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A New Take on Detecting Insider Threats: Exploring the use of Hidden Markov Models

Tabish Rashid
Department of Computer Science,
University of Oxford
tabish.rashid@cs.ox.ac.uk

Ioannis Agrafiotis
Department of Computer Science,
University of Oxford
ioannis.agrafiotis@cs.ox.ac.uk

Jason R. C. Nurse
Department of Computer Science,
University of Oxford
jason.nurse@cs.ox.ac.uk

ABSTRACT

The threat that malicious insiders pose towards organisations is a significant problem. In this paper, we investigate the task of detecting such insiders through a novel method of modelling a user's *normal* behaviour in order to detect anomalies in that behaviour which may be indicative of an attack. Specifically, we make use of Hidden Markov Models to *learn* what constitutes normal behaviour, and then use them to detect significant deviations from that behaviour. Our results show that this approach is indeed successful at detecting insider threats, and in particular is able to accurately learn a user's behaviour. These initial tests improve on existing research and may provide a useful approach in addressing this part of the insider-threat challenge.

Keywords

Insider threat; Anomaly detection system; Machine learning

1. BACKGROUND AND RELATED WORK

Organisational computer systems are increasingly threatened by insiders. The Breach Level Index, which tracks publicly disclosed breaches, shows that almost 40% of data breaches are attributed to malicious insiders or accidental loss due to insiders [6]. It is evident that insider threats now represent a significant portion of the cyber-attacks an organisation faces, even if we do not take into account the unreported incidents. In addition, they are often the most costly type of attack [14] due to the elevated level of trust and access that an insider is afforded.

As insider threats have become more prevalent, there have been numerous advances in both industry and research towards attack prevention and detection. At the programme level, the CERT division at CMU maintains a comprehensive research directive on insider threats, and are considered pioneers in the field [2]. One of the major tools used in exploring insider threat by CERT is System Dynamics diagrams, which aid in defining relationships between different precursors and factors indicative of an attack. Instead of separately modelling different types of insider attacks as done in the CERT models, a unifying framework to characterise insider attacks has been presented in [11]. The framework is particularly powerful for analysing cases, in order to understand behaviours that may lead to an attack, the reasons for an attack, the types of attacks that may be launched, and most importantly, to compare this data across other cases.

The U.S. Department of Homeland Security published a report in 2014: "Combating the Insider Threat"[4]. The report is primarily concerned with the behavioural aspects of the insider threat, and how certain traits can indicate an increased likelihood of a threat. The authors suggest that one of the best prevention measures is educating individuals to report certain behaviours that they observe in their peers. These "Characteristics of Insiders at Risk of Becoming a Threat" are vague (Ethical Flexibility, Introversion, etc.) and can often be hard to quantify. In the report they also provide a short list of behavioural indicators which could signal an insider threat, such as "Remotely accesses the network while on vacation, sick or at odd times", which are easier to observe. Underscoring all of this advice is the concept of a baseline of normal behaviour, which is a prerequisite in attempting to observe significant levels of deviation of a certain behaviour.

Machine learning-based approaches have been central to work on insider-threat detection. The actions that an employee takes over a period of time on a system (e.g., logging on/off, file accesses, etc.) can be modelled as a sequence. The sequences that are seen often or on a usual basis, can then be considered as the user's *normal* behaviour. Observed actions which do not resemble those normal sequences can be regarded as anomalous behaviour, which then may indicate a potential insider threat or at least an event to be investigated. This is the approach proposed by Parveen and Thuraisingham [13]. They extend this line of reasoning, and introduce "concept-drift", which is the gradual change in a user's actions over time. They postulate that this more accurately detects anomalous behaviour, since a user's actions often change over time (due to increasing skill or responsibility), and these changes would be regarded as anomalous in a model which did not account for the drift. This is a sensible assumption to make as it strictly generalises the static behavioural approach, and also introduces the flexibility and adaptability that is expected of machine learning.

