EVOLVING INSIDER THREAT DETECTION USING STREAM ANALYTICS AND BIG DATA

by

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Dedicated to the Almighty Creator, the Most Gracious, the Most Merciful.

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DISSERTATION

Presented to the Faculty of

The University of Texas at Dallas

in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY IN

COMPUTER SCIENCE

THE UNIVERSITY OF TEXAS AT DALLAS

December 2013

ACKNOWLEDGMENTS

First and foremost, all praises to Almighty God for allowing me to write this dissertation.

Second, I would like to express my gratitude to my PhD advisor, Professor Bhavani Thuraisingham, for her constant support during my PhD studies. It was my great privilege that she supported me as a research assistant during my MS studies (part of it) at UT Dallas. During my graduate research, she gave me a lot of opportunity to work independently with minimal interference.

Third, I would like to thank my wonderful committee members from the bottom of my heart. In particular, during my job hunting, Professor Farokh Bastani was a great resource for me. He was an immense help for preparing my job interview at VCE. During my graduate studies, I took a number of courses with Dr. Haim Schweitzer, and I really enjoyed his teaching and courses. I would like to also acknowledge Dr. Weili Wu and Dr. I-Ling Yen for their support on various occasions.

Fourth, I would like to thank Dr. Robert Herklotz for his support. This work is supported by the Air Force Office of Scientific Research, under grant FA-9550-09-1-0468 & FA9550-08-1-0260.

Fifth, during my research work, I interacted with a number of co-workers, students and staff. Their constant help shaped my research in the right direction. It would be an injustice if I do not mention their names. They are: Dr. Jeffrey L. Partyka, Dr. James McGlothlin, Dr. Lei Wang, Dr. Li Liu, Nate McDaniel, Vaibhav Khadilkar, Sanjay Bysani, Pratik P. Desai, Rhonda Walls, Eric Modem and Norma Richardson. I would like to thank Amanda Aiuvalasit and Wanda Trotta in the Office of the Graduate Dean for their time proofing my dissertation.

Finally, I received a wonderful and constant support during my PhD journey from my family, including parents, parents-in-law and sisters.

October 2013

PREFACE

This dissertation was produced in accordance with guidelines which permit the inclusion as part of the dissertation the text of an original paper or papers submitted for publication. The dissertation must still conform to all other requirements explained in the "Guide for the Preparation of Master's Theses and Doctoral Dissertations at The University of Texas at Dallas." It must include a comprehensive abstract, a full introduction and literature review, and a final overall conclusion. Additional material (procedural and design data as well as descriptions of equipment) must be provided in sufficient detail to allow a clear and precise judgment to be made of the importance and originality of the research reported.

It is acceptable for this dissertation to include as chapters authentic copies of papers already published, provided these meet type size, margin, and legibility requirements. In such cases, connecting texts which provide logical bridges between different manuscripts are mandatory. Where the student is not the sole author of a manuscript, the student is required to make an explicit statement in the introductory material to that manuscript describing the student's contribution to the work and acknowledging the contribution of the other author(s). The signatures of the Supervising Committee which precede all other material in the dissertation attest to the accuracy of this statement.

EVOLVING INSIDER THREAT DETECTION USING STREAM ANALYTICS AND BIG DATA

Publication No. ___________________

Pallabi Parveen, PhD
The University of Texas at Dallas, 2013

Supervising Professor: Dr. Bhavani Thuraisingham

Evidence of malicious insider activity is often buried within large data streams, such as system logs accumulated over months or years. Ensemble-based stream mining leverages multiple classification models to achieve highly accurate anomaly detection in such streams, even when the stream is unbounded, evolving, and unlabeled. This makes the approach effective for identifying insiders who attempt to conceal their activities by varying their behaviors over time.

This dissertation applies ensemble-based stream mining, supervised and unsupervised learning, and graph-based anomaly detection to the problem of insider threat detection. It demonstrates that the ensemble-based approach is significantly more effective than traditional single-model methods, supervised learning outperforms unsupervised learning, and increasing the cost of false negatives correlates to higher accuracy. It shows effectiveness over non sequence data.

For sequence data, this dissertation proposes and tests an unsupervised, ensemble based learning algorithm that maintains a compressed dictionary of repetitive sequences found throughout dynamic data streams of unbounded length to identify anomalies. In unsupervised learning, compression-based techniques are used to model common behavior sequences. This results in a classifier exhibiting a substantial increase in classification accuracy for data streams containing insider threat anomalies. This ensemble of classifiers allows the unsupervised approach to outperform traditional static learning approaches and boosts the effectiveness over supervised learning approaches. One of the bottlenecks to construct compress dictionary is scalability. For this, an efficient solution is proposed and implemented using Hadoop and MapReduce framework.

We could extend the work in the following directions. First, we will build a full fledge system to capture user input as stream using apache flume and store it on the Hadoop distributed file system (HDFS) and then apply our approaches. Next, we will apply MapReduce to calculate edit distance between patterns for a particular user's command sequence data.

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CHAPTER 1

INTRODUCTION

对比传统的内部攻击检测，SVM为代表，时间长效果不好，因为其分析的97%的数据都是于攻击无关的，只有不到3%的数据与攻击建模有关。

监督式学习和非监督式学习都是机器学习领域的概念。监督式学习指的是输入数据已经经过标记，即来自于正常还是异常是已知的，主要的作用是用来分类；
而非监督式学习通常用于数据聚类。

There is a growing consensus within the intelligence community that malicious insiders are perhaps the most potent threats to information assurance in many or most organizations (Brackney and Anderson, 2004; Hampton and Levi, 1999; Matzner and Hetherington, 2004; Salem and Stolfo, 2011). One traditional approach to the *insider threat* detection problem is *supervised learning*, which builds data classification models from training data. Unfortunately, the training process for supervised learning methods tends to be time-consuming and expensive, and generally requires large amounts of well-balanced training data to be effective. In our experiments we observe that less than 3% of the data in realistic datasets for this problem are associated with insider threats (the minority class); over 97% of the data is associated with non-threats (the majority class). Hence, traditional support vector machines (SVM)(Chang and Lin, 2011; Manevitz and Yousef, 2002), trained from such imbalanced data are likely to perform poorly on test datasets.

One-class SVMs (OCSVM)(Manevitz and Yousef, 2002) address the rare-class issue by building a model that considers only normal data (i.e., non-threat data). During the testing phase, test data is classified as normal or anomalous based on geometric deviations from the model. However, the approach is only applicable to bounded-length, static data streams. In contrast, insider threat-related data is typically continuous, and threat patterns evolve over time. In other words, the data is a stream of unbounded length. Hence, effective classification models must be adaptive (i.e., able to cope with evolving concepts) and highly efficient in order to build the model from large amounts of evolving data.

Data that is associated with insider threat detection and classification is often continuous. In these systems, the patterns of average users and insider threats can gradually evolve

一般用户

over time. A novice programmer can develop his skills to become an expert programmer over time. An insider threat can change his actions to more closely mimic legitimate user processes. In either case, the patterns at either end of these developments can look drastically different when compared directly to each other. These natural changes will not be treated as anomalies in our approach. Instead, we classify them as natural concept drift. The traditional static supervised and unsupervised methods raise unnecessary false alarms with these cases because they are unable to handle them when they arise in the system. These traditional methods encounter high false positive rates. Learning models must be adept in coping with evolving concepts and highly efficient at building models from large amounts of data to rapidly detecting real threats.

普通用户和攻击者的行为模式都会随着时间而连续地变化，比如攻击者会使得自己的行为越来越像普通用户。因此我们的系统将这种正常的变化视作是一种非异常的自然现象。传统的检测方法都将模式固定为一种静态固定的状态，因此当遇到此类模式的正常偏移时就会表现出较高的误报率。

For these reasons, the insider threat problem can be conceptualized as a stream mining problem that applies to continuous data streams. Whether using a supervised or unsupervised learning algorithm, the method chosen must be highly adaptive to correctly deal with concept drifts under these conditions. Incremental learning and Ensemble based learning (Masud, Chen, Gao, Khan, Aggarwal et al., 2010; Masud et al., 2011a; Masud, Gao et al., 2008; Masud et al., 2013; Masud, Woolam et al., 2011; Masud et al., 2011b; Al-Khateeb, Masud, Khan, Aggarwal et al., 2012; Masud, Al-Khateeb et al., 2011; Masud,Chen, Gao, Khan, Han and Thuraisingham, 2010) are two adaptive approaches in order to overcome this hindrance. An ensemble of K models that collectively vote on the final classification can reduce the false negatives (FN) and false positives (FP) for a test set. As new models are created and old ones updated to be more precise, the least accurate models are discarded to always maintain an ensemble of exactly K current models.

监督式学习算法和非监督式算法

提到了监督式学习算法和非监督式学习算法。增量学习和整体学习方法可以帮助解决行为模式自然变化的问题。

An alternative approach to supervised learning is *unsupervised learning*, which can be effectively applied to purely unlabeled data—i.e., data in which no points are explicitly identified as anomalous or non-anomalous. *Graph-based anomaly detection (GBAD)* is one important form of unsupervised learning (Cook and Holder, 2007; Eberle and Holder, 2007;

非监督式学习算法适用于非标签数据，即这些数据并没有表明来自于异常节点还是正常节点。典型的方法是基于图的异常检测GBAD，但是GBAD局限于静态、有限长度的数据集合，当考虑时间变化时趋向于无穷大的状态。

Cook and Holder, 2000), but has traditionally been limited to static, finite-length datasets. This limits its application to streams related to insider threats, which tend to have unbounded length and threat patterns that evolve over time. Applying GBAD to the insider threat problem therefore requires that the models used be adaptive and efficient. Adding these qualities allow effective models to be built from vast amounts of evolving data.

In this dissertation we cast insider threat detection as a stream mining problem and propose two methods (supervised and unsupervised learning) for efficiently detecting anomalies in stream data (Parveen, McDaniel et al., 2013). To cope with concept-evolution, our supervised approach maintains an evolving ensemble of multiple OCSVM models (Parveen, Weger et al., 2011). Our unsupervised approach combines multiple GBAD models in an *ensemble* of classifiers (Parveen, Evans et al., 2011). The ensemble updating process is designed in both cases to keep the ensemble current as the stream evolves. This evolutionary capability improves the classifier's survival of *concept-drift* as the behavior of both legitimate and illegitimate agents varies over time. In experiments, we use test data that records system call data for a large, Unix-based, multiuser system.

本文将内部攻击检测看作一个数据流挖掘问题，提出了监督式和非监督式两种算法。监督式算法主要包含一个进化的整体多元OCSVM模型；而非监督式算法则包含多元的GBAD模型。我们的方法使得二者都可以更好地适应用户（合法/非法）的行为模式的自然变化。我们使用的数据是一个类Unix的多用户系统的系统调用数据集。

1.1 Sequence Stream Data

The above approach may not work well for sequence data (Parveen and Thuraisingham, 2012; Parveen, McDaniel et al., 2012). For sequence data, our approach maintains an ensemble of multiple unsupervised stream based sequence learning (USSL) (Parveen, McDaniel et al., 2012). During the learning process, we store the repetitive sequence patterns from a user's actions or commands in a model called a Quantized Dictionary. In particular, longer patterns with higher weights due to frequent appearances in the stream are considered in the dictionary. An ensemble in this case is a collection of K models of type Quantized Dictionary. When new data arrives or is gathered, we generate a new Quantized Dictionary model from this new dataset. We will take the majority voting of all models to find the

对于流数据序列我们使用的是一种多元的非监督式流数据学习模型USSL。这里将每一个用户的行为和命令的模型存储在一个量子数据库中，该数据库的K模型集合就是我们所说的全体数据。然后根据新的输入数据，为现有的模型进行投票，如果一个新的目录优于其他目录，则更新全体库。

anomalous pattern sequences within this new data set. We will update the ensemble if the new dictionary outperforms others in the ensemble and will discard the least accurate model from the ensemble. Therefore, the ensemble always keeps the models current as the stream evolves, preserving high detection accuracy as both legitimate and illegitimate behaviors evolve over time. Our test data consists of real-time recorded user command sequences for multiple users of varying experience levels and a concept drift framework to further exhibit the practicality of this approach.

1.2 Big Data Issue

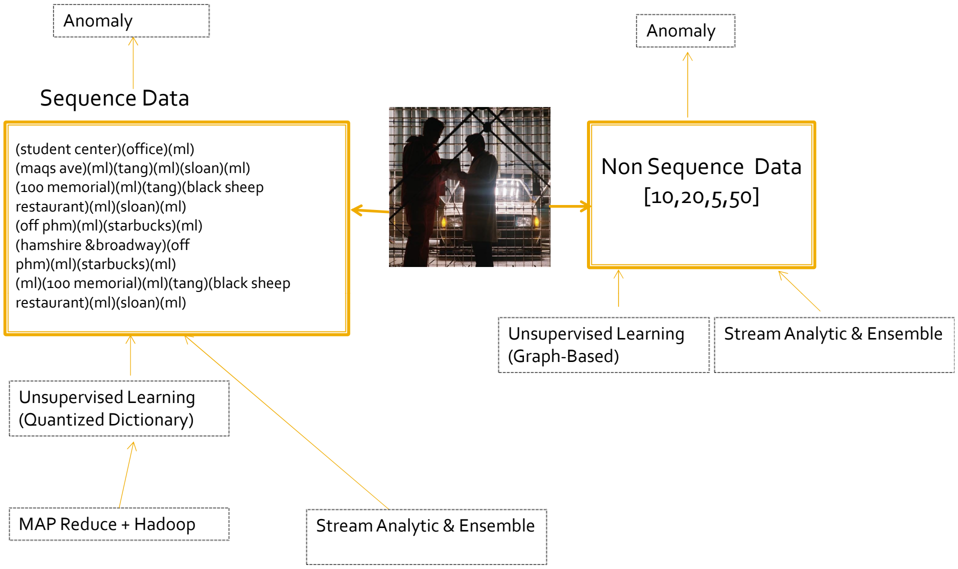
构建量子化目录计算量很大，因此其可扩展性和可用性是瓶颈。这里通过分布式计算来解决这个问题，具体就是使用hadoop框架以及mapreduce编程。

Quantized dictionary construction is time consuming. Scalability is a bottleneck here. We exploit distributed computing to address this issue. There are two ways we can achieve this goal. The first one is parallel computing with shared memory architecture that exploits expensive hardware. The latter approach is distributing computing with *shared nothing architecture* that exploits commodity hardware. For our case, we exploit the latter choice. Here, we use MapReduce based framework to facilitate quantization using Hadoop Distributed File System (HDFS). We propose a number of algorithms to quantize dictionary. For each of them we discuss the pros and cons and report performance results on a large dataset.

1.3 Contribution

The main contributions of this work can be summarized as follows (see Figure 1.1).

1. We show how stream mining can be effectively applied to detect insider threats.
2. With regard to Non sequence Data
   (a) We propose a supervised learning solution that copes with evolving concepts using one-class SVMs.


Anomaly
Sequence Data
(student center)(office)(ml)
(maqs ave)(ml)(tang)(ml)(sloan)(ml)
(100 memorial)(ml)(tang)(black sheep restaurant)(ml)(sloan)(ml)
(off phm)(ml)(starbucks)(ml)
(hamshire &broadway)(off phm)(ml)(starbucks)(ml)
(ml)(100 memorial)(ml)(tang)(black sheep restaurant)(ml)(sloan)(ml)
Unsupervised Learning (Quantized Dictionary)
MAP Reduce + Hadoop
Stream Analytic & Ensemble
Anomaly
Non Sequence Data
[10,20,5,50]
Unsupervised Learning (Graph-Based)
Stream Analytic & Ensemble

USSL(非监督流数据学习模型)

For Big Data

通过单类SVM实现的监督式学习算法，并且通过设置权重的方法降低了误报率

监督式数据学习：借助改进的单类SVM方法；
非监督式数据学习：借助GBAD和MDA;
二者如果要可以处理流数据，必须结合流数据挖掘中的全局学习方法（Ensembly based)

Figure 1.1. Contribution in Visual Form

(b) We increase the accuracy of the supervised approach by weighting the cost of false negatives.

(c) We propose an unsupervised learning algorithm that copes with changes based on GBAD.

(d) We effectively address the challenge of limited labeled training data (rare instance issues).

(e) We exploit the power of stream mining and graph-based mining by effectively combining the two in a unified manner. This is the first work to our knowledge to harness these two approaches for insider threat detection.

(f) We compare one and two class support vector machines on how well they handle stream insider threat problems.

   (g) We compare supervised and unsupervised stream learning approaches and show which has superior effectiveness using real-world data.

3. With regard to Sequence Data

   (a) For sequence data, we propose a framework that exploits an unsupervised learning (USSL) to find pattern sequences from successive user actions or commands using stream based sequence learning.

   (b) We effectively integrate multiple USSL models in an ensemble of classifiers to exploit the power of ensemble based stream mining and sequence mining.

   (c) We compare our approach with the supervised model for stream mining and show the effectiveness of our approach in terms of TPR and FPR on a benchmark dataset.

4. With regard to Big Data

   (a) scalability is an issue to construct benign pattern sequences for quantized dictionary. For this, we exploit MapReduce based framework and show effectiveness of our work.

1.4 Organization

The remainder of the dissertation is organized as follows. Chapter 2 presents related work. Chapter 3 presents our ensemble-based approaches to insider threat. Chapter 4 discusses the background of supervised and unsupervised learning methods for anomaly detection. Chapter 5 describes our experiments and testing methodology and presents our results and findings on non sequence data. Chapter 6 presents our proposed unsupervised sequence learning for anomaly detection on sequence data. Chapter 7 presents results of our approach hadoop/mapreduce

on sequence data. Chapter 8 presents scalability issue and solution for quantized dictionary construction. Finally, Chapter 9 concludes with an assessment of the viability of stream mining for real-world insider threat detection.

CHAPTER 2

RELATED WORK

Here, first we will present related work with regard to insider threat and stream mining area. Next, we will present related work with regard to big data and analytics perspective.

2.1 Insider Threat and Stream Mining

Insider threat detection work has applied ideas from both intrusion detection and external threat detection (Schonlau et al., 2001; Wang et al., 2003; Maxion, 2003; Schultz, 2002). Supervised learning approaches collect system call trace logs containing records of normal and anomalous behavior (Forrest et al., 1996; Hofmeyr et al., 1998; Nguyen et al., 2003; Gao et al., 2004), extract n-gram features from the collected data, and use the extracted features to train classifiers. Text classification approaches treat each system call as a word in a bag-of-words model (Liao and Vemuri, 2002). Various attributes of system calls, including arguments, object path, return value, and error status, have been exploited as features in various supervised learning methods (Krügel et al., 2003; Tandon and Chan, 2003).

Hybrid high-order Markov chain models detect anomalies by identifying a *signature behavior* for a particular user based on their command sequences (Ju and Vardi, 2001). The Probabilistic Anomaly Detection (PAD) algorithm (Stolfo et al., 2005) is a general purpose algorithm for anomaly detection (in the windows environment) that assumes anomalies or noise is a rare event in the training data. Masquerade detection is argued over by some individuals. A number of detection methods were applied to a data set of ”truncated” UNIX shell commands for 70 users (Schonlau et al., 2001). Commands were collected using the UNIX acct auditing mechanism. For each user a number of commands were gathered over a period of time. The detection methods were supervised by a multi-step Markovian model and a combination of Bayes and Markov approaches. It was argued that the data set was not appropriate for the masquerade detection task (Maxion, 2003). It was pointed out that the period of data gathering varied greatly from user to user (from several days to several months). Furthermore, commands were not logged in the order in which they were typed. Instead, they were coalesced when the application terminated the audit mechanism. This leads to the unfortunate consequence of possible faulty analysis of strict sequence data. Therefore, in this proposed work we have not considered this dataset.

同传统的方法比较而言，我们的方法可以通过不断变化演进的流数据建立动态的检测模型，这是传统的方法无法比拟的。

These approaches differ from our supervised approach in that these learning approaches are static in nature and do not learn over evolving streams. In other words, stream characteristics of data are not explored further. Hence, static learning performance may degrade over time. On the other hand, our supervised approach will learn from evolving data streams. Our proposed work is based on supervised learning and it can handle dynamic data or stream data well by learning from evolving streams.

单类SVM算法（OCSVM）根据正常数据建立模型，然后依靠训练数据的几何分布将测试数据分类为正常和异常数据。我们的贡献之一就是将OCSVM推广到了流数据领域，使得其可以适应变化的数据。

In anomaly detection, one class SVM algorithm is used (Stolfo et al., 2005). OCSVM builds a model by training on normal data and then classifies test data as benign or anomalous based on geometric deviations from that normal training data. For masquerade detection, one class SVM training is as affective as two class training (Stolfo et al., 2005). Investigations have been made into SVMs using binary features and frequency based features. The one class SVM algorithm with binary features performed the best.

Recursive mining has been proposed to find frequent patterns (Szymanski and Zhang, 2004). One class SVM classifier were used for masquerade detection after the patterns were encoded with unique symbols and all sequences rewritten with this new coding.

To the best of our knowledge there is no work that extends this OCSVM in a stream domain. Although our approach relies on OCSVM, it is extended to the stream domain so that it can cope with changes (Parveen, Weger et al., 2011; Parveen, McDaniel et al., 2013).

我们的工作，针对监督式学习数据主要基于单类SVM的扩展；而对于非监督式学习主要基于图分析，如GBAD和MDL（图异常检测和最小描述路径）

Past works have also explored unsupervised learning for insider threat detection, but only to static streams to our knowledge (Liu et al., 2005; Eskin et al., 2002, 2000). Static graph based anomaly detection (GBAD) approaches (Cook and Holder, 2007; Eberle and Holder, 2007; Cook and Holder, 2000; Yan and Han, 2002) represent threat and non-threat data as a graph and apply unsupervised learning to detect anomalies. The *minimum description length (MDL)* approach to GBAD has been applied to email, cell phone traffic, business processes, and cybercrime datasets (Staniford-Chen et al., 1996; Kowalski et al., 2008). Our work builds upon GBAD and MDL to support dynamic, evolving streams (Parveen, Evans et al., 2011; Parveen, McDaniel et al., 2013).

在介绍了关于监督式学习与非监督式学习的实现之后，接下来是其中关键的流数据挖掘的技术，即针对数据持续变化的过程进行挖掘。这里有两种可供选择的方法：增量学习与全局学习，我们使用后一种方法，因为后一种方法证实更为有效。

Stream mining (Fan, 2004) is a relatively new category of data mining research that applies to continuous data streams. In such settings, both supervised and unsupervised learning must be adaptive in order to cope with data whose characteristics change over time. There are two main approaches to adaptation: *incremental learning* (Domingos and Hulten, 2001; Davison and Hirsh, 1998) and *ensemble-based learning* (Masud, Chen, Gao, Khan, Aggarwal et al., 2010; Masud et al., 2011a; Fan, 2004). Past work has demonstrated that ensemble-based approaches are the more effective of the two, motivating our approach.

