    e) Daily

16. Did you feel that there was enough background information for you to perform the task effectively?

    a) No, needed a lot more information
    b) No, needed a bit more information
    c) Just right
    d) Yes, a bit more information might have helped
    e) Yes, plenty of information was provided

17. Did you feel that you had enough time to complete the task?

    a) No, needed a lot more time
    b) No, needed a bit more time
    c) Just right
    d) Yes, a bit more time might have helped
    e) Yes, plenty of time was provided

18. What time period do you think would have been more appropriate to perform this task?

19. What would you have done differently (if anything) if you had more time to perform the task?

20. What would you have done differently (of anything) if you had less time to perform the task?

21. Did the scenario narrative affect the way in which you performed the task?

    a) Yes
    b) No

22. If you were to perform the same task without the assigned narrative (*i.e.* you have access to someone else's computer, not necessarily your office mate, or someone you know, and not necessarily limited to 15 minutes), would there be any differences in your approach?

a) Yes

b) No

If yes, please explain:

23. How do you feel you were performing the task compared to your own normal behavior?

    a) Very differently

    b) Somewhat differently

    c) Neutral

    d) Somewhat similar

    e) Very similar

24. Which portions of the task differed from your own normal methodology?

25. Did anything else influence your decision to use a certain approach to complete the task?

    a) Yes

    b) No

    If yes, please list:

26. If you wanted to prevent others from discovering the purpose of your task, what would you do?

27. If you wanted to prevent others from discovering the purpose of your task, would you have performed the task incrementally (e.g. on different days)?

    a) Yes

    b) No

    If yes, how?

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Appendix C

Decoy File Placement

Table C.1: Decoy Document Placement

Decoy File Number	**Directory where Decoy was Placed**
1	C:\Documents and Settings\username \My Documents\Personal\Shopping\
2	C:\Documents and Settings\username\My Documents\Taxes\
3	C:\
4	F:\
5	C:\Documents and Settings\username\My Documents\Receipts\
6	C:\Documents and Settings\username\Desktop\
7	C:\Documents and Settings\username\My Documents\Financial\Bank Statements\
8	C:\Documents and Settings\Administrator\
9	C:\Documents and Settings\username\My Documents\
10	C:\Documents and Settings\username\My Documents\Financial\
11	C:\Documents and Settings\username\My Documents\Private\
12	C:\Documents and Settings\username\My Documents\Personal\
13	C:\Documents and Settings\username\My Documents\Private\Medical
14	C:\Documents and Settings\username\My Documents\Downloads\
15	C:\Documents and Settings\username\My Documents\Financial\Lost Card\
16	C:\Documents and Settings\username\My Documents\Financial\Disputes\
17	C:\Documents and Settings\username\My Documents\onn\bills and all\eBay\
18	C:\Documents and Settings\username\Desktop\Important\
19	C:\Program Files\License \
20	C:\Windows\Temp\
21	C:\Documents and Settings\username\My Documents\Personal\Visa Applications\
22	C:\Documents and Settings\username\My Documents\Private Vacation \
23	C:\Windows\
24	C:\Documents and Settings\username\My Documents\Confidential\
25	C:\Documents and Settings\username\Cookies\
26	C:\Documents and Settings\username\Favorites\
27	C:\Documents and Settings\username\workspace\
28	C:\Documents and Settings\username\My Documents\Investments\
29	C:\Documents and Settings\username\My Documents\Resume\
30	C:\Documents and Settings\username\Desktop\My Journal\
31	C:\Backup\
32	C:\Documents and Settings\username\My Pictures\
33	C:\Documents and Settings\username\Desktop\Notes\
34	C:\Documents and Settings\username\My Documents\Confidential\Employee Evaluations\
35	C:\Documents and Settings\username\Recent\
36	C:\Documents and Settings\username\Start Menu\
37	C:\Documents and Settings\username\Desktop\Insurance\
38	C:\Documents and Settings\username\Local Settings\
39	C:\Documents and Settings\username\My Documents\401K\
40	C:\Documents and Settings\username\My Documents\Mortgage\
41	C:\Documents and Settings\username\My Music\
42	C:\Documents and Settings\username\My Documents\Miscellaneous\

Appendix D

IRB Human Subjects Study Description Data Sheet

Table D.1: Columbia University Human Subjects Study Description Data Sheet

Protocol	IRBAAAC4240(Y1M00)
Protocol Status	Approved
Effective Date	05/28/2007
Initial Expiration Date	05/27/2009
Originating Department	COMPUTER SCIENCE (167)
Submitting To	Morningside
Title	Insider Threat/Masquerader Detection
Sponsor Protocol Version#	
Abbreviated title	Insider Threat Detection
IRB of record	Columbia University Morningside
IRB number used	
Affiliated Institutions	Standard Columbia Submission
Protocol Begin Date	05/01/2007
Initial Protocol End Date	11/30/2009
Principal Investigator	Salvatore Stolfo (167)
Study Description	The study will assess proposed statistical features used to represent the behavior of a typical computer user and to use said features to model a specific user's actions. We seek to augment typical computer security features (such as user names and passwords or pins) with behavior information to authenticate a user and prevent unwanted harmful actions.

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Part II

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