In addition to using data collected on a user's actions, the literature on characterising the insider threat suggests that behavioural and personality characteristics are equally (if not more) important. Brdiczka et al. [1], combine structural

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anomaly detection with psychological profiling, in order to reduce the rate of false positives compared to using anomaly detection alone. Under the assumptions that the majority of users in a data set are not malicious insiders, and that their common patterns define normalcy, they propose the use of graph partitioning algorithms in order to discover a user's regular patterns.

The assumption that the majority of users are not threats is common in the literature, as is taking a user's common patterns as normalcy. However, whether it is necessary to adjust the baseline of normalcy over a period of time is often contested in the literature. On the one hand it is argued that a user's actions are constantly evolving and that this is not indicative of anomalous behaviour[13, 12], whereas others [18, 3] proceed without adjusting their baseline and still obtain good results. We are of the opinion that a learning-based approach which modifies the baseline is advantageous, and should be pursued whenever possible.

In this paper we attempt to extend existing work and propose a novel approach to detect insider threats. In particular, we aim to build on the approach to anomaly detection via modelling a user's normal behaviour as a sequence ([13]) through the use of Hidden Markov Models (HMMs) [15]. HMMs provide algorithms for learning parameters from a set of observed sequences, and also for predicting the probability of observing a given sequence. Previous research has demonstrated how HMMS may be used to design intrusion detection systems that either detect attacks on system calls into the kernel of an operating system [20] or novel n-grams in computer audit [10] or in more recent research code-reuse attacks executing maliciously intended instruction sequences [22]. Thus, they are an ideal candidate for consideration in our goal of insider-threat detection. We can use them to learn parameters as more sequences are observed, and also to classify sequences as anomalous (thus potentially indicative of a concerning insider event) if their probability of observation is significantly low. To the best of our knowledge, we are the first articles to consider the use of this approach to detect insider threats.

The remainder of this article is structured as follows. Section 2 presents the research context including the motivation for using HMMs and the feature set we will consider for our implementation and experimentation. Next, in Section 3 we detail our approach and implementation, and discuss algorithms used and how we train our model to detect insider threats. This is then followed by a report on the validation exercises and case study conducted in Section 4. Finally we conclude in Section 5, also presenting limitation of our work and outlining avenues for future research.

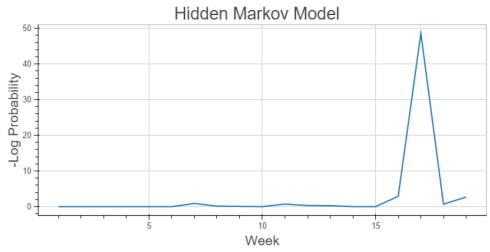
2. RESEARCH CONTEXT

2.1 Overview

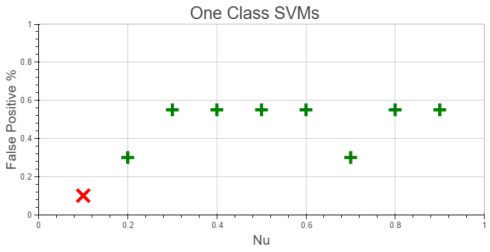
As discussed in Section 1, we will approach the problem of insider-threat detection through the modelling of a user's normal behaviour and then searching for anomalies in that behaviour. A sequence is a natural choice for modelling actions and events through time, and so the difficulty becomes one of finding anomalous sequences in a dataset.

Hidden Markov Models (HMM) have been used extensively in areas such as Computational Linguistics and Bioinformatics due to their temporal pattern recognition capabilities. They are well suited to capturing sequential behaviour and have had many successes in the analysis of biological sequences and recognising patterns in language [15]. HMMs provide algorithms for learning parameters from a set of observed sequences, and also for predicting the probability of observing a given sequence. This differs to approaches such as One-class Support Vector Machines (OCSVM), which are a type of SVM in which the algorithm attempts to separate the data points from the origin via a hyperplane of maximum distance from the origin [16].

Let us consider a simple example in order to illustrate the difference in functionality of HMMs over other ML techniques such as a One-Class Support Vector Machine (SVM) when sequential patterns in data is of importance. Assume data consisting of 19 sequences which are generated by repeating $\{1, 0, 0, 1\}$ between 1 and 4 times, as well as a single sequence which repeats $\{1, 0, 2, 1\}$ 2 times. We intend for this dataset to represent basic actions carried out over a time period. The fictional user performs normal actions for 16 time steps, then an anomalous action (indicated by the 2) followed by 3 more normal actions. Thus, the anomalous sequence is the 17^{th} sequence in the dataset.