通过维持在K模型的全局上针对最终的分类投票，误报率和漏报率都得到有效降低。

Ensembles have been used in the past to bolster the effectiveness of positive/negative classification (Masud, Gao et al., 2008; Masud et al., 2011a). By maintaining an ensemble of K models that collectively vote on the final classification, the number of *false negatives (FN)* and *false positives (FP)* for a test set can be reduced. As better models are created, poorer models are discarded to maintain an ensemble of size exactly K. This helps the ensemble evolve with the changing characteristics of the stream and keeps the classification task tractable.

A comparison of the above related works is summarized in Table 2.1. A more complete survey is available in (Salem et al., 2008).

Insider threat detection work has utilized ideas from intrusion detection or external threat detection areas (Schonlau et al., 2001; Wang et al., 2003). For example, supervised learning

Table 2.1. Capabilities and focuses of various approaches for Non Sequence Data

	learn	**concept**	**insider**	**graph**
Approach	**ing**	**drift**	**threat**	**based**
(Hofmeyr et al., 1998)	S	✗	✓	✗
(Eskin et al., 2002)	S	✓	✗	✗
(Liu et al., 2005)	U	✗	✓	✗
(Cook and Holder, 2007) GBAD	U	✗	✓	✓
(Masud, Gao et al., 2008)	S	✓	N/A	N/A
(Parveen, Evans et al., 2011)	S/U	✓	✓	✓

has been applied to detect insider threats. System call traces from normal activity and anomaly data are gathered (Hofmeyr et al., 1998); features are extracted from this data using n-gram and finally, trained with classifiers. Authors (Liao and Vemuri, 2002) exploit the text classification idea in the insider threat domain where each system call is treated as a word in bag of words model. System call, and related attributes, arguments, object path, return value and error status of each system call are served as features in various supervised methods (Krügel et al., 2003; Tandon and Chan, 2003). A supervised model based on hybrid high-order Markov chain model was adopted by researchers (Ju and Vardi, 2001). A *signature behavior* for a particular user based on the command sequences that the user executed is identified and then anomaly is detected.

Schonlau et al. (Schonlau et al., 2001) applied a number of detection methods to a data set of "truncated" UNIX shell commands for 70 users. Commands were collected using the UNIX acct auditing mechanism. For each user a number of commands were gathered over a period of time. The detection methods are supervised based on multistep markovian model, and combination of Bayes and Markov approach. Maxion et al. (Maxion, 2003) argued that Schonlau data set was not appropriate for the masquerade detection task and created new data set using Calgary dataset and apply static supervised model.

These approaches differ from our work in the following ways. These learning approaches are static in nature and do not learn over evolving stream. In other words, stream characteristics of data are not explored further. Hence, static learner performance may degrade over time. On the other hand, our approach will learn from evolving data stream. In this paper, we show that our approach is unsupervised and is as effective as supervised model (incremental).

Researchers have explored *unsupervised learning* (Liu et al., 2005) for insider threat detection. However, this learning algorithm is static in nature. Although our approach is unsupervised, it learns at the same time from evolving stream over time, and more data will be used for unsupervised learning.

In anomaly detection, one class support vector machine (SVM) algorithm (OCSVM) is used. OCSVM builds a model from training on normal data and then classifies a test data as benign or anomaly based on geometric deviations from normal training data. Wang et al. (Wang et al., 2003) showed, for masquerade detection, one-class SVM training is as effective as two-class training. The authors have investigated SVMs using binary features and frequency based features. The one-class SVM algorithm with binary features performed the best. To find frequent patterns, Szymanski et al. (Szymanski and Zhang, 2004) proposed recursive mining, encoded the patterns with unique symbols, and rewrote the sequence using this new coding. They used a one-class SVM classifier for masquerade detection. These learning approaches are static in nature and do not learn over evolving stream.

2.1.1 Stream Mining

Stream mining is a new data mining area where data is continuous (Masud et al., 2013; Masud, Woolam et al., 2011; Masud et al., 2011b; Al-Khateeb, Masud, Khan, Aggarwal et al., 2012; Masud, Al-Khateeb et al., 2011; Masud,Chen, Gao, Khan, Han and Thuraisingham, 2010). In addition, characteristics of data may change over time (concept drift). Here, supervised and unsupervised learning need to be adaptive to cope with changes. There are two ways adaptive learning can be developed. One is incremental learning and the other is ensemble-based learning. Incremental learning is used in user action prediction (Domingos and Hulten, 2000), but not for anomaly detection. Davidson et al. (Davison and Hirsh, 1998) introduced Incremental Probabilistic Action Modeling (IPAM), based on one-step command transition probabilities estimated from the training data. The probabilities were continuously updated with the arrival of a new command and modified with the usage of an exponential decay scheme. However, the algorithm is not designed for anomaly detection.

Therefore, to the best of our knowledge, there is almost no work from other researchers that handles insider threat detection in stream mining area. This is the first attempt to detect insider threat using stream mining (Parveen, Evans et al., 2011; Parveen and Thuraisingham, 2012; Parveen, McDaniel et al., 2012).

Recently, unsupervised learning has been applied to detect insider threat in a data stream (Parveen, McDaniel et al., 2013; Parveen, Weger et al., 2011). This work does not consider sequence data for threat detection. Recall that sequence data is very common in insider threat scenario. Instead, it considers data as graph/vector and finds normative patterns and apply ensemble based technique to cope with changes. On the other hand, in our proposed approach, we consider user command sequences for anomaly detection and construct quantized dictionary for normal patterns.

Users' repetitive daily or weekly activities may constitute user profiles. For example, a user's frequent command sequences may represent normative pattern of that user. To find normative patterns over dynamic data streams of unbounded length is challenging due to the requirement of one pass algorithm. For this, an unsupervised learning approach is used by exploiting a compressed/quantized dictionary to model common behavior sequences. This unsupervised approach needs to identify normal user behavior in a single pass (Parveen, McDaniel et al., 2012; Parveen and Thuraisingham, 2012; Chua et al., 2011). One major challenge with these repetitive sequences is their variability in length. To combat this problem, we generate a dictionary which will contain any combination of possible normative patterns existing in the gathered data stream. In addition, we have incorporated power of

Table 2.2. Capabilities and focuses of various approaches for Sequence Data

Approach	Learn ing	concept drift	insider threat	sequence based
(Ju and Vardi, 2001)	S	✗	✓	✓
(Maxion, 2003)	S	✗	✓	✗
(Liu et al., 2005)	U	✗	✓	✓
(Wang et al., 2003)	S	✗	✓	✗
(Masud et al., 2011a)	S	✓	✗	✗
(Parveen, Weger et al., 2011)	U	✓	✓	✗
(Parveen, McDaniel et al., 2012)	U	✓	✓	✓

stream mining to cope with gradual changes. We have done experiments and shown that our USSL approach works well in the context of concept drift and anomaly detection.

Our work (Parveen, McDaniel et al., 2012; Parveen and Thuraisingham, 2012) differs form the work of (Chua et al., 2011) in the following ways. First, (Chua et al., 2011) focuses on dictionary construction to generate normal profiles. In other words, their work does not address insider threat issue which is our focus. Second, (Chua et al., 2011) does not consider ensemble based techniques; our work exploits ensemble based technique with the combination of unsupervised learning (i.e., dictionary for benign sequences). Finally, when a number of users will grow, dictionary construction will become a bottleneck. The work of (Chua et al., 2011) does not consider scalability issue; in our case, we address scalability issue using MapReduce framework.

In (Parveen and Thuraisingham, 2012) an incremental approach is used. Ensemble based techniques are not incorporated, but the literature used shows that ensemble based techniques are more effective than those of the incremental variety for stream mining (Masud, Chen, Gao, Khan, Aggarwal et al., 2010; Masud et al., 2011a; Fan, 2004). Therefore, this dissertation focuses on ensemble based techniques (Parveen, McDaniel et al., 2012).

Refer to Table 2.2 on which related approaches are unsupervised or supervised, and whether they focus on concept drift, detecting insider threat and sequenced data from stream mining.

2.2 Big Data: Scalability Issue

Stream data are continuously coming with high velocity and large size (Al-Khateeb, Masud, Khan, and Thuraisingham, 2012). This conforms characteristics of big data.

"Big Data" is data whose scale, diversity, and complexity require new architecture, techniques, algorithms, and analytics to manage it and extract value and hidden knowledge from it. Therefore, big data researchers are looking for tools to manage, analyze, summarize, visualize, and discover knowledge from the collected data in a timely manner and in a scalable fashion. Here, we will list some and discuss what problems we are solving in big data.

2.2.1 With Regard to Big Data Management

There are a number of techniques available that allow massively scalable data processing over grids of inexpensive commodity hardware such as:

The Google File System (Chang et al., 2006; Dean and Ghemawat, 2008) is a scalable distributed file system that utilizes clusters of commodity hardware to facilitate data intensive applications. The system is fault tolerance where failure of machine is norm due to usage of commodity hardware. To cope with failure, data will replicated into multiple nodes. If one node is failing, the system will utilize the other node where replicated data exists.

MapReduce (Chang et al., 2006; Dean and Ghemawat, 2008) is a programming model that supports data-intensive applications in a parallel manner. MapReduce paradigm supports map and reduce function. Map generates a set of intermediate key and value pairs and then reduce function combines the results and deduces it. In fact, the map/reduce paradigm can solve many real world problems as shown in (Chang et al., 2006; Dean and Ghemawat, 2008).

Hadoop (Bu et al., 2010; Xu et al., 2010; Abouzeid et al., 2009) is an open source apache project that supports Google file system and mapReduce paradigm. Hadoop is widely used to address scalability issue along with mapReduce. For example, with huge amount of semantic web datasets, Husain et al. (Husain et al., 2009, 2010, 2011) showed that Hadoop can be used to provide scalable queries. In addition, MapReduce technology has been exploited by BioMANTA[1] project (Ding et al., 2005) and SHARD [2].

Amazon develops Dynamo (DeCandia et al., 2007), a distributed key-value store. Dynamo does not support master-slave architecture which is supported by Hadoop. Nodes in Dynamo communicate via a gossip network. To achieve high availability and performance, Dynamo supports a model called eventual consistency by sacrificing rigorous consistency. In eventual consistency, updates will be propagated to nodes in the cluster asynchronously and a new version of the data will be produced for each update.

Google develops BigTable (Chang et al., 2006, 2008), column-oriented data storage system. BigTable utilizes the Google File System and Chubby (Burrows, 2006), a distributed lock service. BigTable is a distributed multi-dimensional sparse map based on row keys, column names and time stamps.

Researchers (Abouzeid et al., 2009) exploited combining power of MapReduce and relational database technology.

2.2.2 With Regard to Big Data Analytics Mahout

There are handfuls of works related to big data analytics. For example, on one hand, some researcher focus on generic analytics tool to address scalability issue. On the other hand, other researcher focus on specific analytics problems.

With regard to tool, Mahout is an open source big data analytics to support classification, clustering, and recommendation system for big data. In (Chu et al., 2006), researchers customized well-known machine learning algorithms to take advantage of multicore machines

[1] http://www.itee.uq.edu.au/ eresearch/projects/biomanta

[2] http://www.cloudera.com/blog/2010/03/how-raytheon-researchers-are-using-hadoop-to-build-a-scalable-distributed-triple-store

and MapReduce programming paradigm. MapReduce has been widely used for mining petabytes of data (Moretti et al., 2008).

With regard to specific problems, Al-Khateeb et al. (Al-Khateeb, Masud, Khan, and Thuraisingham, 2012) and Haque et al. (Haque et al., 2013a,b) proposed scalable classification over evolving stream by exploiting MapReduce and Hadoop framework. There are some research works on parallel boosting with MapReduce. Palit et al. (Palit and Reddy, 2012) proposed two parallel boosting algorithms, ADABOOST.PL and LOGITBOOST.PL.

论文的整体目标是建立可以根据行为模式演进的动态检测系统，具体为：
1．通过单类SVM（OCSVM）解决监督式学习问题；
2．通过图异常检测和最小路径描述来解决非监督式数据；
3．使用全局学习的方式处理变化的流数据；
4．利用hadoop和mapreduce来处理系统的效能瓶颈；

CHAPTER 3

ENSEMBLE-BASED INSIDER THREAT DETECTION

Data relevant to insider threats is typically accumulated over many years of organization and system operations, and is therefore best characterized as an unbounded data stream. Such a stream can be partitioned into a sequence of discrete *chunks*; for example, each chunk might comprise a week's worth of data. 将流数据分成离散的数据块,比如每周的数据为一个块

图标3.1显示了当数据流中发现概念偏移的时候分类器的决定边界如何变化

Figure 3.1 illustrates how a classifier's decision boundary changes when such a stream observes concept-drift. Each circle in the picture denotes a data point having , with unfilled circles representing *true negatives (TN)* (i.e., non-anomalies) and solid circles representing *true positives (TP)* (i.e., anomalies). The solid line in each chunk represents the decision boundary for that chunk, while the dashed line represents the decision boundary for the previous chunk.

Shaded circles are those that embody a new concept that has drifted relative to the previous chunk. In order to classify these properly, the decision boundary must be adjusted to account for the new concept. There are two possible varieties of *misapprehension* (false detection):

1. The decision boundary of chunk 2 moves upward relative to chunk 1. As a result, some non-anomalous data is incorrectly classified as anomalous, causing the FP (false positive) rate to rise.

2. The decision boundary of chunk 3 moves downward relative to chunk 2. As a result, some anomalous data is incorrectly classified as non-anomalous, causing the FN (false negative) rate to rise.

Figure-1详细表示了模式迁移对系统的影响；
实线表示真实的情况；
虚线表示传统的检测方法划分的界限；
2相对于1而言，真实的异常只有两个，而检测系统却识别出了4个，即false positive（误报）；
3相对于1而言，异常为6个，但是检测系统却认为只有3个，即false negtive（漏报）；

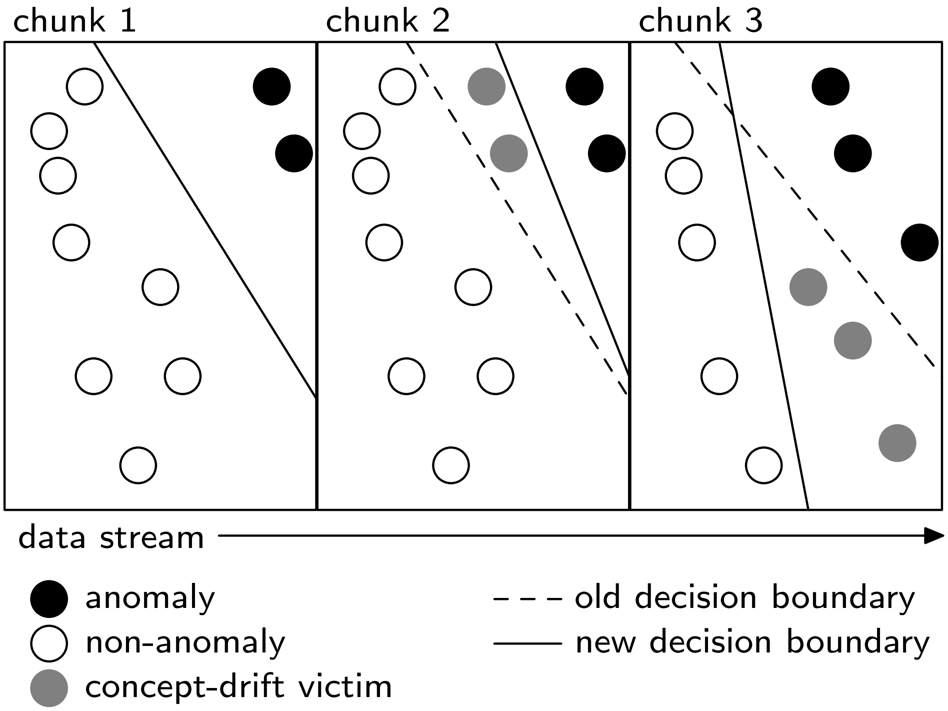


Figure 3.1. Concept drift in stream data

In general, the old and new decision boundaries can intersect, causing both of the above cases to occur simultaneously for the same chunk. Therefore, both FP and FN counts may increase.

这个例子告诉我们，单独依靠一个数据块或者数据块中有限的开头部分来建立模型都是不够的，这激励着我们采用全局的学习机制，即使用K模型的进化集来分类数据。

These observations suggest that a model built from a single chunk or any finite prefix of chunks is inadequate to properly classify all data in the stream. This motivates the adoption of our ensemble approach, which classifies data using an evolving set of K models.

3.1 Ensemble Learning

维护着一个动态的K-模型分类器，通过对每个块的K分类器投票得到块正常/异常的判断。

The ensemble classification procedure is illustrated in Figure 3.2. We first build a model using OCSVM (supervised approach) or GBAD (unsupervised approach) from an individual chunk (Parveen, Weger et al., 2011; Parveen, McDaniel et al., 2013; Parveen, Evans et al., 2011). In the case of GBAD *normative substructures* are identified in the chunk, each represented as a subgraph. To identify an anomaly, a test substructure is compared against

针对一个块的判断基于一个模型族，运用族中的每个模型检测该数据块流，得到相应的输出结果，然后综合加权得到判定结果。

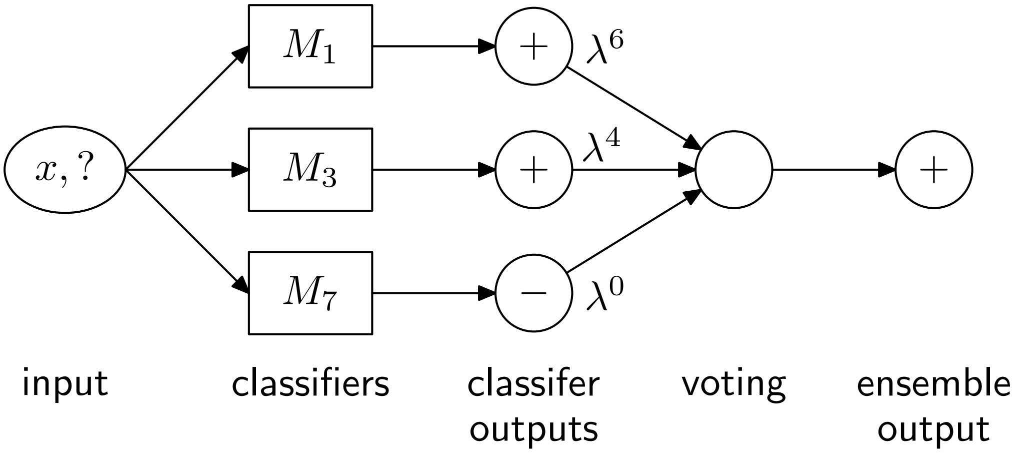


Figure 3.2. Ensemble classification

each model of the ensemble. A model will classify the test substructure as an anomaly based on how much the test differs from the model's normative substructure. Once all models cast their votes, weighted majority voting is applied to make a final classification decision.

K模型，一直维持着K个块，每到一个就从已有的块中丢弃一个。

Ensemble evolution is arranged so as to maintain a set of exactly K models at all times. As each new chunk arrives, a $K+1$st model is created from the new chunk and one victim model of these $K+1$ models is discarded. The discard victim can be selected in a number of ways. One approach is to calculate the prediction error of each of the $K+1$ models on the most recent chunk and discard the poorest predictor. This requires the *ground truth* to be immediately available for the most recent chunk so that prediction error can be accurately measured. If the ground truth is not available, we instead rely on majority voting; the model with least agreement with the majority decision is discarded. This results in an ensemble of the K models that best match the current concept.

当一个新的块到来，为其建立新的模型，这时共有k+1个模型；然后根据特定的机制淘汰一个模型，比如可以比较这k+1个模型在最近的数据块上（正常/异常）判断的正确率，错误最多的排除；如是可以保证我们的k个模型始终与当前的特征最为吻合。

Algorithm 1 Unsupervised Ensemble Classification and Updating

```
Input: $E$ (ensemble), $t$ (test graph), and $S$ (chunk)
Output: $A$ (anomalies), and $E'$ (updated ensemble)
$M' \leftarrow$ NewModel($S$)
$E' \leftarrow E \cup \{M'\}$
for each model $M$ in ensemble $E'$ do
    $c_M \leftarrow 0$
    for each $q$ in model $M$ do
        $A_1 \leftarrow GBAD_P(t, q)$
        $A_2 \leftarrow GBAD_{MDL}(t, q)$
        $A_3 \leftarrow GBAD_{MPS}(t, q)$
        $A_M \leftarrow ParseResults(A_1, A_2, A_3)$
    end for
end for
for each candidate $a$ in $\bigcup_{M \in E'} A_M$ do
    if round(WeightedAverage(E',a))=1 then then
        $A \leftarrow A \cup \{a\}$
        for each model $M$ in ensemble $E'$ do
            if $a \in A_M$ then then
                $c_M \leftarrow c_M + 1$
            end if
        end for
    else
        for each model $M$ in ensemble $E'$ do
            if $a \notin A_M$ then then
                $c_M \leftarrow c_M + 1$
            end if
        end for
    end if
end for
$E' \leftarrow E' - \{choose(\arg\min_M(c_M))\}$
```

3.1.1 Ensemble for Unsupervised Learning

Algorithm 1 summarizes the unsupervised classification and ensemble-based updating algorithm[1] [2]. Lines 3–4 build a new model from the most recent chunk and temporarily add it to the ensemble. Next, Lines 5–13 apply each model in the ensemble to test graph t for possible anomalies. We use three varieties of GBAD for each model (P, MDL, and MPS), each discussed in Section 4.2. Finally, Lines 14–30 update the ensemble by discarding the model with the most disagreements from the weighted majority opinion. If multiple models have the most disagreements, an arbitrary poorest-performing one is discarded. Note that no ground truth is used. However, majority voting of models serve so called "ground truth".