(a) The negative logarithm probability of the model generating each sequence (thought of as actions in a given time step). We can clearly see a large spike, indicating that the model thinks the 17^{th} sequence is very unlikely compared to the rest.



(b) The false positive rate for a One-Class SVM for a range of Nu (An upper bound on the percentage of elements in the dataset which can be classified as anomalous. i.e. Setting Nu=0.1 means we can only classify 10 of our dataset as anomalous) values. A red cross indicates the anomalous sequence was not flagged, and a green plus indicates that it was flagged as anomalous.

Figure 1: The results of running the HMM and One-Class SVM on our example dataset

In order to make use of a One-Class SVM we must pad our sequences to all be of length 16 (interpreted as 16 dimensional vectors by the SVM, which is the maximum length of a sequence in our dataset). We would then train the SVM on the entire dataset as a whole, and ask it to classify instances as anomalous (-1) or normal ($+1$). Conversely, for the HMM we would train it on the first instance, and then feed it the remaining sequences one by one and ask it to predict their log likelihood, and also to learn from them. This therefore represents a somewhat more intelligent approach when sequence in which actions occur are of importance.

Figure 1 shows the results of running both models. It is evident from Figure 1 that the HMM is superior, not only because it clearly identifies the anomalous sequence but also

since it is much better suited to handling temporal information. The SVM has no concept of a temporal relation between the sequences, nor does it handle variable length sequences well. We have considered only One-Class SVMs as they are representative of fixed-length vector based approaches such as k-Nearest Neighbours (e.g., [9]). This is a very simple example, and so we would expect perfect performance from an anomaly detection method that can cope with significantly more complicated examples.

2.2 Feature set for Insider Threat Detection

Based on the literature related to characterising insider threats, anomalous behaviour is a good indicator of an attack [4]. Thus, we require suitable features that allow us to model a user's normal behaviour as well as capture characteristics which once observed are indicative of insider threat. These could be deviations in the features used to describe the insider threat profile of a user. Hence, it is useful to identify different actions a user can take (logging on, accessing a file, sending an email, etc.) that allow their behaviour to be modelled based on how insiders act and use them as our features. Amongst those high-level features, we can then break them down further to give us a more detailed description of a user's behaviour. For instance, we can consider the case of a computer logon, and break that down into: remote logon, logon out of hours, logon on the weekend/holiday, etc. Since our chosen approach is based on modelling a user's behaviour we can only consider actions that a user takes as features.

This precludes us from making use of information about a user, such as their psychometric scores, their job title, salary, performance reviews, etc. One could imagine augmenting our behavioural based approach with an approach that uses a user's contextual information as described in Brdiczka et al. [1]. Nonetheless, the features described above allow us to capture different types of insider threat, such as Intellectual property theft (log in activity, file activity and email usage or usb usage are features which are deemed important) or sabotage (login activity and deletion of files activity are important).

Our approach is intended to be very modular, and can be used with any feature set. However, in order to test our model we must select a particular dataset to use. Here we make use of the CERT Insider Threat Dataset [8], which is a synthetic dataset compromising of mainly log files describing a user's computer-based activity, since it is the only such comprehensive dataset available publicly. The features we have chosen are quite general, and could be used across many domains to model user behaviour. However, we have chosen them with regard to the dataset we are using, which constrains the features we can use (e.g., we cannot use a feature to denote an employee entering the building since we do not have that information).

For the purposes of our experiments we will consider 2 feature sets based on the CERT Dataset. The Simple set (7 features) is as follows: Logon (User logged onto a computer/unlocked a computer); Logoff (User logged off a computer); File (User copied a file to a removable drive); Email (User sent an email); Website (User visited a website); Connect (User inserted a removable drive); Disconnect (User removed a removable drive).