Weighted majority opinions are computed in Line 15 using the formula

$$WA(E,a) = \frac{\sum_{\{i \,|\, M_i \in E,\, a \in A_{M_i}\}} \lambda^{\ell - i}}{\sum_{\{i \,|\, M_i \in E\}} \lambda^{\ell - i}} \tag{3.1}$$

where $M_i \in E$ is a model in ensemble E that was trained from chunk i, A_{M_i} is the set of anomalies reported by model M_i, $\lambda \in [0,1]$ is a constant *fading factor* (Chen et al., 2009), and ℓ is the index of the most recent chunk. Model M_i's vote therefore receives weight $\lambda^{\ell-i}$, with the most recently constructed model receiving weight $\lambda^0 = 1$, the model trained from the previous chunk receiving weight λ^1 (if it still exists in the ensemble), etc. This has the effect of weighting the votes of more recent models above those of potentially outdated ones when $\lambda < 1$. Weighted average $WA(E,a)$ is then rounded to the nearest integer (0 or 1) in Line 15 to obtain the weighted majority vote.

[1] c 2011 IEEE. Reprinted, with permission, from Pallabi Parveen, Jonathan Evans, Bhavani M. Thuraisingham, Kevin W. Hamlen, Latifur Khan: Insider Threat Detection Using Stream Mining and Graph Mining. SocialCom/PASSAT 2011: 1102-1110

[2] c 2013 World Scientific Publishing/Imperial College Press. Reprinted, with permission, from Pallabi Parveen, Nathan Mcdaniel, Zackary Weger, Jonathan Evans, Bhavani M. Thuraisingham, Kevin W. Hamlen, Latifur Khan: Evloving Insider Threat Detection Stream Mining Perspective. International Journal on Artificial Intelligence Tools Vol. 22, No. 5 (2013) 1360013 (24 pages). World Scientific Publishing Company DOI: 10.1142/S0218213013600130

For example, in Figure 3.2, models M_1, M_3, and M_7 vote positive, positive, and negative, respectively, for input sample x. If $\ell = 7$ is the most recent chunk, these votes are weighted λ^6, λ^4, and 1, respectively. The weighted average is therefore $WA(E, x) = (\lambda^6 + \lambda^4)/(\lambda^6 + \lambda^4 + 1)$. If $\lambda \leq 0.86$, the negative majority opinion wins in this case; however, if $\lambda \geq 0.87$, the newer model's vote outweighs the two older dissenting opinions, and the result is a positive classification. Parameter λ can thus be tuned to balance the importance of large amounts of older information against smaller amounts of newer information.

Our approach uses the results from previous iterations of GBAD to identify anomalies in subsequent data chunks. That is, normative substructures found in previous GBAD iterations may persist in each model. This allows each model to consider all data since the model's introduction to the ensemble, not just that of the current chunk. When streams observe concept-drift, this can be a significant advantage because the ensemble can identify patterns that are normative over the entire data stream or a significant number of chunks but not in the current chunk. Thus, insiders whose malicious behavior is infrequent can still be detected.

Algorithm 2 Supervised Ensemble Classification Updating

```
Input: $D_u$ (most recently labeled chunk), and $A$ (ensemble)
Output: $A'$ (updated ensemble)
for each model $M$ in ensemble $A$ do
    $test(M, D_u)$
end for
$M_n \leftarrow OCSVM(D_u)$
$test(M_n, D_u)$
$A' \leftarrow \{K : M_n \cup A\}$
```

Algorithm 3 Supervised Testing Algorithm

```
1: Input: $D_u$ (most recent unlabeled chunk), and $A$ (ensemble)
2: Output: $D'_u$ (labeled/predicted $D_u$)
3: $F_u \leftarrow ExtractandSelectFeatures(D_u)$
4: for each feature $x_j \in F_u$ do
5:     $R \leftarrow NULL$
6:     for each model $M$ in ensemble $A$ do
7:         $R \leftarrow R \cup$ predict$(x_j, M)$
8:     end for
9:     anomalies $\leftarrow$ MajorityVote$(R)$
10: end for
```

3.1.2 Ensemble for Supervised Learning

Algorithm 2 shows the basic building blocks of our supervised algorithm[3]. Here, we first present how we update the model. Input for algorithm 2 will be as follows: D_u is the most recently labeled data chunk (most recent training chunk) and A is the ensemble. Lines 3–4 calculate the prediction error of each model on D_u. Line 6 builds a new model using OCSVM on D_u. Line 7 produces $K + 1$ models. Line 8 discards the model with the maximum prediction error, keeping the K best models.

Algorithm 3, focuses on ensemble testing. Ensemble A and the latest unlabeled chunk of instance D_u will be the input. Line 3 performs feature extraction and selection using the latest chunk of unlabeled data. Lines 4–9 will take each extracted feature from D_u and do an anomaly prediction. Lines 6–7 use each model to predict the anomaly status for a particular feature. Finally, Line 9 predicts anomalies based on majority voting of the results.

Our ensemble method uses the results from previous iterations of OCSVM executions to identify anomalies in subsequent data chunks. This allows the consideration of more than just the current data being analyzed. Models found in previous OCSVM iterations are also analyzed, not just the models of the current dataset chunk. The ensemble handles the

[3] c 2011 IEEE. Reprinted, with permission, from Pallabi Parveen, Zackary R. Weger, Bhavani M. Thuraisingham, Kevin W. Hamlen, Latifur Khan: Supervised Learning for Insider Threat Detection Using Stream Mining. ICTAI 2011: 1032-1039

execution in this manner because patterns identified in previous chunks may be normative over the entire data stream or a significant number of chunks but not in the current execution chunk. Thus insiders whose malicious behavior is infrequent will be detected. It is important to note that we always keep our ensemble size fixed. Hence, an outdated model which is performing worst on the most recent chunks will be replaced by the new one.

It is important to note that the size of the ensemble remains fixed over time. Outdated models that are performing poorly are replaced by better-performing, newer models that are more suited to the current concept. This keeps each round of classification tractable even though the total amount of data in the stream is potentially unbounded.

CHAPTER 4

DETAILS OF LEARNING CLASSES

This chapter will describe the different classes of learning techniques for non sequence data (Parveen, Evans et al., 2011; Parveen, McDaniel et al., 2013; Parveen, Weger et al., 2011). It serves the purpose of providing more detail as to exactly how each method arrives at detecting insider threats and how ensemble models are built, modified and discarded. The first subsection goes over supervised learning in detail and the second subsection goes over unsupervised learning. Both contain the formulas necessary to understand the inner workings of each class of learning.

4.1 Supervised Learning

监督式学习：
对于一个数据块我们利用单类SVM建立模型，主要分两步：
1．将训练数据映射到一个高维空间；
2．算法找到分割数据最好的最大边界超平面；

In a chunk, a model is built using one class support vector machine (OCSVM) (Manevitz and Yousef, 2002). The OCSVM approach first maps training data into a high dimensional feature space (via a kernel). Next, the algorithm iteratively finds the maximal margin hyperplane which best separates the training data from the origin. The OCSVM may be considered as a regular two-class SVM. Here the first class entails all the training data, and the second class is the origin. Thus, the hyperplane (or linear decision boundary) corresponds to the classification rule:

$$f(x) = \langle w, x \rangle + b \tag{4.1}$$

where w is the normal vector and b is a bias term. The OCSVM solves an optimization problem to find the rule with maximal geometric margin. This classification rule will be used to assign a label to a test example x. If $f(x) < 0$, we label x as an anomaly, otherwise it is labeled normal. In reality there is a trade-off between maximizing the distance of the

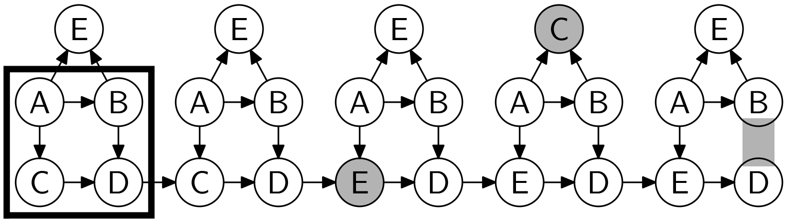


Figure 4.1. A graph with a normative substructure (boxed) and anomalies (shaded)

hyperplane from the origin and the number of training data points contained in the region separated from the origin by the hyperplane.

4.2 Unsupervised Learning

基于图的异常检测主要观察三个因素：顶点和边的修改、增加以及删除。
本文通过2005年Ketkar等人提出的SUBDUE方法来寻找规范子图。最好的规范子图应当具有最小的描述距离。

Algorithm 1 uses three varieties of graph based anomaly detection(GBAD) (Cook and Holder, 2007; Eberle and Holder, 2007; Cook and Holder, 2000; Yan and Han, 2002) to infer potential anomalies using each model. GBAD is a graph-based approach to finding anomalies in data by searching for three factors: modifications, insertions, and deletions of vertices and edges. Each unique factor runs its own algorithm that finds a normative substructure and attempts to find the substructures that are similar but not completely identical to the discovered normative substructure. A normative substructure is a recurring subgraph of vertices and edges that, when coalesced into a single vertex, most compresses the overall graph. The rectangle in Figure 4.1 identifies an example of normative substructure for the depicted graph.

Our implementation uses SUBDUE (Ketkar et al., 2005) to find normative substructures. The best normative substructure can be characterized as the one with minimal description length (MDL):

$$L(S, G) = DL(G \mid S) + DL(S) \tag{4.2}$$

where G is the entire graph, S is the substructure being analyzed, $DL(G \mid S)$ is the description length of G after being compressed by S, and $DL(S)$ is the description length of the substructure being analyzed. Description length $DL(G)$ is the minimum number of bits necessary to describe graph G (Eberle et al., 2011).

Insider threats appear as small percentage differences from the normative substructures. This is because insider threats attempt to closely mimic legitimate system operations except for small variations embodied by illegitimate behavior. We apply three different approaches for identifying such anomalies, discussed below.

4.2.1 GBAD-MDL

Upon finding the best compressing normative substructure, GBAD-MDL searches for deviations from that normative substructure in subsequent substructures. By analyzing substructures of the same size as the normative one, differences in the edges and vertices' labels and in the direction or endpoints of edges are identified. The most anomalous of these are those substructures for which the fewest modifications are required to produce a substructure isomorphic to the normative one. In Figure 4.1, the shaded vertex labeled E is an anomaly discovered by GBAD-MDL.

4.2.2 GBAD-P

In contrast, GBAD-P searches for insertions that, if deleted, yield the normative substructure. Insertions made to a graph are viewed as extensions of the normative substructure. GBAD-P calculates the probability of each extension based on edge and vertex labels, and therefore exploits label information to discover anomalies. The probability is given by

$$P(A{=}v) = P(A{=}v \mid A)\, P(A) \tag{4.3}$$

where A represents an edge or vertex attribute and v represents its value. Probability $P(A{=}v \mid A)$ can be generated by a Gaussian distribution:

$$\rho(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{4.4}$$

where μ is the mean and σ is the standard deviation. Higher values of $\rho(x)$ correspond to more anomalous substructures.

Using GBAD-P therefore ensures that malicious insider behavior that is reflected by the actual data in the graph (rather than merely its structure) can be reliably identified as anomalous by our algorithm. In Figure 4.1, the shaded vertex labeled C is an anomaly discovered by GBAD-P.

4.2.3 GBAD-MPS

Finally, GBAD-MPS considers deletions that, if re-inserted, yield the normative substructure. To discover these, GBAD-MPS examines the parent structure. Changes in size and orientation in the parent signify deletions amongst the subgraphs. The most anomalous substructures are those with the smallest transformation cost required to make the parent substructures identical. In Figure 4.1, the last substructure of A-B-C-D vertices is identified as anomalous by GBAD-MPS because of the missing edge between B and D marked by the shaded rectangle.

CHAPTER 5

EXPERIMENTS AND RESULTS

5.1 Dataset

我们在1998年的林肯实验室的入侵检测数据集上测试我们的两个算法。该数据集包含了7周的日常系统日志，该日志通过基本安全模式审计系统收集得到。

We tested both of our algorithms on the 1998 Lincoln Laboratory Intrusion Detection dataset (Kendall, 1998). This dataset consists of daily system logs containing all system calls performed by all processes over a 7 week period. It was created using the Basic Security Mode (BSM) auditing program. Each log consists of tokens that represent system calls using the syntax exemplified in Figure 5.1.

数据集记号的构成

The token arguments begin with a header line and end with a trailer line. The header line reports the size of the token in bytes, a version number, the system call, and the date and time of execution in milliseconds. The second line reports the full path name of the executing process. The optional `attribute` line identifies the user and group of the owner, the file system and node, and the device. The next line reports the number of arguments to the system call, followed by the arguments themselves on the following line. The `subject` line reports the audit ID, effective user and group IDs, real user and group IDs, process ID, session ID, and terminal port and address, respectively. Finally, the `return` line reports the outcome and return value of the system call.

面对数量繁多的标记，我们重点关注用户相关的系统调用，如对以下程序的调用：exec\execve\utime\login\logout\su\setegid\seteuid\setuid\rsh\rexecd\passwd\rexd\ftp

Since many system calls are the result of automatic processes not initiated by any particular user, they are therefore not pertinent to the detection of insider threat. We limit our attention to user-affiliated system calls. These include calls for `exec`, `execve`, `utime`, `login`, `logout`, `su`, `setegid`, `seteuid`, `setuid`, `rsh`, `rexecd`, `passwd`, `rexd`, and `ftp`. All of these correspond to logging in/out or file operations initiated by users, and are therefore relevant to insider threat detection. Restricting our attention to such operations helps to reduce

```
header,129,2,execve(2),,Tue Jun 16 08:14:29 1998, +
        518925003 msec
path/op/local/bin/tcsh
attribute,100755,root,other,8388613,79914,0
exec_args,1,
-tcsh
subject,2142,2142,rjm,2142,rjm,401,400,24
        1 135.13.216.191
return,success,0
trailer,129
```

Figure 5.1. A sample system call record from the MIT Lincoln dataset

```
Time, userID, machineIP, command, arg, path, return
1 1:29669 6:1 8:1 21:1 32:1 36:0
```

Figure 5.2. Feature set extracted from Figure 5.1

extraneous noise in the dataset. Further, some tokens contain calls made by users from the outside, via web servers, and are not pertinent to the detection of *insider* threats. There are six such users in this data set and have been pulled out. Table 5.1 reports statistics for the dataset after all irrelevant tokens have been filtered out and the attribute data in Figure 5.3 has been extracted. Preprocessing extracted 62K tokens spanning 500K vertices. These reflected the activity of all users over 9 weeks.

Figure 5.2 shows the features extracted from the output data in Figure 5.1 for our supervised approach and Figure 5.3 depicts the subgraph structure yielded for our unsupervised approach.

The first number in Figure 5.2 is the classification of the token as either anomalous (-1) or normal (1). The classification is used by 2-class SVM for training the model, but is unused

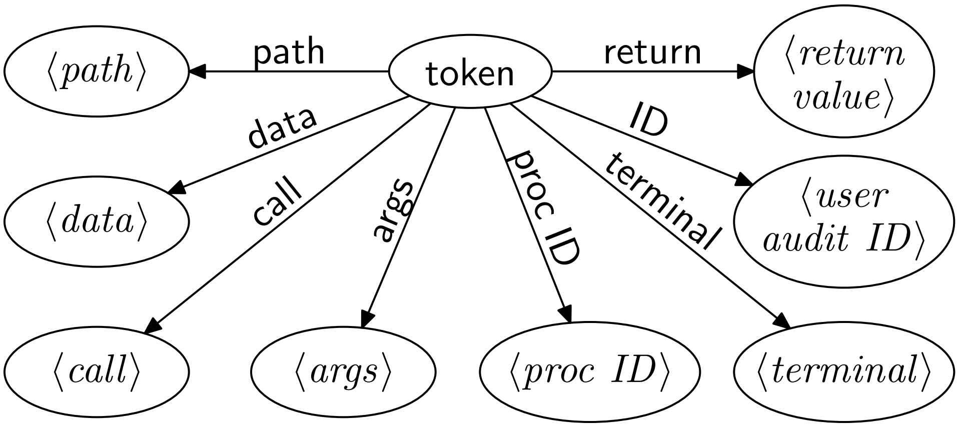


Figure 5.3. A token subgraph

(although required) for one class SVM. The rest of the line is a list of index-value pairs, which are separated by a colon (:). The index represent the dimension for use by SVM, and the value is the value of the token along that dimension. The value must be numeric. The list must be ascending by index. Indices that are missing are assumed to have a value of 0. Attributes which are categorical in nature (and can take the value of any one of N categories) are represented by N dimensions. In Figure 5.2, 1:29669 means that the time of day (in seconds) is 29669. 6:1 means that the user's ID (which is categorical) is 2142, 8:1 means that the machine IP address (also categorical) is 135.13.216.191, 21:1 means that the command (categorical) is execve, 32:1 means the path begins with /opt, and, and 36:0 means that the return value is 0. The mappings between the data values and the indices were set internally by a configuration file.

All of these features are important for different reasons. The time of day could indicate that the user is making system calls during normal business hours, or, alternatively, is logging in late at night, which could be anomalous. The path could indicate the security level of the system call being made for instance, a path beginning with */sbin* could indicate use of important system files, while a path like */bin/mail* could indicate something more benign, like sending mail. The user ID is important to distinguish events, what is anomalous for one user may not be anomalous for another. A programmer that normally works from 9 A.M. to 5 P.M.

would not be expected to login at midnight, but a maintenance technician (who performs maintenance on server equipment during off hours, at night), would. Frequent changes in machine IP address or changes that are not frequent enough could indicate something anomalous. Lastly, the system call itself could indicate an anomaly most users would be expected to login and logout, but only administrators would be expected to invoke super user privileges with a command such as *su*.

5.2 Experimental Setup

5.2.1 Supervised Learning

We used LIBSVM (Chang and Lin, 2011) to build our models and to generate predictions for our test cases in our supervised approach. First, we will give an overview of our use of SVM software, which is standard procedure and is well documented in LIBSVMs help files. We chose to use the RBF (radial-based function) kernel for the SVM. It was chosen because it gives good results for our data set. Parameters for the kernel (in the case of two-class SVM, C and γ, and in the case of one-class SVM, ν and γ) were chosen so that the F_1 measure was maximized. We chose to use the F_1 measure in this case (over other measures of accuracy) because, for the classifier to do well according to this metric, it must minimize false positives while also minimizing false negatives. Before training a model with our feature set, we used LIBSVM to scale the input data to the range $[0, 1]$. This was done to ensure that dimensions which takes on high values (like time) do not outweigh dimensions that take on low values (such as dimensions which represent categorical variables). The parameters that were used to scale the training data for the model are the same parameters that were used to scale that model's test data. Therefore, the model's test data will be in the vicinity of the range $[0, 1]$.

We conducted two experiments with the SVM. The first, as seen in Table 5.2, was designed to compare one-class SVM with two-class SVM for the purposes of insider threat

Table 5.1. Dataset statistics after filtering and attribute extraction

Statistic	**Value**
No of vertices	500,000
No of tokens	62,000
No of normative substructures	5
No of users	all
Duration	9 weeks

detection, and the second, as seen in Table 5.3, was designed to compare a stream classification approach with a more traditional approach to classification. We will begin by describing our comparison of one-class and two-class SVM. For this experiment, we took the 7 weeks of data, and randomly divided it into halves. We deemed the first half training data and the other half testing data. We constructed a simple one-class and two-class model from the training data and recorded the accuracy of the model in predicting the test data.

For the insider threat detection approach we use an ensemble-based approach that is scored in real time. The ensemble maintains K models that use one-class SVM, each constructed from a single day and weighted according to the accuracy of the models previous decisions. For each test token, the ensemble reports the majority vote of its models.

The stream approach outlined above is more practical for detecting insider threats because insider threats are stream in nature and occur in real time. A situation like that in the first experiment above is not one that will occur in the real world. In the real world, insider threats must be detected as they occur, not after months of data has piled in. Therefore, it is reasonable to compare our updating stream ensemble with a simple one-class SVM model constructed once and tested (but not updated) as a stream of new data becomes available, see Table 5.3.

5.2.2 Unsupervised Learning

For our unsupervised approach (based on graph based anomaly detection), we needed to accurately depict the effects of two variables. Those variables are K, the number of ensembles

Table 5.2. Exp. A: One Class vs. Two Class SVM

	One Class SVM	**Two Class SVM**
False Positives	3706	0
True Negatives	25701	29407
False Negatives	1	5
True Positives	4	0
Accuracy	0.87	0.99
False Positive Rate	0.13	0.0
False Negative Rate	0.2	1.0

Table 5.3. Exp. B: Updating vs. Non Updating Stream Approach

	Updating Stream	**Non Updating Stream**
False Positives	13774	24426
True Negatives	44362	33710
False Negatives	1	1
True Positives	9	9
Accuracy	0.76	0.58
False Positive Rate	0.24	0.42
False Negative Rate	0.1	0.1

Table 5.4. Summary of data subset A (Selected/Partial)

Statistic	**Dataset A**
User	Donaldh
No of vertices	269
No of edges	556
Week	2–8
Weekday	Friday

maintained, and q, the number of normative substructures maintained for each model in the ensemble. We used a subset of data during this wide variety of experiments, as depicted in Table 5.4, in order to complete them in a manageable time. The decision to use the small subset of data was arrived at due to the exponential growth in cost for checking subgraph isomorphism.

Each ensemble iteration was run with q values between 1 and 8. Iterations were made with ensemble sizes of K values between 1 and 6.

5.3 Results

5.3.1 Supervised Learning

Performance and accuracy was measured in terms of total false positives (FP) and false negatives (FN) throughout 7 weeks of test data as discussed in Table 5.4(week 2- week 8). The Lincoln Laboratory dataset was chosen for both its large size and because its set of anomalies is well known, facilitating an accurate performance assessment via misapprehension counts.

Table 5.2 shows the results for the first experiment using our supervised method. One-class SVM outperforms two-class SVM in the first experiment. Simply, two-class SVM is unable to detect any of the positive cases correctly. Although the two-class SVM does achieve a higher accuracy, it is at the cost of having a 100% false negative rate. By varying the parameters for the two-class SVM, we found it possible to increase the false positive rate (the SVM made an attempt to discriminate between anomaly and normal data), but in no case could the two-class SVM predict even one of the truly anomalous cases correctly. One-class SVM, on the other hand, achieves a moderately low false negative rate (20%), while maintaining a high accuracy (87.40%). This demonstrates the superiority of one-class SVM over two-class SVM for insider threat detection.

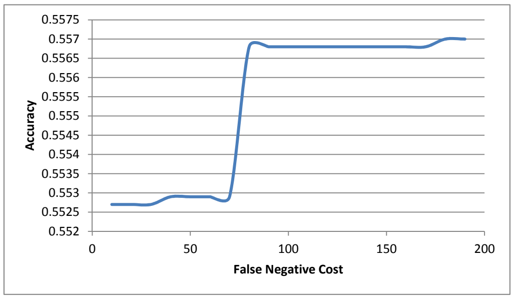
The superiority of one-class SVM over two-class SVM for insider threat detection further justifies our decision to use one-class SVM for our test of stream data. Table 5.3 gives a summary of our results for the second experiment using our supervised method. The updating stream achieves much higher accuracy than the non-updating stream, while maintaining an equivalent, and minimal, false negative rate (10%). The accuracy of the updating stream is 76%, while the accuracy of the non-updating stream is 58%.