The Comprehensive set (16 Features) is as follows: Weekday Logon (User logged onto a computer on a weekday between 8am and 5pm); Afterhours Weekday Logon (User logged onto a computer not between 8am and 5pm on a weekday); Weekend logon (User logged onto a computer during the weekend); Logoff (User logged off a computer); File exe (User copied an exe file to a removable drive); File jpg (User copied a jpg file to a removable drive); File zip (User copied a zip file to a removable drive); File txt (User copied a txt file to a removable drive); File doc/pdf (User copied a doc or pdf file to a removable drive); Internal Email (User sent an email where all recipients are company email addresses); External Email (User sent an email where there is an external address); Website (User visited a website); Weekday Connect (User inserted a removable drive on a weekday between 8am and 5pm); Afterhours Weekday Connect (User inserted a removable drive not between 8am and 5pm on a weekday); Weekend Connect (User inserted a removable drive on the weekend); Disconnect (User removed a removable drive).

The features considered are designed to provide anomalous behaviour indicative of an insider threat, thus deferring from any normal intrusion system which may correlate events relevant to malicious activity in general. We are pursuing the task of insider threat detection by making the assumption that anomalous behaviour on the part of a user is indicative of an insider threat. As insiders, we refer to any users who have legitimate access in any system of the organisation. There are many scenarios in which this assumption does not hold, such as employees organising a surprise birthday party for a colleague, or a sudden deadline. The case of contractors or employees who attack shortly after beginning their employment is also an area in which our model is weak, since we do not have sufficient time to model their *normal* behaviour.

3. APPROACH AND IMPLEMENTATION

In this section we will explain the algorithms and procedures used for testing our model on the CERT Dataset. Figure 2 shows a graphical overview of the processing approach and pipeline we use, and the remainder of this section is dedicated to describing each stage in it. The pipeline is designed to be very modular and thus we can easily swap out components without affecting it as a whole. For instance, we could change the features we feed into our model, or we could change our model completely without having to change the other components.

3.1 Feature Extraction

The CERT Dataset contains many log files which describe a particular kind of activity for all users (users being the same as employees), for instance `http.csv` contains logs pertaining to web browsing (website, date accessed, username, etc.). We load each file, and assign a symbol (a number as opposed to text for convenience) to each entry based on the current set of features we are using. After this, we join all of these files, partition them by each user and then finally sort them based on the respective timestamps. For each user we get a list of actions and the time at which they undertook them. We then group these actions into weeks, which gives us the final output for the feature extraction phase: for each week we have a sequence of actions the user took. We have chosen to group based on weeks in order to allow a user's behaviour to change throughout the week (e.g., fewer emails sent on a Friday afternoon) whilst keeping the sequence sizes

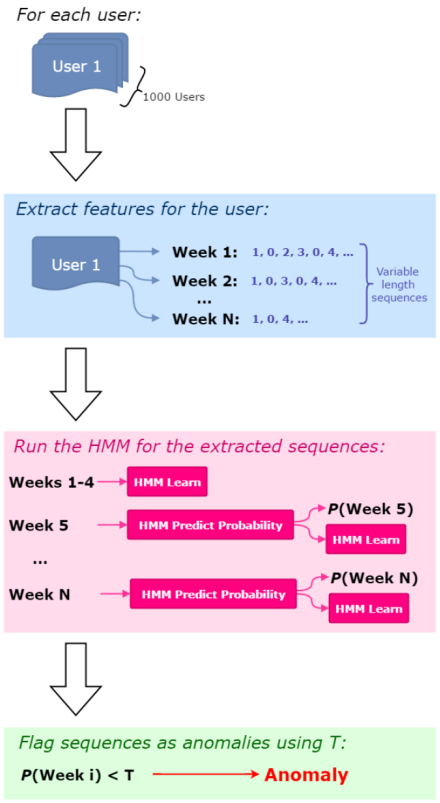


Figure 2: An overview of the pipeline we use to detect anomalies

relatively short. Experimenting with the time-scale we use is an interesting avenue of research that we have not explored in this paper, but reserve for future study. We should note that the CERT Dataset contains the ground truth for each user (when they are acting maliciously or not), which allows us to monitor the success or failure of our experiment.