The superiority of updating stream over non updating stream for insider threat detection further justifies our decision to use updating stream for our test of stream data. By using labeled data, we establish a ground truth for our supervised learning algorithm. This ground truth allows us to place higher weights on false negatives or false positives. By weighing one more than the other, we punish a model more for producing that which we have increased the weight for. When detecting insider threats it is more important that we do not miss a threat (false negative) than identify a false threat (false positive). Therefor, we weigh false negative more heavily–i.e. we add a *FN cost*. Figure 5.4 and figure 5.5 show the results of weighting the false negatives more heavily than false positives with this established ground truth. This is to say, that at a FN cost of 50, a false negative that is produced will count against a model 50 times more than a false positive will. Increasing the FN cost also increases the accuracy of our OCSVM, updating stream approach. We can see that that increasing the FN cost up to 30 only increases the total cost without affecting the accuracy, but after this, the accuracy climbs and the total cost comes down. Total cost, as calculated by equation 5.1, represents the total number of false positives and false negative after they have been modified by the increase FN Cost. We see this trend peak at a FN cost of 80 where accuracy reaches nearly 56% and the total cost is at a low of 25229.

$$TotalCost = \mathit{TotalFalsePositives} + (\mathit{TotalFalseNegatives} * FNCost) \tag{5.1}$$

The false negatives are weighted by cost more heavily than false positives because it is more important to catch all insider threats. False positives are acceptable in some cases, but an insider threat detection system is useless if it does not catch all positive instances of insider threat activity. This is why models who fail to catch positive cases and produce these false negatives are punished, in our best case result, 80 times more heavily than those who produce false positives.

Table 5.5 reinforces our decision to include *FN cost* during model elimination that heavily punishes models who produce false negatives over those that produce false positives. Including FN cost increases the accuracy of the ensemble and provides a better F_2 Measure.



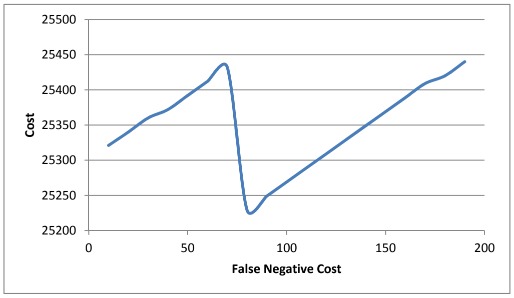


Figure 5.4. Accuracy by FN Cost

Figure 5.5. Total Cost by FN Cost

Table 5.5. Impact of FN Cost

	Accuracy	F_2 Measure
w/ FN Cost	0.55682	0.00159
w/o FN Cost	0.45195	0.00141

5.3.2 Unsupervised Learning

We next investigate the impact of parameters K (the ensemble size) and q (the number of normative substructures per model) on the classification accuracy and running times for our unsupervised approach. To more easily perform the larger number of experiments necessary to chart these relationships, we employ the smaller datasets summarized in Table 5.4 for these experiments. Dataset A consists of activity associated with user **`donaldh`** during weeks 2–8. This user displays malicious insider activity during the respective time period. This dataset evince similar trends for all relationships discussed henceforth; therefore we report only the details for dataset A throughout the remainder of the section.

Figure 5.6 shows the relationship between the cutoff q for the number of normative substructures and the running time in dataset A. Times increase approximately linearly until $q = 5$ because there are only 4 normative structures in dataset A. The search for a 5th structure therefore fails (but contributes running time), and higher values of q have no further effect.

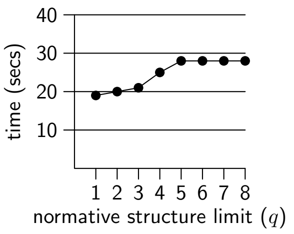


Figure 5.6. The effect of q on runtimes for fixed $K = 6$ on dataset A

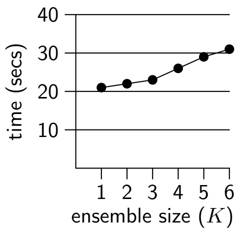


Figure 5.7. The effect of K on runtimes for fixed $q = 4$ on dataset A

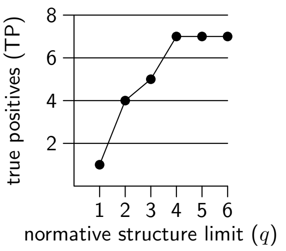


Figure 5.8. The effect of q on TP rates for fixed $K = 6$ on dataset A

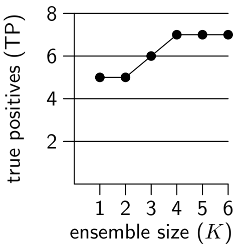


Figure 5.9. The effect of K on TP rates for fixed $q = 4$ on dataset A

Figure 5.7 shows the impact of ensemble size K and runtimes for dataset A. As expected, runtimes increase approximately linearly with the number of models (2 seconds per model on average in this dataset).

Increasing q and K also tends to aid in the discovery of true positives (TP). Figures 5.8 and 5.9 illustrate by showing the positive relationships of q and K, respectively, to TP. Once $q = 4$ normative substructures are considered per model and $K = 4$ models are consulted per ensemble, the classifier reliably detects all 7 true positives in dataset A. These values of q and K therefore strike the best balance between coverage of all insider threats and the efficient runtimes necessary for high responsiveness.

Increasing q to 4 does come at the price of raising more false alarms, however. Figure 5.10 shows that the false positive rate increases along with the true positive rate until $q = 4$. Dataset A has only 4 normative structures, so increasing q beyond this point has no effect. This is supported with $q = 4, 5, 6$ showing no increase in TP.

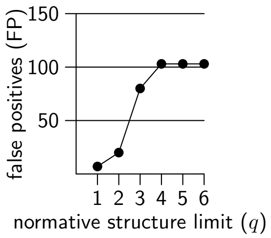


Figure 5.10. The effect of q on FP rates for fixed $K = 6$ on dataset A

Table 5.6. Impact of fading factor λ (weighted voting)

	$K = 2$		$K = 3$		$K = 4$	
	λ=1	λ=0.9	λ=1	λ=0.9	λ=1	λ=0.9
TP	10	10	10	10	14	14
FP	79	79	85	85	124	85
TN	96	96	90	90	51	90
FN	4	4	4	4	0	0

Table 5.6 considers the impact of weighted versus unweighted majority voting on the classification accuracy. The unweighted columns are those for $\lambda = 1$, and the weighted columns use fading factor $\lambda = 0.9$. The dataset consists of all tokens associated with user ID 2143. Weighted majority voting has no effect in these experiments except when $K = 4$, where it reduces the FP rate from 124 (unweighted) to 85 (weighted) and increases the TN rate from 51 (unweighted) to 90 (weighted). However, since these results can be obtained for $K = 3$ without weighted voting, we conclude that weighted voting merely serves to mitigate a poor choice of K; weighted voting has little or no impact when K is chosen wisely.

Table 5.7 gives a summary of our results comparing our supervised and unsupervised learning approaches. For example, on dataset A the supervised learning achieves much higher accuracy (71%) than the unsupervised learning (56%), while maintaining lower false positive rate (31%) and false negative rate (0%). On the other hand, unsupervised learning achieves 56% accuracy, 54% false positive rate and 42% false negative rate.

Table 5.7. Supervised vs. Non Supervised Learning Approach on dataset A

	Supervised	**Unsupervised**
False Positives	55	95
True Negatives	122	82
False Negatives	0	5
True Positives	12	7
Accuracy	0.71	0.56
False Positive Rate	0.31	0.54
False Negative Rate	0.0	0.42

CHAPTER 6

INSIDER THREAT DETECTION FOR SEQUENCE DATA

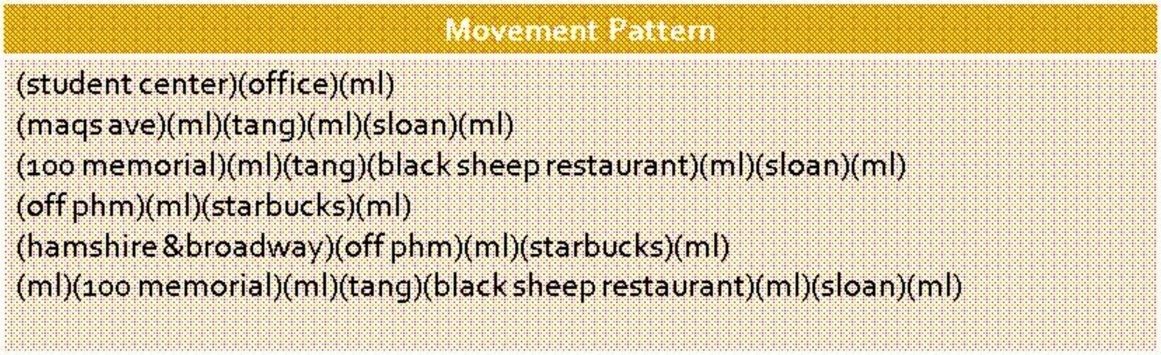
A sequence is an ordered list of objects (or events). Sequence contains members (also called elements, or terms). In a set, element order does not matter. On the other hand, in a sequence order matters, and hence, exactly the same elements can appear multiple times at different positions in the sequence (Qumruzzaman et al., 2013). For example, (U,T,D) is a sequence of letters with the letter 'U' first and 'D' last. This sequence differs from (D,T,U). The sequence (U,T,D,A,L,L,A,S), which contains the alphabet 'A' at two different positions, is a valid sequence. In the Figure 6.1 illustrates some sequence of movement pattern of a user. First row represents a particular user's one movement pattern sequence: student center, office, and ml. In this sequence, the user was first at student center and ml (media Lab) at last (Eagle and (Sandy) Pentland, 2006).

这里所说的序列数据指的是对象的有序排列，即考虑顺序的因素，但是不考虑元素的唯一性。

As the length of the sequence is defined as the number of ordered elements, sequence data can be finite or infinite in length. Infinite sequences are known as stream sequence data.

Insider threat detection related sequence data is stream based in nature. Sequence data may be gathered over time, maybe even years. In this case, we assume a continuous data stream will be converted into a number of chunks. For example, each chunk may represent a week and contain the sequence data which arrived during that time period.

Figure 6.2 demonstrates how the classifier decision boundary changes over time (from one chunk to next chunk). Data points are associated with two classes (normal and anomalous). In particular, a user command or a sub-sequence of commands may form a pattern/phrase which will be called here as data point. Non repetitive pattern/phrase for a user may form anomaly. There are three contiguous data chunks as shown in the Figure 6.2. The dark



Movement Pattern
(student center)(office)(ml)
(maqs ave)(ml)(tang)(ml)(sloan)(ml)
(100 memorial)(ml)(tang)(black sheep restaurant)(ml)(sloan)(ml)
(off phm)(ml)(starbucks)(ml)
(hamshire &broadway)(off phm)(ml)(starbucks)(ml)
(ml)(100 memorial)(ml)(tang)(black sheep restaurant)(ml)(sloan)(ml)

Figure 6.1. Example of Sequence Data related to Movement Pattern

straight line represents the decision boundary of its own chunk, whereas the dotted straight line represents the decision boundary of previous chunk. If there were no concept drift in the data stream, the decision boundary would be the same for both the current chunk and its previous chunk (the dotted and straight line). White dots represent the normal data (True Negative), blue dots represent anomaly data (True Positive), and striped dots represent the instances victim of concept drift.

We show the two different cases in the Figure 6.2 are as follows.

Case 1: the decision boundary of the second chunk moves upwards compared to that of the first chunk. As a result, more normal data will be classified as anomalous by the decision boundary of the first chunk, thus FP will go up. Recall that a test point having true benign (normal) category classified as an anomalous by a classifier is known as a FP.

Case 2: the decision boundary of the third chunk moves downwards compared to that of the first chunk. So, more anomalous data will be classified as normal data by the decision boundary of the first chunk, thus FN will go up. Recall that a test point having true malicious category classified as benign by a classifier is known as a FN.

In the more general case, the decision boundary of the current chunk can vary, which causes the decision boundary of the previous chunk to mis-classify both normal and anomalous data. Therefore, both FP and FN may go up at the same time.

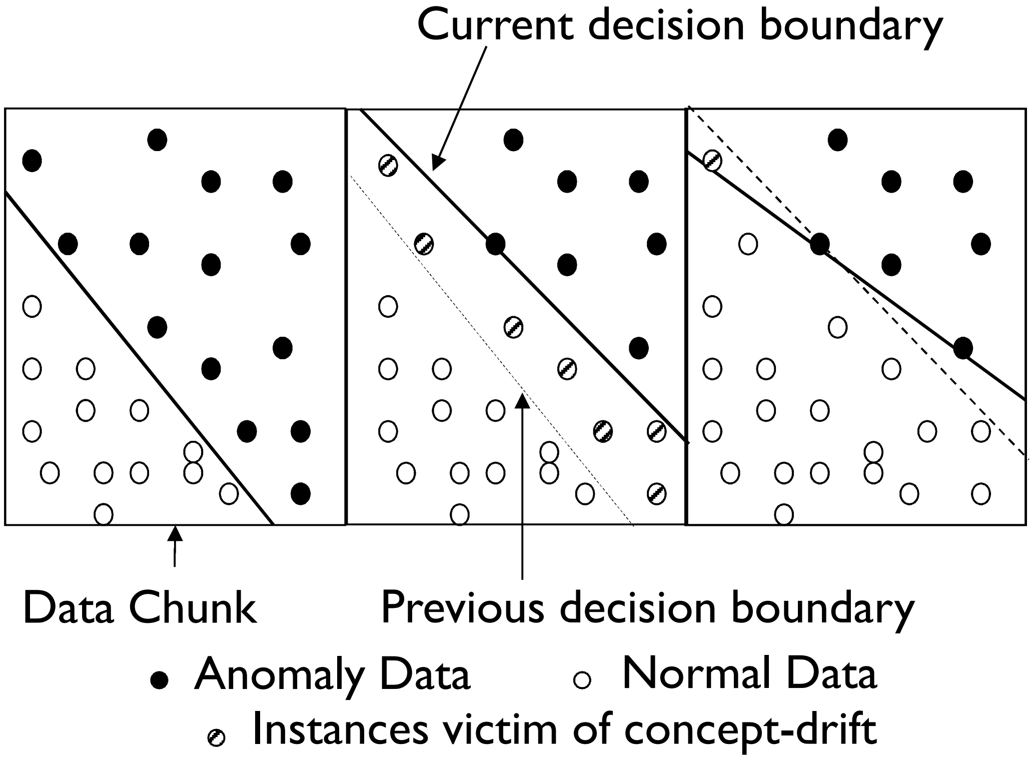

Current decision boundary
Data Chunk
Previous decision boundary
● Anomaly Data
○ Normal Data
⊘ Instances victim of concept-drift

Figure 6.2. Concept drift in stream data

This suggests that a model built from a single chunk will not suffice. This motivates the adoption of adaptive learning. In particular, we will exploit two approaches:

- Incremental Learning[1]: A single dictionary is maintained (Parveen and Thuraisingham, 2012). When a normative sequence pattern is learned from a chunk and it will be simply added to the dictionary. To find normative pattern we will exploit unsupervised stream based sequence learning (USSL). The incremental learning classification procedure is illustrated in Figure 6.3. Here, first from a new chunk patterns will be extracted and next these patterns will be merged with old quantized dictionary from previous chunks. Finally, new merged dictionary will be quantized in Figure 6.4.

[1] c 2012 IEEE. Reprinted, with permission, from Pallabi Parveen, Bhavani M. Thuraisingham: Unsupervised incremental sequence learning for insider threat detection. ISI 2012: 141-143

- Ensemble Learning[2]: A number of dictionaries are maintained (Parveen, McDaniel et al., 2012). In the ensemble we maintain K models. For each model, we maintain a single dictionary. Our ensemble approach, which classifies data using an evolving set of K models. The ensemble classification procedure is illustrated in Figure 6.5. Recall that we use unsupervised stream based sequence learning (USSL) to train models from an individual chunk. USSL identifies the normative patterns in the chunk and stores it in a quantized dictionary.

根据已有的研究成果，全局学习要比增量学习效果要好，因此这里选择采用全局学习。

In the literature (Masud, Chen, Gao, Khan, Aggarwal et al., 2010; Masud et al., 2011a; Masud, Gao et al., 2008) it shows that ensemble based learning is more effective than incremental learning. Here, we will focus on ensemble based learning.

To identify an anomaly, a test point will be compared against each model of the ensemble. Recall that a model will declare the test data as an anomalous based on how much the test differs from the model's normative patterns. Once all models cast their vote, we will apply majority voting to make the final decision as to whether the test point is an anomalous or not (as shown in Figure 3.2).

6.1 Model Update

We always keep an ensemble of fixed size models (K in that case). Hence, when a new chunk is processed, we already have K models in the ensemble and the $K + 1st$ model will be created from the current chunk. We need to update ensemble by replacing a victim model with this new model. Victim selection can be done in a number of ways. One approach is to calculate the prediction error of each model on the most recent chunk relative to the majority vote. Here, we assume *ground truth* on the most recent chunk is not available. If

[2] c 2012 IEEE. Reprinted, with permission, from Pallabi Parveen, Nate McDaniel, Varun S. Hariharan, Bhavani M. Thuraisingham, Latifur Khan: Unsupervised Ensemble Based Learning for Insider Threat Detection. SocialCom/PASSAT 2012: 718-727

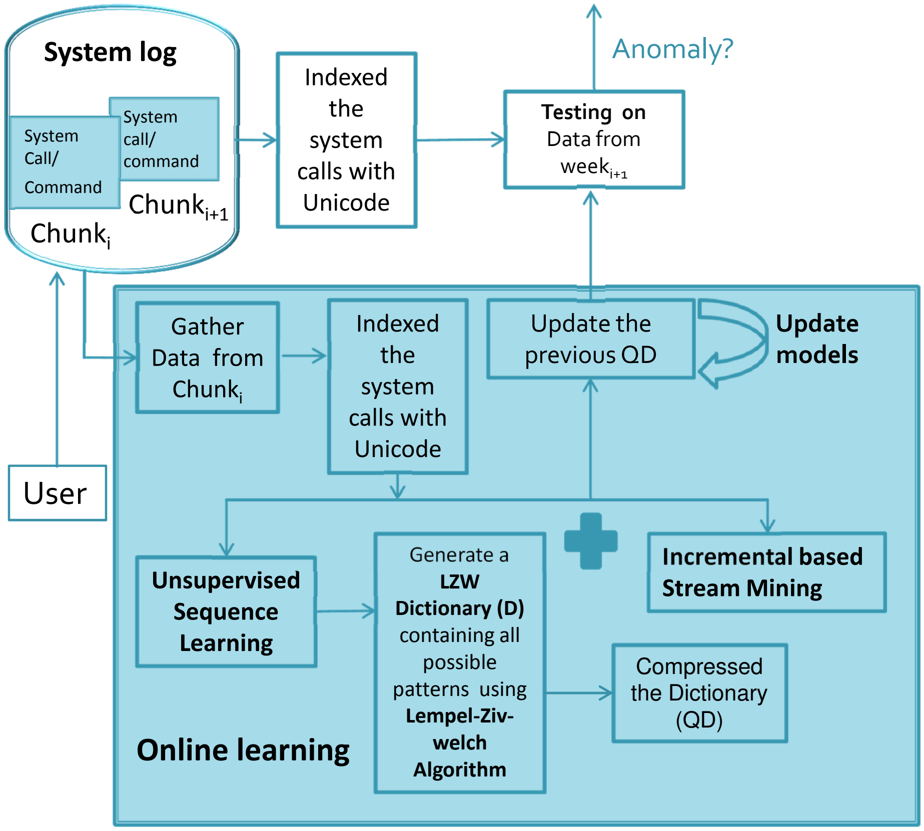

System log
System Call/ Command
System call/ command
Chunk$_{i+1}$
Chunk$_i$
Indexed the system calls with Unicode
Testing on Data from week$_{i+1}$
Anomaly?
User
Gather Data from Chunk$_i$
Indexed the system calls with Unicode
Update the previous QD
Update models
Unsupervised Sequence Learning
Generate a LZW Dictionary (D) containing all possible patterns using Lempel-Ziv-welch Algorithm
Incremental based Stream Mining
Compressed the Dictionary (QD)
Online learning

Figure 6.3. Unsupervised stream sequence learning using incremental learning

ground truth is available we can exploit this knowledge for training. The new model will replace the existing model from the ensemble which gives the maximum prediction error.

6.2 Unsupervised Stream based Sequence Learning (USSL)

Normal user profiles are considered to be repetitive daily or weekly activities which are frequent sequences of commands, system calls etc. These repetitive command sequences are called normative patterns. These patterns reveal the regular, or normal, behavior of a user. When a user suddenly demonstrates unusual activities that indicate a significant excursion from normal behavior an alarm is raised for potential insider threat.

正常的用户行为模式会重复一些多次使用的命令模式，因此当一个用户的行为突然偏离了这种模式的时候，就应当认为是潜在的内部攻击威胁。

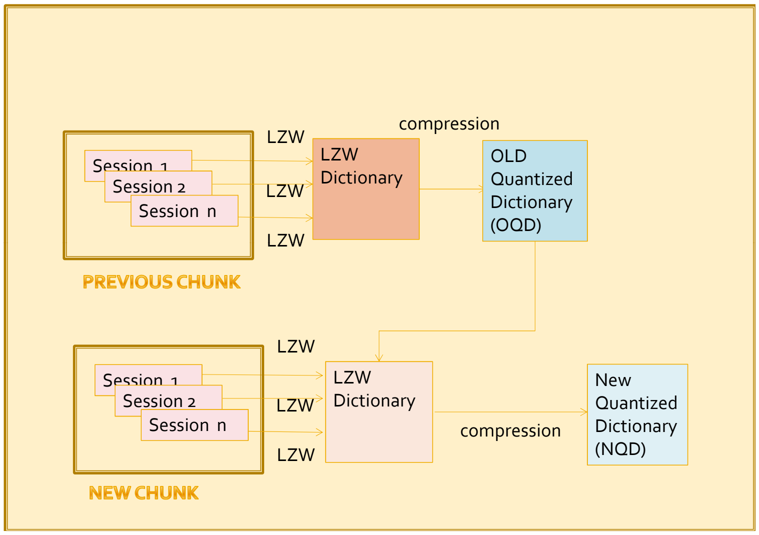


Figure 6.4. Details block diagram of incremental learning

So, in order to identify an insider threats, first we need to find normal user behavior. For that we need to collect sequences of commands and find the potential normative patterns observed within these command sequences in an unsupervised fashion. This unsupervised approach also needs to identify normal user behavior in a single pass. One major challenge with these repetitive sequences is their variability in length. To combat this problem, we need to generate a dictionary which will contain any combination of possible normative patterns existing in the gathered data stream. Potential variations that could emerge within the data include the commencement of new events, the omission or modification of existing events, or the reordering of events in the sequence. *Eg., liftliftliftliftliftcomcomecomecomecome-come,* is a sequence of commands represented by the alphabets given in a data stream. . We will consider all patterns *li,if,ft,tl, lif, ift, ftl, lift, iftl etc.*, as our possible normative patterns. However, the huge size of the dictionary presents another significant challenge.

We have addressed the above two challenges in the following ways. First, we extract possible patterns from the current data chunk using single pass algorithm (e.g., LZW, Lempel-Ziv-

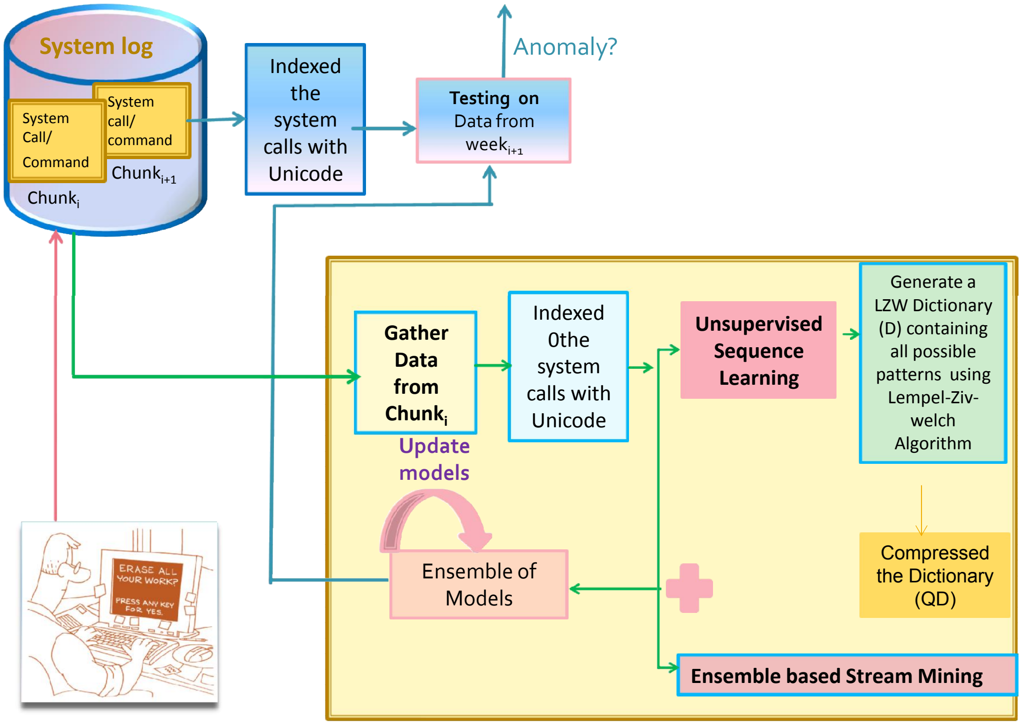

System log
System Call/ Command
System call/ command
Chunk$_i$
Chunk$_{i+1}$
Indexed the system calls with Unicode
Testing on Data from week$_{i+1}$
Anomaly?
Gather Data from Chunk$_i$
Indexed 0the system calls with Unicode
Unsupervised Sequence Learning
Generate a LZW Dictionary (D) containing all possible patterns using Lempel-Ziv-welch Algorithm
Update models
Ensemble of Models
Compressed the Dictionary (QD)
Ensemble based Stream Mining
ERASE ALL YOUR WORK? PRESS ANY KEY FOR YES

Figure 6.5. Ensemble based unsupervised stream sequence learning

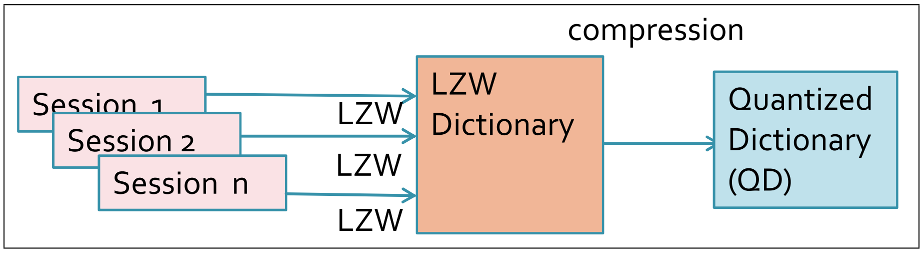


Figure 6.6. Unsupervised Stream based Sequence Learning(USSL)from a chunk in Ensemble based case

Welch algorithm (Ziv and Lempel, 1977)) to prepare a dictionary. We called it LZW dictionary. LZW dictionary has a set of patterns and their corresponding weights according to

$$w_i = \frac{f_i}{\sum_{i=1}^{n} f_i} \tag{6.1}$$

where w_i is the weight of a particular pattern p_i in the current chunk, f_i is the number of times the pattern p_i appears in the current chunk and n is the total number of distinct patterns found in that chunk.

Next, we compress the dictionary by keeping only the longest, frequent unique patterns according to their associated weight and length, while discarding other subsumed patterns. This technique is called compression method (CM) and the new dictionary is a Quantized dictionary (QD). The Quantized dictionary has a set of patterns and their corresponding weights. Here, we use edit distance to find the longest pattern. Edit distance is a measure of similarity between pairs of strings (Borges et al., 2011; Vladimir, 1966). It is the minimum number of actions required to transfer one string to another, where an action can be substitution, addition or deletion of a character into the string. As in case of the earlier example mentioned, the best normative pattern in the quantized dictionary would be lift, come etc.

This process is a lossy compression, but is sufficient enough to extract the meaningful normative patterns. The reason behind this is the patterns that we extract are the superset of the subsumed patterns. Moreover, as frequency is another control parameter in our experiment, the patterns which do not appear often cannot be regular user patterns.

Data relevant to insider threat is typically accumulated over many years of organization and system operations, and is therefore best characterized as an unbounded data stream. As our data is a continuous stream of data, we use ensemble based learning to continuously update our compressed dictionary. This continuous data stream is partitioned into a sequence of discrete chunks. For example, each chunk might be comprised of a day or weeks worth of data and may contain several user sessions. We generate our Quantized dictionary (QD) and

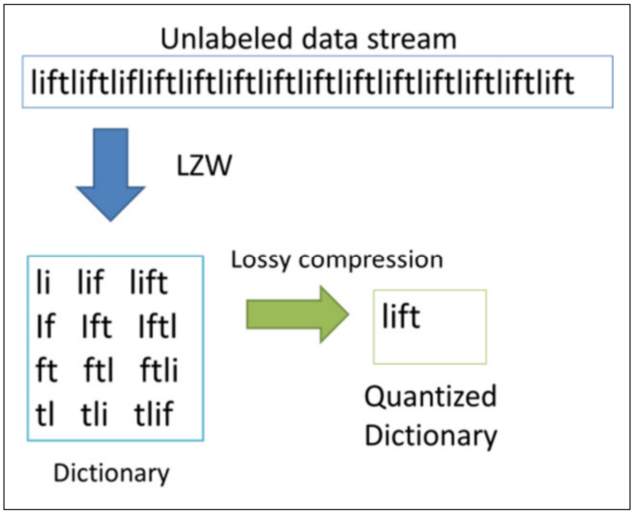


Figure 6.7. Quantization of dictionary

their associated weight from each chunk. Weight is measured as the normalized frequency of a pattern within that chunk.

When a new chunk arrives we generate a new Quantized dictionary (QD) model and update the ensemble as mentioned earlier. Figure 6.6 shows the flow diagram of our *dynamic*, Ensemble based, Unsupervised Stream Sequence Learning method.

Algorithm 4 shows the basic building block for updating the Ensemble. Algorithm 4 takes the most recent data chunk S, ensemble E and test chunk T. Lines 3 to 4 generate a new Quantized Dictionary model from the most recent chunk S and temporarily add it to the ensemble E. Lines 5 to 9 test chunk T for anomalies for each model in the ensemble. Lines 13 to 24 find and label the anomalous patterns in test Chunk T according to the majority voting of the models in the ensemble. Finally, line 29 updates the ensemble by discarding the model with lowest accuracy. An arbitrary model is discarded in the case of multiple models having the same low performance.

6.2.1 Construct the LZW dictionary by selecting the patterns in the data stream

针对系统调用命令序列，利用LZW方法提取出命令序列字典，如ls简写为l，cp简写为c，find简写为f等，得到的命令序列字典类似于li,if,ft,lif,..

At the beginning, we consider that our data is not annotated (i.e., unsupervised). In other words, we don't know the possible sequence of future operations by the user. So, we use LZW algorithm (Ziv and Lempel, 1977) to extract the possible sequences that we can add to our dictionary. These can also be commands like *liftliftliftliftliftcomcomecomecomecomecome,* where each unique letter represents a unique system call or command. We have used Unicode to index each command. E.g., ls, cp, find are indexed as *l*, *c*, and *f*. The possible patterns or sequences are added to our dictionary would be *li*, *if,ft,tl*, *lif,ift*, *ftl*, *lift*, *iftl*, *ftli*, *tc*, *co*, *om*, *mc,com*, *come* and so on. When the sequence *li* is seen in the data stream for the second time, in order to avoid repetition it will not be included in the LZW dictionary. Instead, we increase the frequency by 1 and extend the pattern by concatenating it with the next character in the data stream, thus turning up a new pattern *lif*. We will continue the process until we reach the end of the current chunk. Figure 6.7 demonstrates how we generate an LZW dictionary from the data stream.

6.2.2 Constructing the Quantized Dictionary

LZW字典中只保留出现频率最高的模式，然后针对每个模式，寻找与其距离为1的模式，在其中再保存权重*长度的积最大的模式。不断重复直到找到所有的模式。

Once we have our LZW dictionary, we keep the longest and most frequent patterns and discard all their subsumed patterns. Algorithm 5 shows step by step how a quantized dictionary is generated from LZW dictionary. Inputs of this algorithm are as follows: LZW dictionary D which contains a set of patterns P and their associated weight W. Line 5 picks a pattern (e.g., li). Lines 7 to 9 find all the closest patterns that are 1 edit distance away. Lines 13 to 16 keep the pattern which has the highest weight multiplied by its length and discard the other patterns. We repeat the steps (line 5 to 16) until we find the longest, frequent pattern (*lift*). After that, we start with a totally different pattern (*co*) and repeat the steps until we have explored all the patterns in the dictionary. Finally, we end up with a more compact

Algorithm 4 Update the Ensemble

```
Input: $E$ (ensemble), $T$ (test chunk), $S$ (chunk)
Output: $E'$ (updated ensemble)
$M' \leftarrow \text{NewModel}(S)$
$E' \leftarrow E \cup \{M'\}$
for each model $M$ in ensemble $E$ do
    $A_M \leftarrow T$
    for each pattern $p$ in $M$ do
        if $EditDistance(x, p) \leq \alpha = \frac{1}{3}$ of length then
            $A_M = A_M - x$
        end if
    end for
end for
for each candidate $a$ in $\bigcup_{M \in E'} A_M$ do
    if $round(WeightedAverage(E', a)) = 1$ then
        $A \leftarrow A \cup \{a\}$
        for each model $M$ in ensemble $E'$ do
            if $a \in A_M$ then
                $c_M \leftarrow c_M + 1$
            end if
        end for
    else
        for each model $M$ in ensemble $E'$ do
            if $a \notin A_M$ then
                $c_M \leftarrow c_M + 1$
            end if
        end for
    end if
end for
$E' \leftarrow E' - \{choose(\arg\min_M(c_M))\}$
```

Algorithm 5 Quantized Dictionary

```
Input: $D = \{Pattern, Weight\}$ (LZW Dictionary)
Output: $QD$ (Quantized Dictionary)
$Visited \leftarrow 0$
while $D \neq 0$ do
    $X \leftarrow D_j \mid j \notin Visited, D_j \in D$
    $Visited \leftarrow Visited \cup j$
    for each pattern $i$ in $D$ do
        if $EditDistance(X, D_i) = 1$ then
            $P \leftarrow P \cup i$
        end if
    end for
    $D \leftarrow D - X$
    if $P \neq 0$ then
        $X \leftarrow choose(\arg\max_i(w_i \times l_i)) \mid l_i = Length(P_i), w_i = Weight(P_i), P_i \in P$
        $QD \leftarrow QD \cup X$
        $D \leftarrow D - P$
    end if
    $X \leftarrow D_j \mid j \notin Visited, D_j \in D$
    $Visited \leftarrow Visited \cup j$
end while
```

dictionary which will contain many meaningful and useful sequences. We call this dictionary our quantized dictionary. Figure 6.7 demonstrates how we generate a quantized dictionary from the LZW dictionary.

Once, we identify different patterns *lift*, *come*, etc., any pattern with $X\%(\geq \%30$ in our implementation) deviation from all these patterns would be considered as anomaly. Here, we will use edit distance to identify the deviation.

6.3 Anomaly Detection (Testing)

Given a quantized dictionary, we need to find out the sequences in the data stream which may raise a potential threat. To formulate the problem, given the data stream S and Ensemble E where $E = QD_1, QD_2, QD_3, ...$ and $QD_i = qd_{i1}, qd_{i2}, ...$, any pattern in the data stream is considered as an anomaly if it deviates from all the patterns qd_{ij} in E by more than

Table 6.1. Time Complexity of Quantization Dictionary Construction

Description	**Time Complexity**
Pair of Patterns	$O(n^2 \times K^2)$
u number of user	$O(u \times n^2 \times K^2)$

$X\%(say > 30\%)$. In order to find the anomalies, we need to first find the matching patterns and delete those from the stream S. In particular, we find the pattern from the data stream S that is an exact match or α edit distance away from any pattern, qd_{ij} in E. This pattern will be considered as matching pattern. α can be half, one-third or one-fourth of the length of that particular pattern in qd_{ij}. Next, remaining patterns in the stream will be considered as anomalies.

In order to identify the non matching patterns in the data stream S, we compute a distance matrix L which contains the edit distance between each pattern, qd_{ij} in E and the data stream S. If we have a perfect match, i.e., edit distance 0 between a pattern qd_{ij} and S, we can move backwards exactly the length of qd_{ij} in order to find the starting point of that pattern in S and then delete it from the data stream. On the other hand, if there is an error in the match which is greater than 0 but less than α, in order to find the starting point of that pattern in the data stream, we need to traverse either left, or diagonal or up within the matrix according to which one among the mentioned value *(L[i,j-1], L[i-1,j-1], L[i-1,j])* gives the minimum respectively. Finally, once we find the starting point, we can delete that pattern from the data stream. The remaining patterns in the data stream will be considered as anomalous.

6.4 Complexity Analysis

Here, we will report time complexity of quantized dictionary construction. In order to calculate edit distance between two patterns of length K (in worst case maximum length would be K), our worst case time complexity would be $O(K^2)$.

Suppose we have n patterns in our LZW dictionary. We have to construct quantized dictionary from this LZW dictionary. In order to do this, we need to find patterns in LZW dictionary which have 1 edit distance from a particular pattern (say p). We have to calculate edit distance between all the patterns and the pattern p. Recall that time complexity to find edit distance between two patterns is $O(K^2)$. Since there are total n number of distinct patterns, total time complexity between p and the rest of patterns is $O(n \times K^2)$. Note that p is one of the member of n patters. Therefore, total time complexity between pair of patterns is $O(n^2 \times K^2)$. This is valid for a single user. If there is u of distinct users, total time complexity across u user is $O(u \times n^2 \times K^2)$ (see Table 6.1)

CHAPTER 7

EXPERIMENTS AND RESULTS FOR SEQUENCE DATA

Here, first we will present sequence dataset that we used for experiment. Second, we present how we inject concept drift in the dataset. Finally, we present results showing anomaly detection rate in the presence of concept drift[1].

7.1 Dataset

对于序列数据的测试我们采用了Calgary大学的一个项目，获取到来自168个不同的unix用户的命令痕迹文件。用户分为四组人，业余程序员、专家程序员、计算机科学家以及非程序员。由于现实中的行为模式偏移很难人工实现，因此我们这里采用一种代替。即业余程序员的命令行为会越来越接近于专业程序员，我们来测试这种行为模式的偏移。

The data sets used for training and testing have been created from Trace Files got from the University of Calgary project (Greenberg, 1988). As a part of that, 168 trace files were collected from 168 different users of Unix csh. There were 4 groups of people, namely novice-programmers, experienced-programmers, computer-scientists, non-programmers. The model that we have tried to construct is that of a novice-programmer who has been gaining experience over the weeks and is gradually using more and more command sequences similar to that of an experienced user. These gradual normal behavior changes will be known here as concept-drift. Anomaly detection in the presence of concept drift is difficult to achieve. Hence, our scenario is more realistic. This is a slow process that takes place over several weeks.

The Calgary dataset (Greenberg, 1988) as described above was modified by Maxion et al. (Maxion, 2003) for masquerade detection. Here we followed the same guidelines to inject masquerades commands. From the given list of users, those users who have executed more than 2400 commands (that did not result in an error) were filtered out to form the valid-user

[1] c 2012 IEEE. Reprinted, with permission, from Pallabi Parveen, Nate McDaniel, Varun S. Hariharan, Bhavani M. Thuraisingham, Latifur Khan: Unsupervised Ensemble Based Learning for Insider Threat Detection. SocialCom/PASSAT 2012: 718-727

Table 7.1. Description of Dataset

Description	Number
# of valid users	37
# of invalid users	131
# of valid commands per user	2400
# of anomalous commands in testing chunks	300

pool. This list had 37 users. The remaining users were part of the invalid-user pool. Out of the list of invalid-users, 25 of them were chosen at random and a block of one hundred commands from the commands that they had executed were extracted and put together to form a list of 2500 (25 * 100) commands. The 2500 commands were brought together as 250 blocks of 10 commands each. Out of these 250 blocks, 30 blocks were chosen at random as the list of masquerade commands (300 commands). For each user in the valid users list, the total number of commands was truncated to 2400. These 2400 commands were split into 8 chunks of 300 commands each. The first chunk was kept aside as the training chunk (this contains no masquerade data). The other 7 chunks are the testing chunks. In the testing chunks, a number of masquerade data blocks (each block comprising of 10 commands) were inserted at random positions. As a result, for each user, we have one training chunk with 300 commands (no masquerade data) and seven testing chunks which together have 2100 non-anomalous commands and 300 masquerade commands (see Table 7.1 and Figure 7.1).

7.2 Concept Drift in the training set

Here, we present a framework for concept drift with the goal of introducing artificial drift into data generators. First, we generate a number of chunks having normal and anomalous sequences as described above. Note that the above process does not take into account concept drift. Next, we take sequences of each chunk as input and generate a new sequence with a particular drift for that chunk. New sequences will have concept drift property. The framework processes each training example of user commands once and only once to produce

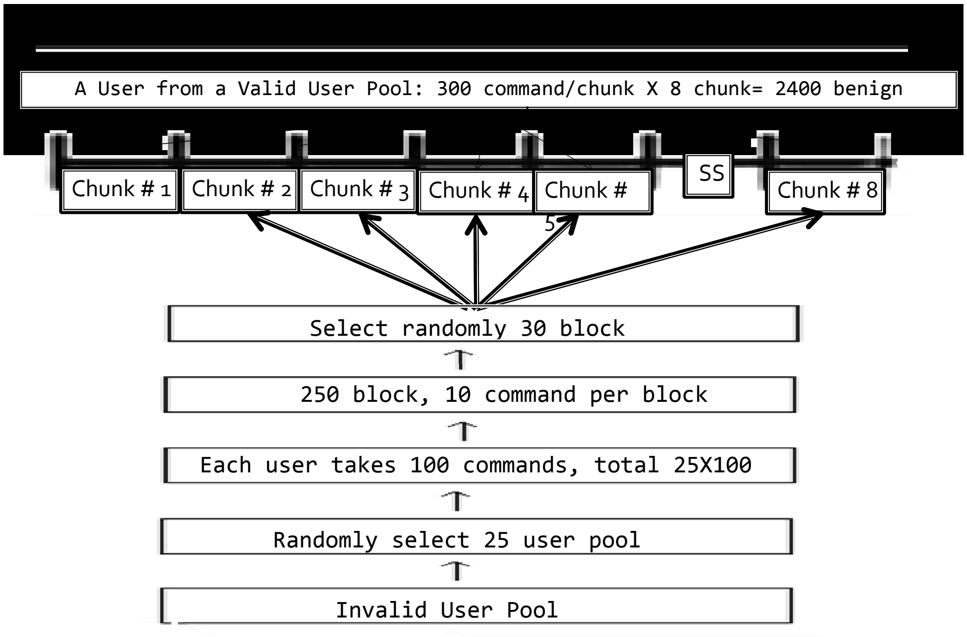

A User from a Valid User Pool: 300 command/chunk X 8 chunk= 2400 benign
Chunk # 1
Chunk # 2
Chunk # 3
Chunk # 4
Chunk # 5
SS
Chunk # 8
Select randomly 30 block
250 block, 10 command per block
Each user takes 100 commands, total 25X100
Randomly select 25 user pool
Invalid User Pool

Figure 7.1. Pictorial Representation for Anomalous Data Generation Process

variation predictions at any time. The framework is passed the next available sequence of commands (say thousand commands for a chunk) from the user data. The framework then processes these commands, updating the data structures with distribution and bounded concept drift variance. The framework is then ready to process the next set of commands, and upon request can produce predicted variants based on the concept drift.

The data being passed into the framework is a set number of commands from different users in sequential order of execution by the user. Although commands are passed into the framework in large groups, each command is treated as an individual observation of that persons behavior. To calculate predicted variations the following drift formula is used (Kranen et al., 2012):

$$drift = \sqrt{\frac{\log \frac{1}{\delta}}{2 \times d \times n}} \tag{7.1}$$

where δ is the variation constant, d is the current distribution of the command over the current number of individual observations, and n is the number of current observations made. A good value for the variation constant is $1 * 10^{-5}$. The variation constant shares an inverse relation to the overall drift values. The expected range in distribution among produced variations is calculated by adding and subtracting the calculated drift from the current distribution.