3.2 Anomaly Detection

Once we have a sequence of actions that each user conducted in a given week, we are able to use our Hidden Markov Model (HMM). Here we introduce how the HMM is used, while Section 3.3 explains the details of the algorithms involved; understanding the these algorithms is key to appreciating how we look to apply HMMs to detect insiders.

To start, the HMM has 3 components which uniquely determine the model: the transition matrix, emission matrix and the starting state probabilities. We initialise these as being uniformly distributed with some small perturbations to break symmetry (Section 3.3.3 contains further details). We then train the model on the first 5 weeks of a user's behaviour in order for it to have some starting point from which to detect anomalous sequences. For the remaining weeks we first predict the probability of our model generating the sequence, and then train the model on that sequence. The procedure is described in Algorithm 1, Figure 3. `HMM.Predict()` is described in Section 3.3.1, and `HMM.Train()` is described in Section 3.3.3.

We acknowledge that our current work makes the significant assumption that the first 5 weeks do not contain anomalous behaviour for each user. This assumption can be

Algorithm 1 Processing the extracted sequences.

```
Initialise HMM
for first 5 sequences do
    HMM.Train(sequence, ...)
end for
for all remaining sequences do
    sequence probability ← HMM.Predict(sequence)
    HMM.Train(sequence, ...)
end for
```

Figure 3: Algorithm 1

violated for a number of reasons (short-time contractors, for instance). In the future, this could possibly be mitigated by manually checking these weeks to ensure that they are representative of normal behaviour, or, perhaps a model based on other users (roles) with similar intended behaviour could be used as the initial parameters. For now however, adopting the first 5 weeks allows us to have some basis for exploring the utility of the HMM approach to insider-threat detection.

Once we have run this algorithm for all users we have the predicted probabilities for each week. We can then set a threshold **T**, which we use to classify sequences as anomalous or not. If the probability of the sequence is below the threshold, we classify it as anomalous. This threshold **T** is a critical parameter of our system which must be set carefully. However, after running Algorithm 1 we can save the probabilities generated and then experiment with many values of **T**. One could also imagine a human security analyst increasing **T** from 0 in order to be presented with more instances which the system deems anomalous.

3.3 Hidden Markov Models

A Hidden Markov Model (HMM) is a Markov Model, in which the model outputs a symbol before transitioning to a new state. Figure 4 shows an ordinary Markov Model and a Hidden Markov Model. It is called a Hidden Markov Model because typically we only observe the emitted symbols, and not the states the model visited (they are hidden from us).

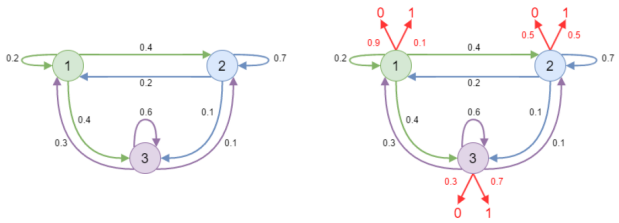


Figure 4: An example of a Markov Model (left) and HMM (right), with the same transition probabilities, but where the HMM outputs symbols {0, 1}

Below we will refer to the state the model is in at timestep i as X_i, and the symbol emitted by the model at timestep i as Y_i. The mechanics of the model are described via 3 distinct quantities, which uniquely define the Hidden Markov Model:

Transition Probabilities

$$P(X_{i+1} = x' | X_i = x) \tag{1}$$

The probability of transitioning from state x to state x' at timestep i. In order to be a Markov process we further have

the condition that:

$$P(X_{i+1} = x'|X_i = x) = P(Xi = x'|X_{i-1} = x) \quad (2)$$

This ensures that transitions are time invariant and hence only depend on the current state (this implies the Markov property). In order to be a well-defined process we also have that:

$$\forall x \in States : \sum_{\forall x' \in States} P(X_{i+1} = x'|X_i = x) = 1 \quad (3)$$

Emission Probabilities

$$P(Y_i = y|X_i = x) \quad (4)$$

The probability of emitting symbol y, given that you are in state x at time step i. Once again we maintain time invariance to ensure the Markov property:

$$P(Y_i = y|X_i = x) = P(Y_{i-1} = y|X_{i-1} = x) \quad (5)$$

At every state we must ensure the probabilities of emitting a symbol form a valid probability distribution.

$$\forall x \in States : \sum_{\forall y \in Symbols} P(Y_i = y|X_i = x) = 1 \quad (6)$$

Starting Probabilities

$$P(X_0 = x) \quad (7)$$

The probability of the first state being state x. These must form a distribution over the set of states:

$$\sum_{\forall x \in States} P(X_0 = x) = 1 \quad (8)$$

Once we have a HMM and a sequence of Symbols, there are 3 types of questions we can ask:

- What is the probability of a given observed sequence with respect to our model?
- What is the most likely sequence of states the model visited when generating a given observed sequence?
- What are the parameters of our model that maximise the probability of observing a given observed sequence?

For the purposes of anomaly detection we will make use of algorithms designed to answer questions 1 and 3. Question 2 can be answered using the Viterbi Algorithm [5], but we will not make use of it in this paper.

3.3.1 Probability of an observed sequence

To calculate the probability of an observed sequence $Y = y_0 y_1 \dots y_{T1}$ with respect to our model, we partition over all sequences of hidden states of length t: The probability of the first state being state x. These must form a distribution over the set of states:

$$P(Y) = \sum_X P(Y|X)P(X) \quad (9)$$

where $X = x_0 x_1 \dots x_{T1}$ with $x_i \in States$. A naive implementation calculating the sum as shown above is $O(TN^T)$ where $N = |States|$, however, $P(Y)$ can be calculated more efficiently using the Forward Algorithm which provides an $O(NT^2)$ runtime.

Due to the limitations of floating point arithmetic, particularly underflow, we run into significant problems when calculating the intermediate values for our calculations. Since all values involved are smaller than 1, they can very quickly tend to 0, which then renders subsequent calculations erroneous due to loss of precision or even underflow to 0. To combat this we use the logarithm of the probabilities instead of the actual probabilities, which is standard practice used in numerical calculations involving probabilities. We thus return $logP(Y)$ instead of $P(Y)$. The full details of this approach for calculating $logP(Y)$ can be referenced in Stamp [17].

3.3.2 Maximise likelihood of a sequence

The task of finding the parameters of an HMM (transition, emission and starting probabilities) that maximise the likelihood of observing a given sequence can be accomplished using the Baum-Welch Algorithm [21]. This is an iterative algorithm that improves the likelihood of a model generating a given sequence on every iteration, i.e., given $Y = y_0 y_1 ... y_{T1}$ on every iteration we have that:

$$P(Y|\theta_{new})P(Y|\theta_{old}) \quad (10)$$

where θ represents the parameters of our model.

However, we are not guaranteed to reach a global maximum and in practise we are very likely to reach a local maximum which is not close to the global maximum. In addition, due to the iterative nature of the algorithm we cannot be sure if we have even reached a local maximum or not. In order to work around these problems we make use of random restarts and use thresholds to determine convergence ($|x_{i+1} - x_i| < \epsilon_{threshold} \Rightarrow converged$). Once again we must make concessions for floating point arithmetic, the full details of which are described in Stamp [17].

3.3.3 Training the model

Here we describe the algorithm we use to train our HMM; an overview can be seen in Figure 5. The function `BaumWelch(..)` refers to running a single iteration of the Baum-Welch algorithm on the model and sequence provided, returning to us the new proposed model.

Essentially the algorithm uses random restarts in order to find other maxima that are potentially better than the first one we may encounter. The parameter $\lambda \in [0, 1]$, which we will refer to as the *inertia*, is used to linearly interpolate between the new proposed model and the old model. A higher inertia means that we will keep more of the old model. Inertia is an important parameter in our model, and as such it is important to set it correctly. We will explore different values for the inertia in Section 4. It is also intended that $\epsilon_{convergence} < \epsilon_{restart}$. Throughout the algorithm θ refers to the parameters of the model: the transition, emission and starting probabilities. The function `RandomParameters()` produces random values for each quantity, sampled uniformly from $(0, 1)$, and then normalised appropriately to ensure valid distributions.