Upon the processing of a sample of user commands, predicted variations can be produced by the framework upon request. The request can be made of any designated size and the concept drift will provide new distributions that fall within the range of the calculated drift for a set of commands of this size. The produced set of commands or new ones can be used to update the concept drift and provide for a constantly evolving command distribution that represents an individual. Sudden changes that do not fit within a calculated concept drift can be flagged as suspicious and therefore, possibly representative of an insider threat.

Algorithm 6 shows how the distribution is calculated for a set of commands and how the predicted variation is produced. As an example we take ten commands, instead of one thousand per chunk, such that we have $[C_1, C_2, C_1, C_2, C_3, C_1, C_4, C_5, C_1, C_1]$. The distributions will be $[C_1 = .5, C_2 = .2, C_3 = .1, C_4 = .1, C_5 = .1]$. With a value of $\delta = 1 * 10^{-5}$ the *Predicted Variance* for each command comes out as

$$C_1 = \sqrt{\frac{\log \frac{1}{1*10^{-5}}}{2 * .5 * 10}} \approx .7071 \# of occurance \tag{7.2}$$

We divide by the number of observation occurrences, in this case 10, because we want the concept drift per occurrence, not just for a sample of 10. Our predicted variation (PV) values are $[C_1 \approx .07071, C_2 \approx .11180, C_3 \approx .15811, C_4 \approx .15811, C_5 \approx .15811]$. The adjusted Min/Max Drift comes out to be $[C_1 = .42929/.57071, C_2 = .08820/.31180, C_3 = 0/.25811, C_4 = 0/.25811, C_5 = 0/.25811]$.

From these drift values we can produce a requested predicted variation for another 10, or any number of, user command values. We look at the original sequence and assemble

Algorithm 6 Concept Drift in Sequence Stream

```
Input: $F$ (file), (size of PV)
Output: $PV$, (prediction variation)
for each command $C \in F$ do
    $D_C \leftarrow distribution(C)$
    $V_C \leftarrow variation(D_C)$
    $MaxDrift_C \leftarrow D_C + V_C$
    $MinDrift_C \leftarrow D_C - V_C$
end for
$PV \leftarrow newPredictedVariation()$
for each command $C \in F$ do
    if $D_C < MinDrift_C$ then
        $PV \leftarrow PV \cup C$
    else
        if $D_C + 1 < MaxDrift_C$ then
            $flipCoin(PV \leftarrow PV \cup C)$
        else
            $discard(C)$
        end if
    end if
end for
```

at least the minimum drift value worth of commands in the variation. In this example the first value is C_1 with a minimum of .42929 distribution. So we add it, bringing its current distribution to 1/10 or .1. This is the case for the first 3 values resulting in $[C_1, C_2, C_1]$. The fourth value is C_2 who has met its minimum distribution drift. Adding it will not go over the maximum distribution so it is either randomly added or not. The new predicted variation could look like $[C_1, C_2, C_1, C_2, C_1, C_1, C_1, C_2, C_3, C_4]$ or $[C_1, C_2, C_1, C_3, C_1, C_4, C_1, C_5, C_3, C_1]$ of which both have command distributions similar to the original that fall within the new variance bounds.

We compare our approach, USSL, with a supervised method modified from the baseline approach suggested by Maxion (Maxion, 2003), which uses Naive Bayes' classifier (NB). The modified version compared in this dissertation is more incremental in its model training, and thus will be referred to as *NB-INC*. All instances of both algorithms were tested using

8 chunks of data. At every test chunk the NB-INC method uses all previously seen chunks to build the model and train for the current test chunk. For test chunk 3, NB builds the classification model and trains on chunks 1 and 2. For test chunk 5 NB builds a model and collectively trains on chunks 1 through 4.

These USSL statistics are gathered in a ”Grow as you Go” (GG) fashion. This is to say that, as the ensemble size being used grows larger the amount of test chunks to go through decreases. For an ensemble size of 1, models are built from chunk 1 and chunks 2 through 8 are considered testing chunks. For an ensemble size of 3, chunks 4 through 8 are considered to be testing chunks. Every new chunk, starting at 4 in this case, is used to update the models in each ensemble after a majority vote is reached and the test data is classified as an anomaly or not. To clarify, in the example of ensemble size of 3 after the new model is built, all models vote on the possible anomaly and contribute to deciding which model is considered the least accurate and thus discarded. However, only models that have survived an elimination round (i.e. deemed not to be least accurate at least once) are used to measure the FP, TP, FN, and TN for an ensemble. In particular, at chunk 4, the ensemble has 3 models from chunk 1, 2, and 3. From chunk 4, new model is built. During elimination round, chunk 3 is eliminated based on accuracy. In other words, at chunk 4, ensemble will have models created from chunks 1, 2, and 4 but not 3.

The model updating process makes use of compression and model replacement. After models are updated the least accurate one is discarded to maintain the highest accuracy and maintain the status quo, since a new model is created before every update and anomaly classification step. There are other ways of updating models and selecting chunks for testing during the classification process not explored in this dissertation. For this purpose, the limited USSL method used for the shown results will be referred to as *USSL-GG*.

7.3 Result

We have compared the NB and USSL-GG algorithms on the basis of true positive rate(TPR), false positive rate(FPR), execution time, accuracy, F_1 measure, and F_2 measure. TPR and FPR as measured by

$$TPR = \frac{true\ positives}{true\ positives + false\ negatives} \tag{7.3}$$

$$FPR = \frac{false\ positives}{false\ positives + true\ negatives} \tag{7.4}$$

are the rates at which actual insider threats are correctly and incorrectly identified by the algorithm. For these calculations a true positive(TP) is an identified anomaly that is actually an anomaly, a true negative(TN) is an identified piece of normal data that is not an anomaly, a false positive(FP) is an identified anomaly that is actually just normal data, and a false negative(FN) is an identified piece of normal data that is actually an anomaly.

Accuracy better measures the algorithms ability to pick out correct and incorrect insider threat instances on a whole. F_1 and F_2 measure are weighted variables calculated from the generic equation 7.6 that penalize for incorrectly identified insider threats (FP) and positive threats that were not identified (FN). The F_1 measure penalizes FP and FN equally while the F_2 measure penalizes FN much more. These values are calculated by

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{7.5}$$

$$F_n = \frac{(1 + n^2)TP}{(1 + n^2)TP + (n^2)FN + FP} \tag{7.6}$$

and represent important parameters in catching insider threats.

Tables 7.2, 7.3 and 7.4 show the details of the value comparisons between NB-INC and USSL-GG for various drift values. USSL-GG has lower FPR and runtime values and higher everything else than NB-INC across the board. USSL-GG runs faster with less false threat identifications while maintaining higher success rates at catching real threats than NB-INC.

Table 7.2. NB-INC vs. USSL-GG for various drift values on TPR and FPR

Drift	TPR for NB-INC	TPR for USSL-GG	FPR for NB-INC	FPR USSL-GG
0.000001	0.34	**0.49**	0.12	**0.10**
0.00001	0.36	**0.58**	0.12	**0.09**
0.0001	0.37	**0.51**	0.11	**0.10**
0.001	0.38	**0.50**	0.11	**0.10**

Table 7.3. NB-INC vs. USSL-GG for various drift values on Accuracy and runtime

Drift	Acc for NB-INC	Acc for USSL-GG	time for NB-INC	time for USSL-GG
0.000001	0.80	**0.85**	52.0	**3.60**
0.00001	0.79	**0.87**	50.8	**3.54**
0.0001	0.82	**0.86**	51.0	**3.55**
0.001	0.81	**0.85**	53.4	**3.60**

Table 7.4. NB-INC vs. USSL-GG for various drift values on F_1 and F_2 Measure

Drift	F_1Msr for NB-INC	F_1Msr for USSL-GG	F_2Msr for NB-INC	F_2Msr for USSL-GG
0.000001	0.34	**0.44**	0.34	**0.47**
0.00001	0.36	**0.50**	0.36	**0.54**
0.0001	0.37	**0.45**	0.37	**0.49**
0.001	0.38	**0.44**	0.38	**0.47**

The USSL-GG data in tables 7.2, 7.3 and 7.4 are for its optimum results at ensemble size 3, which will be shown why this is optimal later.

With our optimization results for USSL-GG we make our final comparison with NB. Figures 7.2 and 7.3 show the TPR and FPR respectively. USSL-GG maintains higher TPR and lower FPR than NB-INC.

7.3.1 Choice of Ensemble Size

In Figure 7.4, we show the various concept drifts and ensemble sizes of USSL-GG compared in terms of TPR. As ensemble size increases, TPR decreases. This is not desired. In Figure 7.5 we show the same set of concept drifts and ensemble sizes compared in terms of FPR. We can see a steady decrease in TPR across all drifts as ensemble size increases. However, we

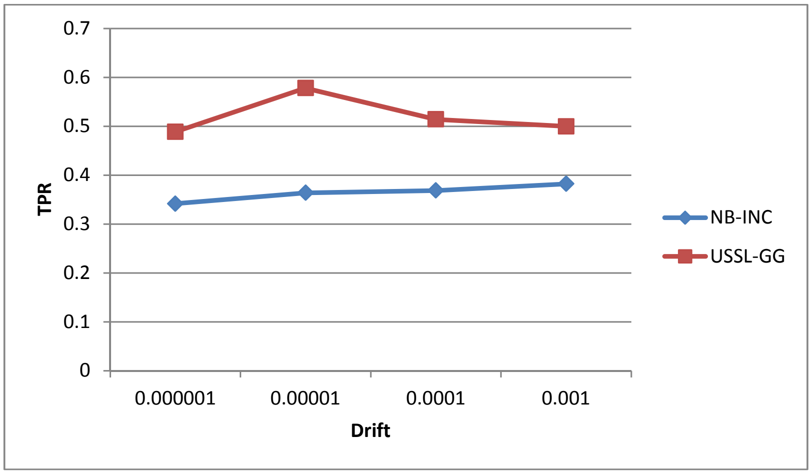


Figure 7.2. Comparison between NB-INC vs. our optimized model, USSL-GG in terms of TPR

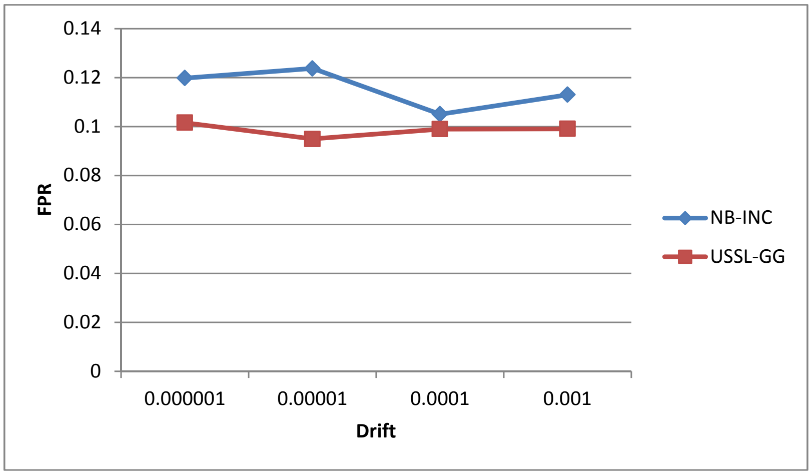


Figure 7.3. Comparison between NB-INC vs. our optimized model, USSL-GG in terms of FPR

see a much larger decrease in FPR from ensemble size 1 to 2 and from 2 to 3 than from 3 to 4 and 4 to 5 across all drift values. As ensemble size increases we achieve a desired lower FPR at the expense of also lowering TPR.

In Figure 7.6, we show that when considering the rate at which positive and negative instances are correctly identified without punishing the algorithms for wrong classifications with the accuracy metric, USSL-GG performs better as ensemble size increases. Figure 7.7

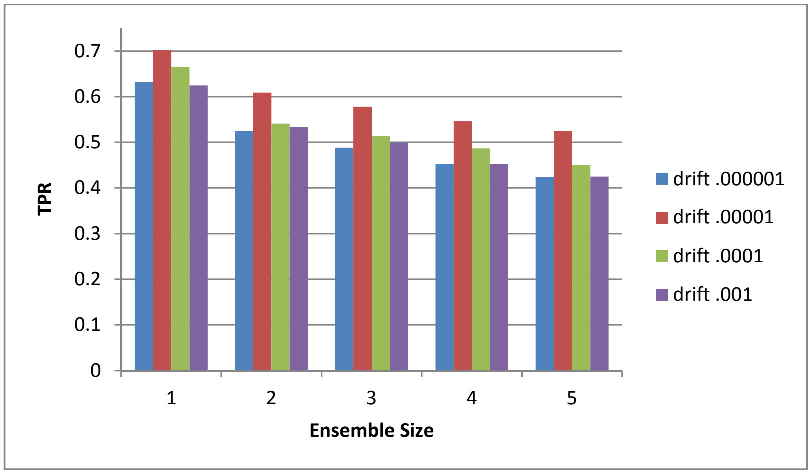


Figure 7.4. Comparison of USSL-GG across multiple drifts and ensemble sizes in terms of TPR

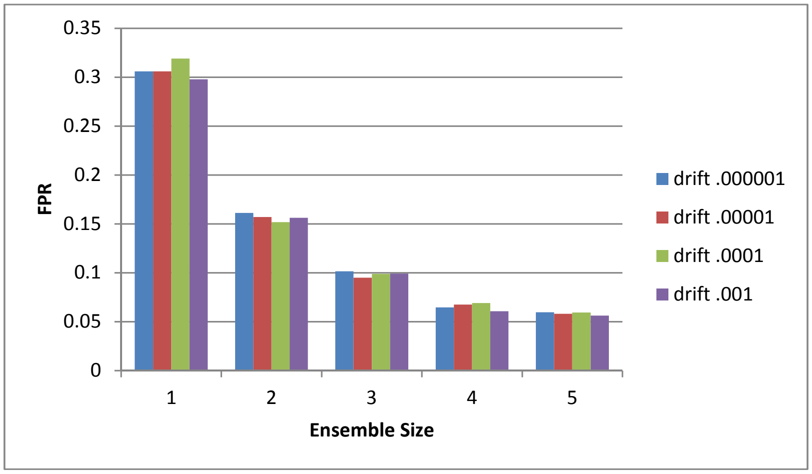


Figure 7.5. Comparison of USSL-GG across multiple drifts and ensemble sizes in terms of FPR

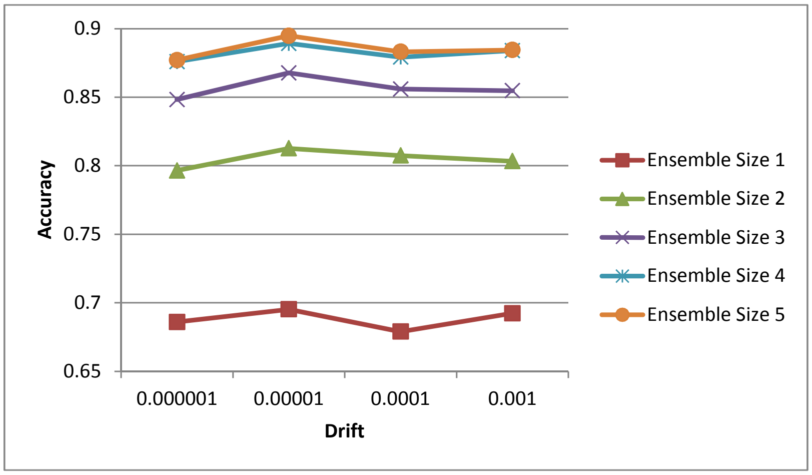


Figure 7.6. Comparison of USSL-GG across multiple drifts and ensemble sizes in terms of Accuracy

shows F_1 Measure and Figure 7.8 shows F_2 Measure. With these two figures, we can see that USSL-GG performs better as ensemble size increases until size 4 or 5. This is due to F measure values penalizing missed insider threats and wrongly classifying harmless instances as threats. It does not give any direct bonuses for how many threats are correctly identified. This is important in insider threat detection because missing even one insider threat can be very detrimental to the system you are protecting. Wrongly classifying harmless instances are not as important, but they add the increased problem of having to double check detected instances. In Figure 7.8, we show a decrease in F_2 Measure after ensemble size 3. This makes USSL-GG most effective at ensemble size 3 because F_2 Measure penalizes false negatives more than the false positives and low FN is the most important part of insider threat detection as stated previously. This makes our final optimization of USSL-GG to include ensemble size 3. With an ensemble size of 3, it is also worthy noting that run times are slower than that of ensemble sizes 1 or 2. For ensemble sizes greater than 3 the run times grow exponentially. These greatly increased times are not desired and therefor ensemble sizes such as 4 or 5 are not optimal.

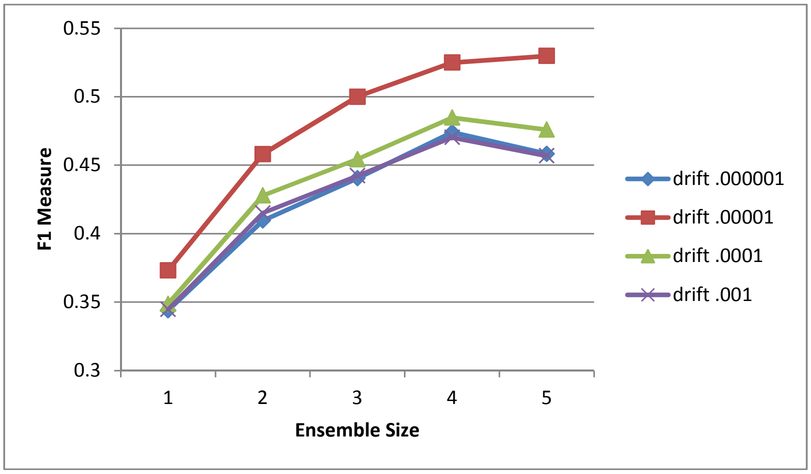


Figure 7.7. Comparison of USSL-GG across multiple drifts and ensemble sizes in terms of F1 measure

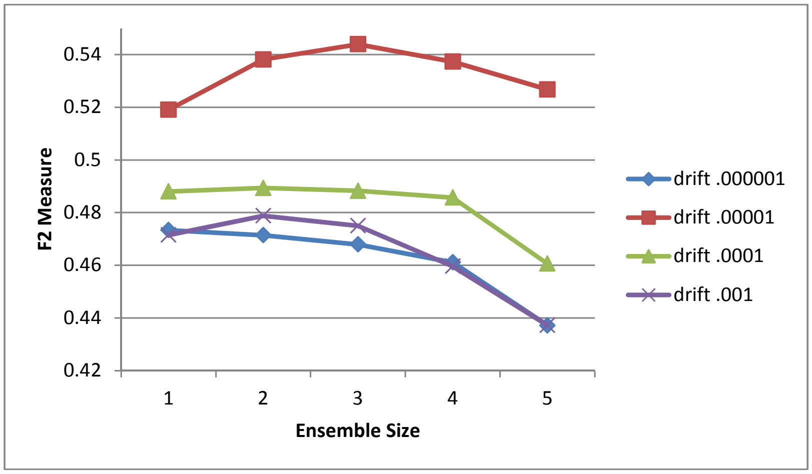


Figure 7.8. Comparison of USSL-GG across multiple drifts and ensemble sizes in terms of F2 measure

CHAPTER 8

SCALABILIY USING HADOOP AND MAPREDUCE

Construction of LZW dictionary and quantized dictionary is time consuming. We would like to address scalability issues of these algorithms. One possible solution is to adopt parallel/distributed computing. Here, we would like to exploit cloud computing based on commodity hardware. Cloud computing is a distributed parallel solution. For our approach, we utilize Hadoop and MapReduce based framework to facilitate parallel computing.

This chapter will be organized in the following ways. First, we will introduce Hadoop Map Reduce(see section 8.1). Second, we will propose scalable LZW and quantized dictionary construction algorithm using Map Reduce (MR) (see section 8.2). Finally, we will present details results of various MR algorithms for the construction of quantized dictionary (see section 8.3).

8.1 Hadoop Map Reduce Background

Hadoop MapReduce is a software framework that stores large volumes of data using large clusters and retrieves relevant data in parallel from large clusters. Those large clusters are built on a commodity hardware in a reliable fault-tolerant manner.

A map reduce job usually splits input data into a number of independent chunks. These independent chunks will be run by map tasks in a parallel manner across clusters. Map tasks emit intermediate key value pairs. The framework sorts output of the maps based on intermediate keys and passes these sorted intermediate key value pairs to the reducer. The reducer accepts the intermediate key and a list of values. Intermediate (key, value) pairs having the same key will be directed to the same reducer. In other words, intermediate (key, value) pairs having the same key cannot go to different reducers. However, Intermediate (key, value) pairs having different key may end up at the same reducer.

In general, both the input and the output of the job are stored in a Hadoop distributed file system (HDFS). Compute node is a node where map and reduce tasks are run. Storage node is a node where HDFS is running to store chunk data. In Haddop compute node and storage node are the same to exploit locality. In other words, map-reduce job strives to work on the local HDFS data to save network bandwidth across clusters.

Here is a simple example for word count from a set of documents as illustrated in Figure 8.1. Splitted input files consists of a set of documents. Each line represents a document. Each line/document is passed to individual mapper instance. Mapper emits each word as intermediate key and value will be count 1. Intermediate output values are not usually reduced together. All values with the same key (word) are presented to a single reducer together. In particular, each distinct word (subset of different keyspace) is assigned to each reducer. These subsets are known as *partitioner*. After shuffling and sorting, reducer will get intermediate key (word) and a list of values (counts). In Figure 8.1 the top most reducer will get Apple key and a list of values will be "{1, 1, 1, 1 }".

Algorithm 7 Word count program for MapReduce

```
Input: $filename, file - contents$
Output: $word, sum$

mapper (filename, file-contents)
for each word in file-contents do
    $emit(word, 1)$
end for

reducer (word, values):
sum = 0
for each value in values do
    $sum = sum + value$
end for
$emit(word, sum)$
```

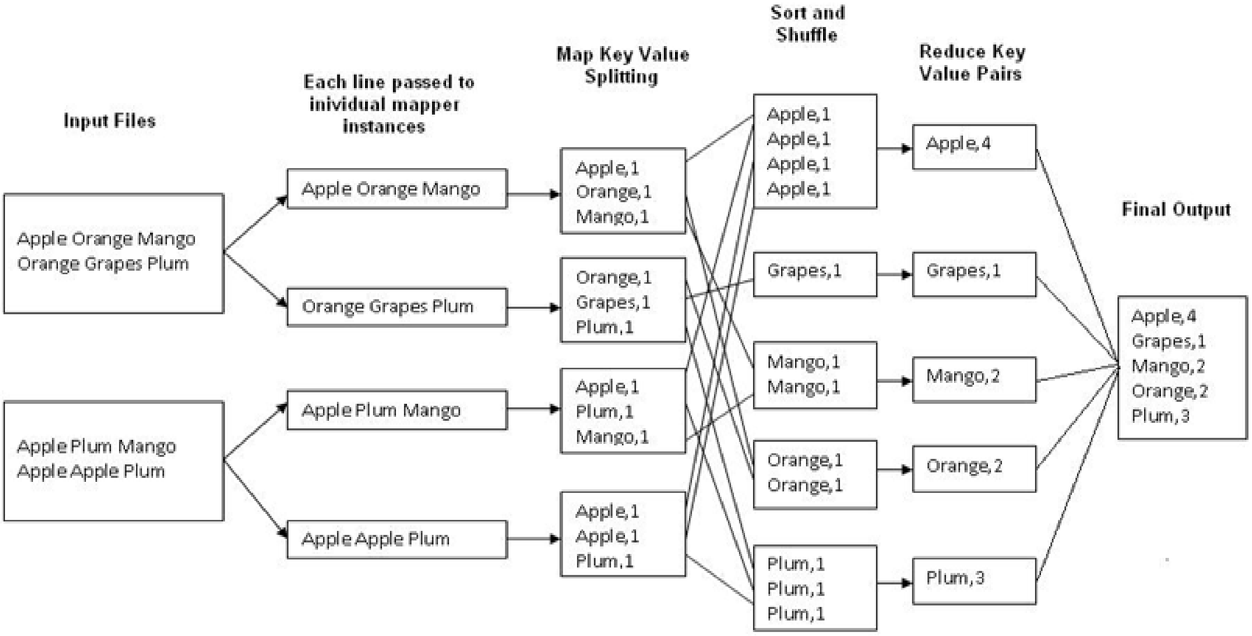
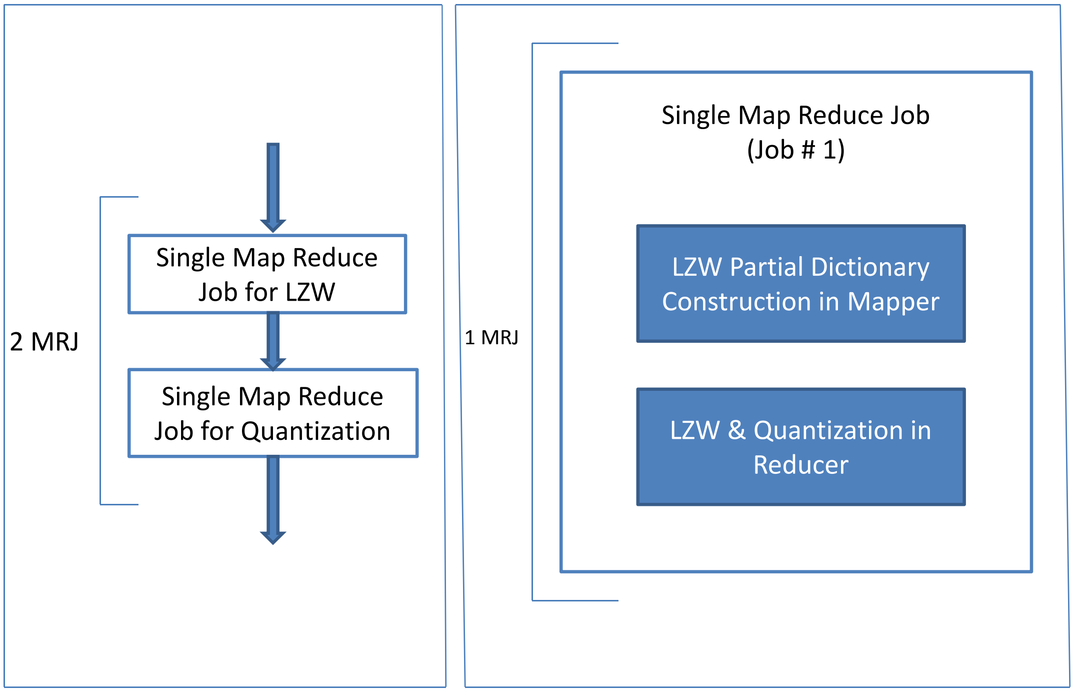


Figure 8.1. Word count example using MapReduce

Here, we have a simple word count program using Map Reduce framework (see Algorithm 7). Mapper tasks input document id as key, and value is the content of the document. Mapper emits (term, 1) as intermediate key value pair where each term appeared in a document is key (see Line 5 in Algorithm 7) . The outputs are sorted by key and then partitioned per reducer. The reducer emits each distinct word as key and frequency count in the document as value (see Line 12 in Algorithm 7).


2 MRJ
Single Map Reduce Job for LZW
Single Map Reduce Job for Quantization
1 MRJ
Single Map Reduce Job (Job # 1)
LZW Partial Dictionary Construction in Mapper
LZW & Quantization in Reducer

(a) 2 MRJ

(b) 1 MRJ

Figure 8.2. Approaches for scalable LZW and quantized dictionary construction using MapReduce Job

8.2 Scalable LZW and Quantized Dictionary Construction using Map Reduce Job

We address scalability issue using the following two approaches. Approaches are illustrated in Figure 8.2. Our proposed approach exploits in one case two map reduce jobs (2MRJ) and the other case it exploits single map reduce job (1MRJ) (Parveen, Thuraisingham, and Khan, 2013b).

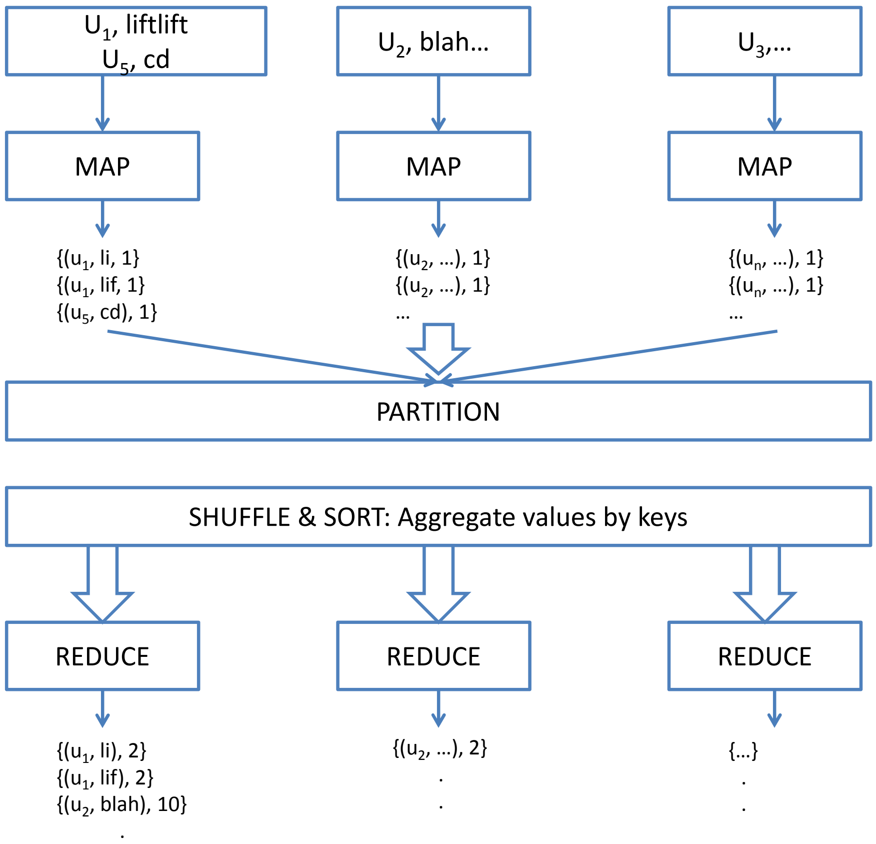


Figure 8.3. First MapReduce job for scalable LZW construction in 2MRJ approach

8.2.1 Two MapReduce Job Approach (2MRJ)

This is a simple approach and requires two map reduce (MR) jobs. It is illustrated in Figure 8.3 and Figure 8.4. The first MR job is dedicated for LZW dictionary construction in (Figure 8.3) and the second MR job is dedicated for quantized dictionary construction in (Figure 8.4). In the first MR job, Mapper takes userid along with command sequence as an input to generate intermediate (key, values) pair having the form ((userid, css), 1). Note that css is a pattern which is a command subsequnce. In Reduce phase intermediate key (userid, css) will be the input. Here, keys are grouped together and values for the same key (pattern

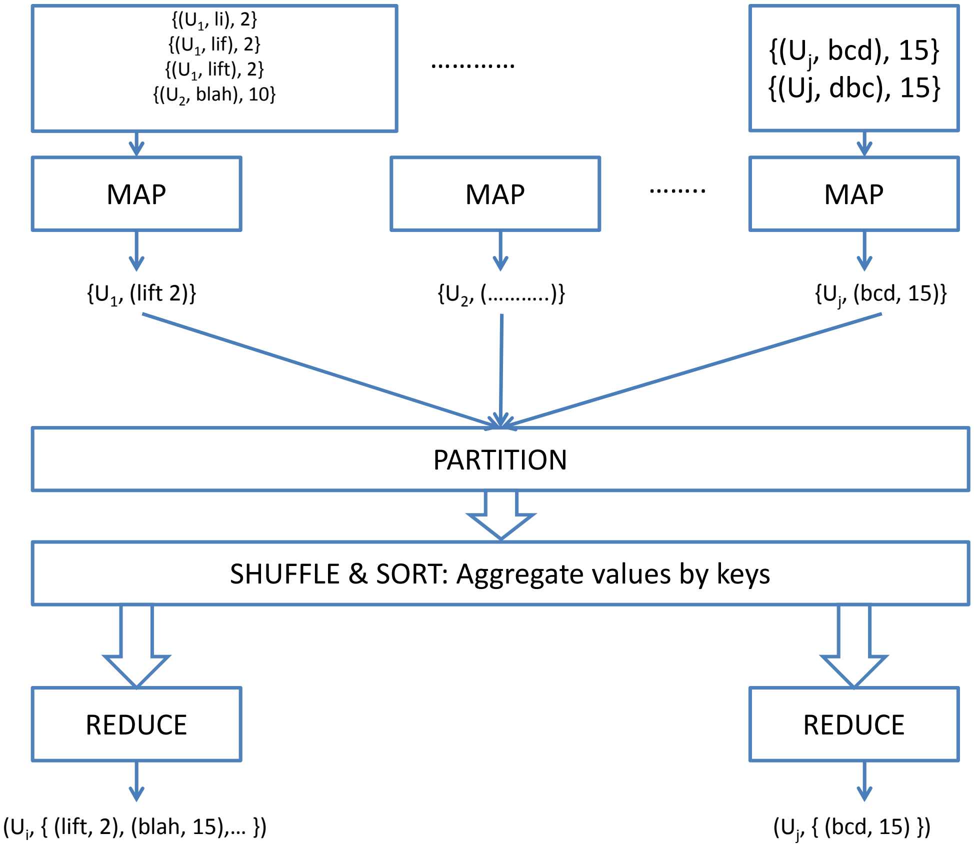


Figure 8.4. Second MapReduce job for quantized dictionary construction in 2MRJ approach

count) are added. For example, a particular user 1, has command sequences ”liftlift”. Map phase emits ((u1, li), 1) ((u1, lif), 1) value as intermediate key value pairs (see middle portion of Figure 8.3). Recall that the same intermediate key will go to a particular reducer. Hence, a particular user id along with pattern/css, i.e., key will arrive to the same reducer. Here, reducer will emit (user id, css) as key and value will be how many times (aggregated one) pattern appears in the command sequence for that user (see bottom portion of Figure 8.3).

Algorithm 8 presents pseudo code for LZW dictionary construction using a map reduce job. In Algorithm 8, input file consists of line by line input. Each line has entries namely, gname (userid) and command sequences (cseq). Next, mapper will take gname (userid) as key and values will be command sequences for that user. In mapper we will look for patterns having length 2, 3, etc. Here, we will check whether patterns exist in the dictionary (line 6). If the pattern does not exist in the dictionary, we simply add that in the dictionary(line 7), and emit intermediate key value pairs (line 8). Here, keys will be composite having gname and pattern. Value will be frequncy count 1. At line 9 and 10, we increment pointer so that we can look for patterns in new command sequences (cseq). If the pattern is in the dictionary, we simply emit at line 12 and cseq's end pointer is incremented. By not incrementing cseq's start pointer we will look for super-set patterns.

Combiner will be run from line 15 to line 20 in Algorithm 8. Combiner is an optional step and acts as "'min reducer." For the same user same pattern may be emitted multiple times with frequency count 1. In combiner we aggregate them at line 18. Finally, in line 20, we emit composite key (gname and pattern) and aggregated frequency count. Combiner helps us to overcome unnecessary communication cost and therefore, improves processing time. Recall that combiner is optional it may run 0 time, or 1 or many times. Hence, the signature of combiner method (input/output parameters) need to match the output signature of mappers and the input signature of reducers. At reducer from line 21 to 26, aggregation is carried as shown in "'Combiner."

In the second map reduce job quantization of the dictionary will be carried out (see Figure 8.4). Mapper will carry simple transformation by generating key based on user id, and value based on pattern frequency. In Algorithm 9, mapper will take each line as an input from input file produced by 1st map reduce job. Here, mapper will take input (userid, pattern) as key and frequency as value. Mapper emits intermediate key value pair where key will be user id and value will be concatenation of pattern and frequency (see middle portion of Figure 8.4 and see from line 4 to line 7 in Algorithm 9). All patterns of a particular user and corresponding frequency will arrive at the same reducer. The reducer will conduct all pairwise edit distance calculation among all patterns for a particular user. Finally, user id as key and longest frequent patterns as value will be emitted by the reducer (see bottom portion of Figure 8.4).

At the reducer, each user (gname) will be input and list of values will be patterns and their frequency count. Here, compression of patterns will be carried out for that user. Recall that some patterns will be pruned using Edit distance. For a user, each pattern will be stored into Hashmap, H. Each new entry in the H will be pattern as key and value as frequency count 1. For existing pattern in the dictionary, we will simply update frequency count(line 11). At line 13 dictionary will be quantized and H will be updated accordingly. Now, from quantized dictionary(QD), patterns along frequency count will be emitted as values and key will be gname (at line 14).

8.2.2 1MRJ:1 MR Job

Here, we will utilize 1 MR job. It is illustrated in Figure 8.5. We are expecting that by reducing the number of jobs we can reduce total processing costs.

Running a job in Hadoop takes a significant overhead. Hence, by minimizing the number of jobs, we can construct dictionary quickly. The overhead for a Hadoop job is associated with disk I/O and network transfers. When a job is submitted to Hadoop cluster the following actions will take place:

1. The Executable file is moved from client machine to Hadoop JobTracker[1],

2. The JobTracker determines TaskTrackers[2] that will execute the job,

[1] `http://wiki.apache.org/hadoop/JobTracker`

[2] `http://wiki.apache.org/hadoop/TaskTracker`

Algorithm 8 LZW Dictionary Construction using Map-Reduce(2MRJ)

```
Input: $gname : groupname$, $cseq : commandsequences$
Output: $Key : (gname, commandpattern(css))$, $count$

$map(stringgname, stringcseq)$
$start \leftarrow 1$, $end \leftarrow 2$
$css = (cs_{start} \cdots cs_{end})$
if $css \notin dictionary$ then
    $Add\ css\ to\ thedictionary$
    $emit(pairs(gname, css), integer1)$
    $start \leftarrow start + 1$
    $end \leftarrow end + 1$
else
    $emit(pairs(gname, css), integer1)$
    $end \leftarrow end + 1$
end if

$combine(pair(gname, css), (cnt1, cnt2, \cdots))$
$Sum \leftarrow 0$
for all $cnt \in (cnt1, cnt2, \cdots)$ do
    $sum \leftarrow sum + cnt$
end for
$emit(pair(gname, css), integersum)$

$reduce(pair(gname, css), (cnt1, cnt2, \cdots))$
$Sum \leftarrow 0$
for all $cnt \in (cnt1, cnt2, \cdots)$ do
    $sum \leftarrow sum + cnt$
end for
$emit(pair(gname, css), integersum)$
```

Algorithm 9 Compression/Quantization using Map-Reduce(2MRJ)

```
Input: $line : gname, commandsequence(css), frequencycount(cnt)$
Output: $Key : (gname, commandpattern(css))$

$map(stringline, string)$
$gname \leftarrow Spilt(line)$
$css \leftarrow Spilt(line)$
$cnt \leftarrow Spilt(line)$
$emit(gname, pair(css, cnt))$

$reduce(gname, (pair(css_1, cnt_1), pair(css_2, cnt_2), \cdots))$
$Sum \leftarrow 0$
for all $pair(css_i, cnt_i) \in ((pair(css_1, cnt_1), pair(css_2, cnt_2) \cdots)$ do
    $H \leftarrow H + pair(css_i, cnt_i)$
end for
$QD = QuantizedDictionary(H)$
$emit(gname, pair(css, integer\ sum))$
for all $css_i \in QD$ do
    $emit(gname, pair(css_i, count(css_i)))$
end for
```

3. The Executable file is distributed to the TaskTrackers over the network,

4. Map processes initiates reading data from HDFS,

5. Map outputs are written to local discs,

6. Map outputs are read from discs, shuffled (transferred over the network to TaskTrackers which would run Reduce processes), sorted and written to remote discs,

7. Reduce processes initiate reading the input from local discs,

8. Reduce outputs are written to discs.

Therefore, if we can reduce number of jobs we can avoid expensive disk operations and network transfers. That is the reason we prefer 1MRJ over 2MRJ.

Algorithm 10 Dictionary construction and compression using single Map-Reduce(1MRJ)

```
Input: $gname : groupname$, $cseq : commandsequences$
Output: $Key : gname, commandpattern(css)$

$map(stringgname, stringcseq)$
$start \leftarrow 1$, $end \leftarrow 2$
$css = (cs_{start} \cdots cs_{end})$
if $css \notin dictionary$ then
    $Add\ css\ to\ thedictionary$
    $emit(gname, css)$
    $start \leftarrow end$
    $end \leftarrow end + 1$
else
    $emit(gname, css)$
    $end \leftarrow end + 1$
end if

$reduce(gname, (css_1, css_2, \cdots)$
$H \leftarrow 0$
for all $css_i \in ((css_1, css_2, \cdots)$ do
    if $css \notin H$ then
        $H \leftarrow H + (css_i, 1)$
    else
        $count \leftarrow getfrequency(H(css_i))$
        $count \leftarrow count + 1$
        $H \leftarrow H + (css_i, count)$
    end if
end for
$QD = QuantizedDictionary(H)$
for all $css_i \in QD$ do
    $emit(gname, pair(css_i, count(css_i)))$
end for
```

Mapper will emit user id as key and value will be pattern (see Algorithm 10). Recall that in mapper partial LZW operation will be completed. The same user id will arrive at the same reducer since user is the intermediate key. For that user id, a reducer will have a list of patterns. In the reducer, incomplete LZW will be completed here. In addition, full quantization operation will be implemented as described in Chapter 6.2.1. Parallelization will be achieved at the user level (*inter-user parallelization*) instead of within users (*intra-user parallelization*). In mapper, parallelization will be carried out by dividing large files into a number of chunks and process a certain number of files in parallel.

Algorithm 10 illustrates the idea. Input file consists of line by line input. Each line has entries namely, gname (userid) and command sequences (cseq). Next, mapper will take gname (userid) as key, and values will be command sequences for that user. In mapper we will look for patterns having length 2, 3, etc. Here, we will check whether patterns exist in the dictionary (line 6). If the pattern does not exist in the dictionary, we simply add that in the dictionary(line 7), and emit intermediate key value pairs (line 8) having keys as gname and values as patterns with length 2, 3 etc. At line 9 and 10, we increment pointer so that we can look for patterns in new command sequences (cseq). If the pattern is in the dictionary, we simply emit at line 12 and cseq's end pointer is incremented so that we can look for super-set command sequence.

At the reducer, each user (gname) will be input and list of values will be patterns. Here, compression of patterns will be carried for that user. Recall that some patterns will be pruned using Edit distance. For a user each pattern will be stored into Hashmap, H. Each new entry in the H will be pattern as key and value as frequency count. For existing pattern in the dictionary, we will simply update frequency count(line 18). At line 20 dictionary will be quantized, and H will be updated accordingly. Now, from quantized dictionary all distinct patterns from H will emitted as values along with key gname.

8.3 Experimental Setup and Results

8.3.1 Hadoop Cluster

Our hadoop cluster (cshadoop0-cshadoop9) is compromised of virtual machines that run in the Computer Science vmware esx cloud - so there are 10 VM's. Each VM is configured as a quad core with 4GB of ram and a 256GB virtual hard drive. The virtual hard drives are stored on the CS SAN (3PAR).

There are three ESX hosts which are Dell Poweredge R720's with 12 cores @2.99GHZ, 128GB of RAM, and fiber to the 3PAR SAN. The VM's are spread across the three ESX hosts in order to balance the load.

"cshadoop0" is configured as the "name node". A"cshadoop1" through "cshadoop9" are configured as the slave "data nodes".

We have implemented our approach using Java JDK version 1.6.0.39. For MapReduce implementation we have used Hadoop version 1.0.4.

8.3.2 Big Dataset for Insider Threat Detection

The Data sets used are created from the trace files from the University of Calgary project. 168 files have been collected from different levels of users of UNIX as described in (Greenberg, 1988; Maxion, 2003). The different levels of users are:

- Novice programmers (56 users)
- Experienced programmers (36 users)
- Computer scientists (52 Users)
- Non-programmers (25 users).

Each file contains the commands used by each of the users over weeks.

Now, in order to get the big data, first we replicated the user files randomly so that we have:

- Novice programmers - (1320 Users) i.e. File starting from ”novice-0001” till ”novice-1320”
- Experienced programmers - (576 Users)
- Computer scientists - (832 Users)
- Non-programmers - (1600 Users)

Total Number of Users = 4328; size is 430 MB; and one command file is for one user.

Next, we gave these files as input to our program (written in Python) which gave unique unicode for each distinct command provided by all users. The output file for all users is 15.5 MB. We dubbed it as *original data (OD).*

Finally, we replicated this data 12 times for each user. And we ended up 187 MB of input file which was given as an input to Map Reduce job of LZW and Compression. We dubbed as *duplicate big data (DBD).*

8.3.3 Results for Big Data Set Related to Insider Threat Detection

First, we experiment on OD, and next, we concentrate on DBD.