4. VALIDATION

The CERT Dataset is comprised of many smaller datasets, which all represent independent logs for 1000 users over some time-framework. We have chosen to use Dataset *r4.2*,

Algorithm 2 Train the Hidden Markov Model

```
function TRAIN(sequence, max_iters, ε_convergence, ε_restart, max_restarts, λ)
    θ_old ← θ_model
    old_score, best_score ← −∞
    Done ← False
    while not Done do
        θ_new ← BAUM-WELCH(sequence, θ_old)
        new_score ← PREDICT(sequence; θ_new)
        if new_score > best_score then
            θ_best ← θ_new
            best_score ← new_score
        end if
        if iterations ≥ max_iters then
            Done ← True
        else if new_score − old_score < ε_restart then
            if restarts < max_restarts − 1 then
                restarts ← restarts + 1
                θ_old ← RANDOMPARAMETERS()
                old_score ← −∞
            else if restarts = max_restarts − 1 then
                restarts ← restarts + 1
                θ_old ← θ_best
                old_score ← −∞
            else if new_score − old_score < ε_convergence then
                Done ← True
            else
                old_score ← new_score
                θ_old ← θ_new
            end if
        else
            old_score ← new_score
            θ_old ← θ_new
        end if
        iterations ← iterations + 1
    end while
    θ_model ← λθ_model + (1 − λ)θ_best
end function
```

Figure 5: Algorithm 2

one of these datasets, for running all of our experiments. This is because it contains many more instances of insider threats compared to the earlier datasets (70 compared to less than 4). This allows us to measure metrics such as the false-positive rate and the true-positive rate without large steps in our results (i.e., we can measure the true-positive rate in 2% or less increments compared to 33%, 50% or even 100% increments). In addition, it also provides more varied instances of attacks, since each user would exhibit their behaviour in non-identical ways. The dataset is considered to be dense, with "an unrealistically high amount" (r4.2/readme.txt) of malicious activity by the creators [8]. However, this should not influence our results compared to a lighter dataset, since each user is treated independently of every other user by our system.

Reflecting on the dataset selected, there are files with user logon data, psychometric data, browsing history, file access data, email data, device usage data and LDAP data. We are provided a list of insiders for every dataset, so that we can determine our performance. The features we are using, as discussed in Section 2.2, only make use of: `logon.csv`, `http.csv`, `file.csv`, `email.csv` and `device.csv`. We do not use the LDAP records or `psychometric.csv` (we do not make use of a user's psychometric scores since they do not help us to model their day-to-day behaviour directly).

As we present our results below, we make use of Receiver Operating Characteristic curves (or ROC curves). These curves are used to plot the true-positive (correct) rate against the false-positive rate for the different possible points in a diagnostic test. In order to produce the ROC curves, we use a process of threshold varying. After obtaining the log probabilities for each sequence from our model, we set a value for the threshold and then check each sequence one-by-one and classify them as anomalous if $logP(sequence) > Threshold$. We then increase the threshold and repeat until no sequences are classified as anomalous. In the subsection next, we detail and discuss our results, and then move to consider a case study.

4.1 Results

We run Algorithm 1 as described in Section 3.2 to obtain our list of potential insiders. We use Algorithm 2 with the following parameters: TRAIN($sequence, max\_iters = 20$, $\epsilon_{convergence} = 0.01$, $\epsilon_{restart} = 0.1$, $max\_restarts = 5$, λ any value within the space $[0.5, 0.8]$)[1]. For the Hidden Markov Model we use 10 states.

Figure 6 shows the results of running our model with those parameters. We can see that the different feature sets differ only slightly. These differences are small enough to be attributed to the differences introduced via the random number generator running many models in parallel. The stochasticity of the scheduler results in the models calling the random number generator in a different order, which affects the initial initialization as well as the call to `RANDOMPARAMETERS` in Algorithm 2. This could also be a side-effect of the synthetic nature of the dataset, and hence the granularity of our features could show noticeable differences in a more *natural* dataset.