On OD Dataset:

We have compared our approaches namely, 2MRJ and 1MRJ on OD dataset. Here, we have varied number of reducers and fixed number of mappers (e.g., HDFS block size equals 64MB). In case 2MRJ, we have varied a number of reducers in 2nd job's reducer and not in first map reduce job. 1MRJ outperforms 2MRJ in terms of processing time on a fixed number of reducers except in the first case (number reducer equals to 1). With the latter

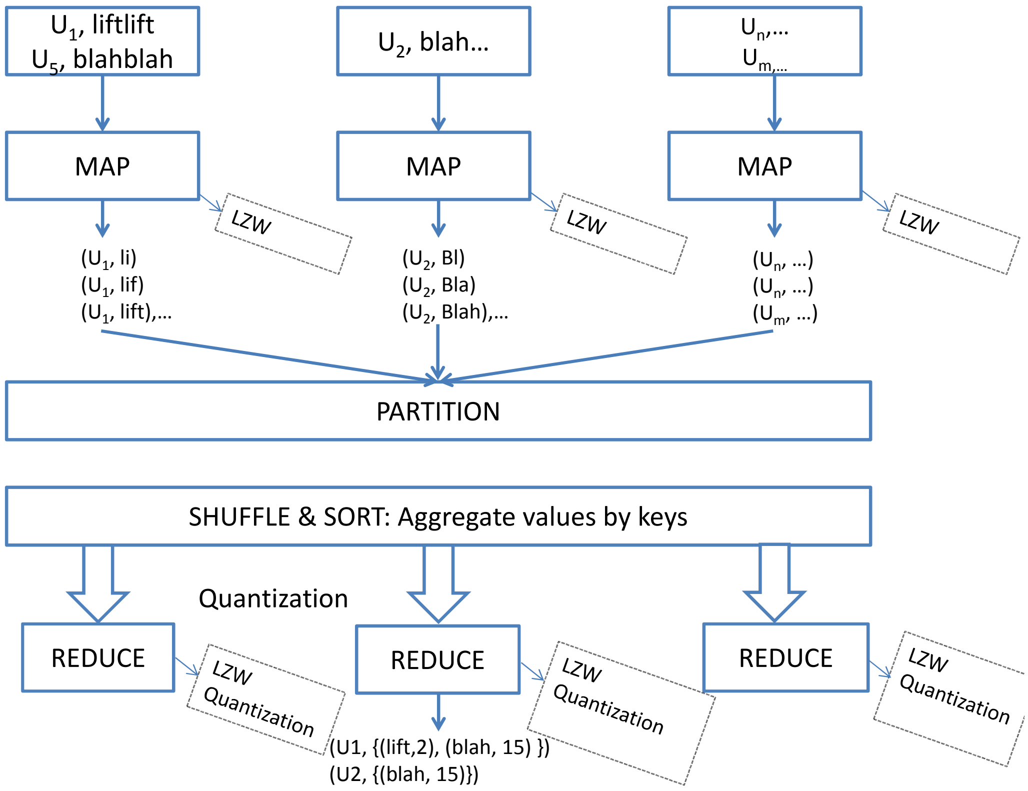


Figure 8.5. 1MRJ: 1 MR Job approach for scalable LZW and quantized dictionary construction

case, parallelization is limited at the reducer phase. Table 8.1 illustrates this. For example, for number of reducer equals 9, total time taken is 3.47 sec and 2.54 sec for 2MRJ and 1MRJ approaches respectively.

With regard to 2MRJ case, Table 8.3 presents input-output statistics of both MapReduce jobs. For example, for first map reduce job mapper emits 65,37,040 intermediate key value pairs and Reducer emits 95.75MB output. This 95.75MB will be the input for mapper for the second MapReduce job.

Table 8.1. Time Performance of 2MRJ vs. 1MRJ for varying number of reducers

# of Reducer	**Time for 2MRJ (M:S)**	**Time for 1MRJ (M:S)**
1	13.5	16.5
2	9.25	9.00
3	6.3	5.37
4	5.45	5.25
5	5.21	4.47
6	4.5	4.20
7	4.09	3.37
8	3.52	3.04
9	3.47	2.54
10	3.38	2.47
11	3.24	2.48
12	3.15	2.46

Here, we will show how HDFS block size will have an impact on LZW dictionary construction in 2MRJ case. First, we vary HDFS block size that will control the number of mappers. With 64 MB HDFS block size and 15.5MB input size, number of mapper equals to 1. For 4MB HDFS block size number of mapper equals 4. Here, we assume that input File split size equals HDFS block size. Smaller HDFS block size (smaller file split size) increases performance (reduce time). More mappers will be run in various nodes in parallel.

Table 8.2 presents total time taken by mapper (part of first MapReduce job) in 2MRJ case on OD dataset. Here, we have varied partition size for LZW Dictionary Construction. For 15.498 MB input file size with 8 MB partition block size, MapReduce execution framework used 2 mappers.

On DBD Dataset:

Table 8.4 shows the details of the value comparisons of 1MRJ across a various number of reducer and HDFS block size values. Here, we have used DBD dataset.

In particular, in Figure 8.6, we show total time taken for a varying number of reducers with a fixed HDFS block size. Here, X axis represents the number of reducer and Y axis

Table 8.2. Time performance of mapper for LZW dictionary construction with varying partition size in 2MRJ

Partition block size	Map (Sec)	No of mappers
1MB	31.3	15
2MB	35.09	8
3MB	38.09	5
4MB	36.06	4
5MB	41.01	3
6MB	41.03	3
7MB	41.01	3
8MB	55.0	2
64MB	53.5	1

Table 8.3. Details of LZW dictionary construction and quantization using MapReduce in 2MRJ on OD dataset

Description	Size/Entries in Second Job	Size/Entries in First Job
Map Input	95.75MB (size)	15.498MB (size)
Map Output	45,75,120 (entries)	65,37,040 (entries)
Reduce Input	17,53,590 (entries)	45,75,120 (entries)
Reduce Output	37.48 MB	95.75 MB (size)

Table 8.4. Time performance of 1MRJ for varying reducer and HDFS block Size on DBD

No of Reducer	64MB	40MB	20MB	10MB
1	39:24	27:20	23:40	24:58
2	17:36	16:11	13:09	14:53
3	15:54	11:25	9:54	9:12
4	13:12	11:27	8:17	7:41
5	13:06	10:29	7:53	6:53
6	12:05	9:15	6:47	6:05
7	11:18	8:00	6:05	6:04
8	10:29	7:58	5:58	5:04
9	10:08	7:41	5:29	4:38
10	11:15	7:43	5:30	4:42
11	10:40	7:30	4:58	4:41
12	11:04	8:21	4:55	3:46

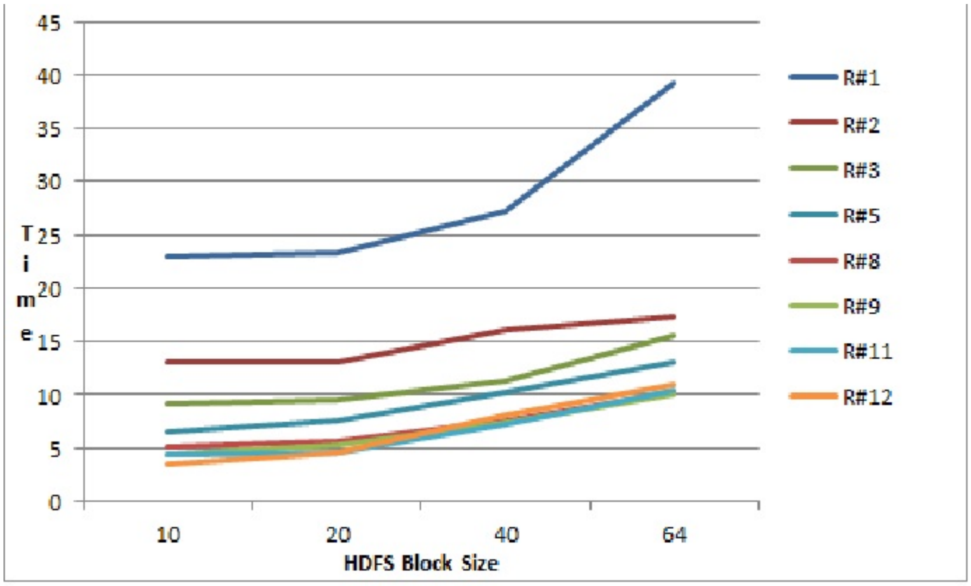


Figure 8.6. Time Taken for Varying Number of HDFS block size in 1MRJ

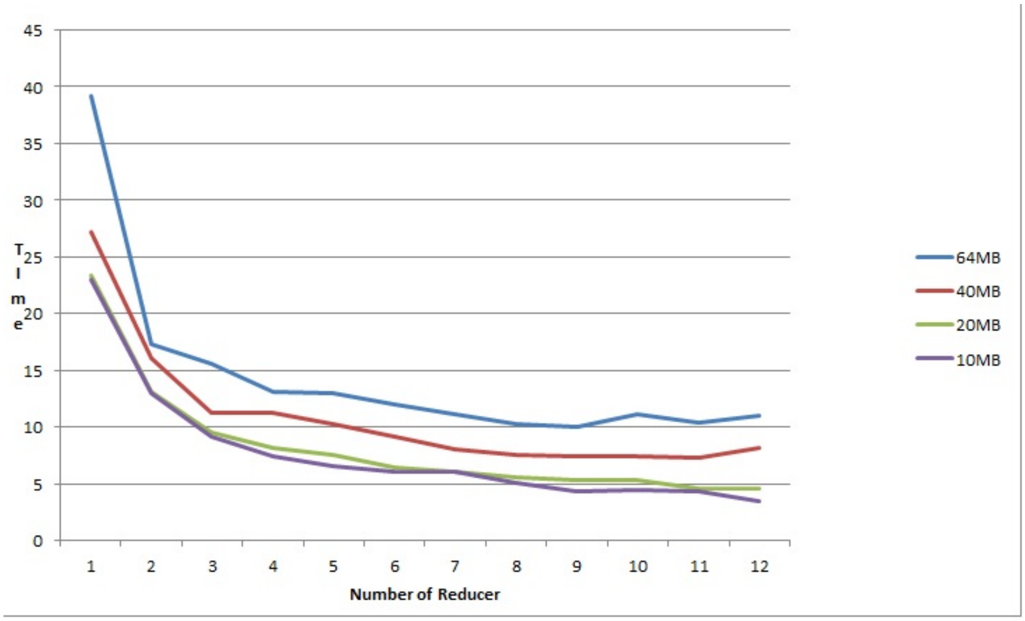


Figure 8.7. Time Taken for Varying Number of Reducer in 1MRJ

represents the total time taken for 1MRJ with a fixed HDFS block size. We demonstrate that with an increasing number of reducers, total time taken will drop gradually. For example, with regard to reducer 1, 5, and 8, total time taken in 1MRJ approach is 39.24, 13.04, 10.08 minutes respectively. This number validates our claim. With more reducers running in parallel, we can run quantization/compression algorithms for various users in parallel. Recall that in 1MRJ reducer will get each distinct user as key and values will be LZW dictionary pattern. Let us assume that we have 10 distinct users and their corresponding patterns. For compression with 1 reducer, compression for 10 user patterns will be carried out in a single reducer. On the other hand for 5 reducers, it is expected that each reducer will get 2 users' patterns. Consequently, 5 reducers will run in parallel and each reducer will execute compression algorithm for 2 users serially instead of 10. Therefore, with an increasing number of reducers, performance(decreases time) improves.

Now, we will show how the number of mappers will affect total time taken in 1MRJ case. The number of mappers is usually controlled by the number of HDFS blocks (dfs.block.size) in the input files. Number of HDFS blocks in the input file is determined by HDFS block size. Therefore, people adjust their HDFS block size to adjust the number of maps.

Setting the number of map tasks is not as simple as setting up the number of reduce tasks. Here, first we determine whether input file is isSplitable. Next, three variables, mapred.min.split.size, mapred.max.split.size, and dfs.block.size, determine the actual split size. By default, min split size is 0 and max split size is Long.MAX and block size 64MB. For actual split size, minSplitSize & blockSize set the lower bound and blockSize & maxSplitSize together sets the upper bound. Here is the function to calculate:

max(minsplitsize, min(maxsplitsize, blocksize))

For our case we use min split size is 0; max split size is Long.MAX and blockSize vary from 10 MB to 64 MB. Hence, actual split size will be controlled by HDFS block size. For example, 190 MB input file with DFS block size 64 MB, the file will be split into 3 with each split having two 64 MB and the rest with 62 MB. Finally, we will end up with 3 maps.

In Figure 8.7 we show the impact of HDFS block size on total time taken for a fixed number of reducers. Here, X axis represents HDFS block size and Y axis represents total time taken for 1MR approach with a fixed number of reducers. We demonstrate that with increasing number of HDFS block size, total time taken will increase gradually for a fixed input file. For example, with regard to HDFS block size 10, 20, 40, 64 MB total time taken in 1MRJ approach were 7.41, 8.17, 11.27, 13.12 minute respectively for a fixed number of reducers (=4). On one hand, when HDFS block size of 10 MB, and input file is 190 MB, 19 maps run where each map processes 10MB input split. On the other hand, for HDFS block size=64 MB, 3 maps will be run where each map will process a 64 MB input split. In the former case (19 maps with 10 MB) each map will process a smaller file and in the latter case (3 maps with 64 MB) we process a larger file which consequently consumes more time. In the former case, more parallelization can be achieved. In our architecture, more than 10 mappers can be run in parallel. Hence, for a fixed input file and fixed number of reducers, total time increases with increasing HDFS block size.

本文主要的工作是引入了“演进”的概念，其实就是特征成为动态变化的，主要依靠动态的K个模型分类器实现该功能，在此基础上，针对同一测试数据集使用监督式学习和非监督式学习分别测试实现，发现监督式学习的效果要好于非监督式学习。
在处理模式字典的过程中，因为效能因素使用了Hadoop和mapreduce架构。

CHAPTER 9

CONCLUSIONS AND FUTURE WORK

9.1 Conclusion

Insider threat detection is a very important problem requiring critical attention. This dissertation presents a number of approaches to detect insider threats through augmented unsupervised and supervised learning techniques on evolving stream. Here, we have considered *sequence* and *non sequence* stream data.

The supervised learning approach to insider threat detection outperformed the unsupervised learning approach. The supervised method succeeded in identifying all 12 anomalies in the 1998 Lincoln Laboratory Intrusion Detection dataset with zero false negatives and a lower false positive rate than the unsupervised approach.

For *unsupervised learning*, *Graph-based anomaly detection (GBAD)* (Cook and Holder, 2007; Eberle and Holder, 2007; Cook and Holder, 2000) is used. However, applying GBAD to the insider threat problem requires an approach that is sufficiently adaptive and efficient so effective models can be built from vast amounts of evolving data.

The technique combines the power of GBAD and one-class SVMS with the adaptiveness of stream mining to achieve effective practical insider threat detection for unbounded evolving data streams. Increasing the weighted cost of false negatives increased accuracy and ultimately allowed our approach to perform well. Though false positives could be further reduced through more parameter tuning, our approach accomplished the goal of detecting all insider threats.

We examine the problem of insider threat detection in the context of command *sequences* and propose an unsupervised ensemble based learning approach that can take into account concept drift. The approach adopts advantages of both compression and incremental learning. A classifier is typically built and trained using large amount of legitimate data. However, training a classifier is very expensive, and furthermore, it has problems when the baseline changes, as is the case in real life networks. We acknowledge this continuously changing feature of legitimate actions, and introduce the notion of concept drift to address the changes. The proposed unsupervised learning system adapts directly to the changes in command sequence data. In addition, to improve accuracy, we use an ensemble of K classifiers, instead of a single one. Voting is used, and a subset of classifiers is used because classifiers with more recent data gradually replace those that are outdated. We address an important problem and propose a novel approach.

For sequence data, our stream guided sequence learning performed well, with limited number of false positives as compared to static approaches. This is because the approach adopts advantages from both compression & ensemble-based learning. In particular, compression offered unsupervised learning in a manageable manner and on the other hand ensemble based learning offered adaptive learning. The approach was tested on real command line dataset and shows effectiveness over static approaches in terms of TP and FP.

Compressed/quantized dictionary construction is computationally expensive. It does not scale well with a number of users. Hence, we look for distributed solution with parallel computing with commodity hardware. For this, all users' quantized dictionary is constructed using a MapReduce framework on Hadoop. A number of approaches are suggested, experimented on benchmark dataset, and discussed. We have shown with 1 map reduce job that quantized dictionary can be constructed and demonstrates effectiveness over other approaches.

9.2 Future Work

We would like to extend the work in the following directions.

9.2.1 Incorporate User Feedback

For unsupervised learning, we assume that no ground truth is available. In fact, over time some ground truth may be available in terms of feedback. Once a model is created in an unsupervised manner, we would like to update the model based on user feedback. Right now, once the model is created it remains unchanged. When ground truth is available over time, we will refine our all models based on this feedback immediately (Masud et al., 2010).

9.2.2 Collusion Attack

During unsupervised learning (see Chapter 4), when we update models, collusion attack (Zhao et al., 2005; Wang et al., 2009) may take place. In that case, a set of models among K models will not be replaced for a while. Each time, when a victim will be selected, these colluded models will survive. Recall that ”collusion” is an agreement between two or more models so that they will always agree on the prediction. In particular, if we have $K = 3$ models, two models may maintain secretive agreement and their prediction will be the same and used as ground truth. Therefore, two colluded/secretive models will always survive and never be victim in model update case. Recall that the learning is unsupervised and majority voting will be taken as ground truth. Hence, we will not be able to catch insider attack. Our goal is to identify colluded attack. For this, during victim selection of models, we will take into account agreement of models over time. If agreement of models persists for a long time and survive, we will choose the victim from there.

9.2.3 Additional Experiment

We will do additional experiment on more sophisticated scenarios, including chunk size. Currently, we assume that chunk size is fixed or uniform. Fixed chunk is easy to implement. But it fails to capture concept drift or anomaly in the stream. Assume that concept drift happens at the end of a chunk (fixed size). We may not be able to detect anomaly until we process the next chunk. For this, the better approach will be creation of dynamic chunk size. Here, chunk size will vary. Variable chunk size will be estimated by using change point detection (Cangussu and Baron, 2006; Baron and Tartakovsky, 2006). Once we observe a new distribution, current chunk ends, and new chunk will emerge.

Instead of one class SVM, we may use other classifiers (Parveen and Thuraisingham, 2006). When we apply insider threat detection across multiple data sources/domains we need to address heterogeneity issues of schema/sources. For this, we will utilize schema matching/ontology alignment (Partyka et al., 2011; Alipanah, Parveen et al., 2010; Alipanah et al., 2011; Alipanah, Srivastava et al., 2010; Khan and Luo, 2002; Khan et al., 2004).

9.2.4 Anomaly Detection in Social Network and Author Attribution

Anomaly detection will be carried out in social network using our proposed supervised and unsupervised approaches.

Twitter, on line social network, allows friends to communicate and stays connected via exchanging short messages (140 character). Spammer presence is prevalent in twitter now.

Spammers post malicious links, send unsolicited messages to legitimate users and hijack trending topics in twitter. At least 3% of messages can be categorized as spammers. We can extend our framework to detect spammer by exploiting anomaly detection.

New authors may appear in blog. Our goal is to identify these new authors in the stream. For this, our anomaly detection can be applied. Feature extraction needs to be changed (i.e., stylometric feature (Jamak et al., 2012)). We would like to carry out our techniques for author attribution (Akiva and Koppel, 2012; Koppel et al., 2009; Seker et al., 2013).

9.2.5 Stream mining as a Big data mining problem

Stream data can be treated as big data.

This is due to well-known properties of stream data such as infinite length, high speed data arrival, online/timely data processing, changing characteristics of data and need for one-pass techniques (i.e., forgotten raw data) etc. In particular, data streams are infinite, therefore efficient storage and incremental learning are required. The underlying concept changes over time are known as concept drift. The learner should adapt to this change and be ready for veracity and variety. New classes evolving in the stream are known as concept evolution, which make classification difficult. New features may also evolve in the stream, such as text streams.

All of these properties conform to characteristics of big data. For example, infinite length of stream data constitutes large ”Volume” of big data. High speed data arrival and on-line processing holds the characteristics of large ”Velocity” of big data. Stream data can be sequence or non sequnce data (vector). This conforms ”verity” characteristics of big data. Characteristics of stream data can be changed over time. New patterns may emerge in evolving stream. Old patterns may be outdated. These properties may support the notion of ”Veracity” of big data. Therefore, stream data possesses characteristics of big data. In spite of the success and extensive studies of stream mining techniques, there is no single work dedicated to a unified study of the new challenges introduced by big data and evolving stream data.

The big data community adopts big data infrastructures that are used to process unbounded continuous streams of data (e.g., S4, Storm). However, their data mining support is rudimentary. A number of open source tools for big data mining have been released to support traditional data mining. Only a few tools support very basic stream mining. Research challenges such as change detection, novelty detection, and feature evolution over evolving streams have been recently studied in traditional stream mining (Domingos and Hulten, 2001; Davison and Hirsh, 1998; Masud, Chen, Gao, Khan, Aggarwal et al., 2010; Masud et al., 2011a; Fan, 2004) but not in big data.

Here, we need a unified picture of how these challenges and proposed solutions can be augmented in these open source tools. In addition to presenting the solutions to overcome stream mining challenges, experience with real applications of these techniques to data mining and security will be shared across the world.

- Big Data Stream Infrastructure: Apache S4 (Neumeyer et al., 2010), Storm, Cassandra (Lakshman and Malik, 2010) etc including batch processing Hadoop.
- Big Data Mining Tool: Apache Mahout (Owen et al., 2011), MOA (Zliobaite et al., 2011), PEGASUS (Kang et al., 2011), GraphLab, SAMOA and their support for Stream Mining.

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VITA

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In June 2013, she joined VCE (joint venture of VMware, Cisco, and EMC) R&D group as a researcher in big data management and analytics.

As of today, she has published more than ten papers including two journal papers and a number of selective conference papers. She also received best paper award from the *23rd IEEE International Conference on Tools with Artificial Intelligence* (ICTAI - under special session category), November, 2011, Boca Raton, Florida, USA. Her current research interests are security, data mining and big data management.

Parveen enjoys traveling and music. In the past, she traveled to Canada, France, Italy, UK, Singapore, Malaysia, Brunei, UAE, Saudi Arabia, Libya, and Iraq.

Currently she is a US citizen and blessed by a beautiful daughter.