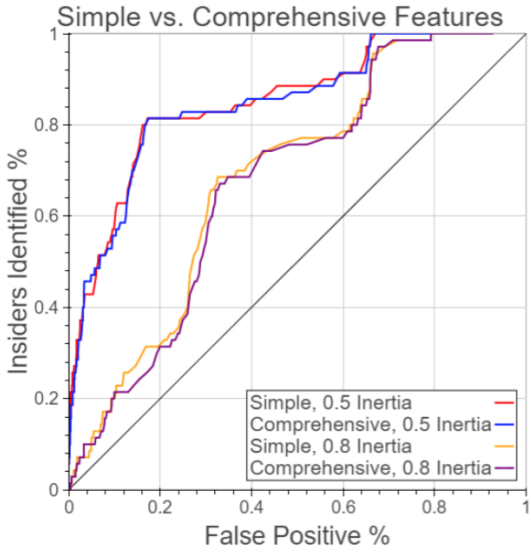


Figure 6: ROC Curve showing the differences between the *Simple* and *Comprehensive* feature sets for an inertia of 0.5 and 0.8

In addition to varying the feature set we use, we can also consider varying the number of states we use for our model. Figure 7 and Table 1 show the results of varying the number of states in the HMM. We used the same parameters as for Figure 6 with the exception of: $max\_iters = 50$, $max\_restarts = 10$ and $\lambda = 0.5$. We can see that increasing the number of states shows some slight improvements, however the computational cost of doing so (combined with increasing the number of iterations to make it viable) is extremely high. Thus, we do not explore further the results of running our models with an increased number of states due to the processing time required being prohibitive for running

[1]We assume here that $Predict(seq)$ returns $logP(seq)$.

many experiments. This large computational cost is diminished if our system is run in an online manner, whereby we only run it for new data points. However, for the purposes of our experiments we must run it for the entire dataset (18 months of data) every single time.

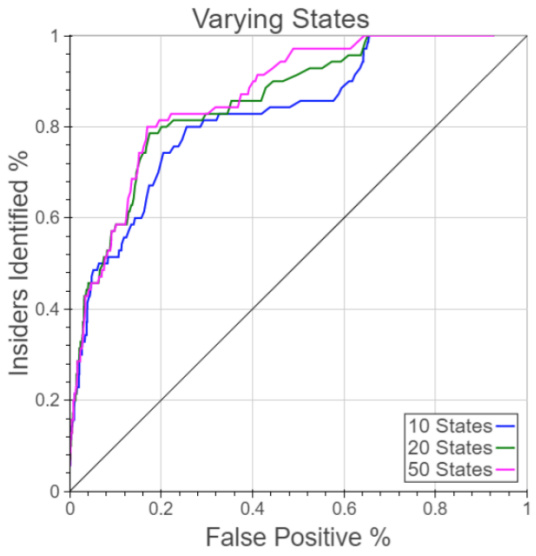


Figure 7: ROC Curve showing the difference between running the model with 10, 20 and 50 states

# States	Area Under Curve (AUC)
10 States	0.755
20 States	0.784
50 States	0.797

Table 1: AUC for each of the runs

An extremely important parameter in our model is the inertia, λ. In Figure 6 we saw a significant difference between $\lambda = 0.5$ and $\lambda = 0.8$. Figure 8 and Table 2 show the results of varying the inertia with the following parameters: TRAIN($sequence$, $max\_iters = 20$, $\epsilon_{convergence} = 0.01$, $\epsilon_{restart} = 0.1$, $max\_restarts = 5$, λ and 10 states in our model. We can clearly see that there is a marked benefit to decreasing the inertia up till around 0.05. This is a surprising result because one would expect that an inertia of 0.05 is too low to allow the model to maintain the behaviour of previous weeks.

Inertia	AUC	Inertia	AUC
0.9	0.535	0.3	0.796
0.8	0.606	0.2	0.805
0.7	0.706	0.1	0.821
0.6	0.756	0.05	0.830
0.5	0.776	0.01	0.829
0.4	0.789		

Table 2: The corresponding AUC values

In order to investigate this further we can check the values for the threshold we use to generate each point on the ROC curve. Figure 9 shows these values for each inertia value we

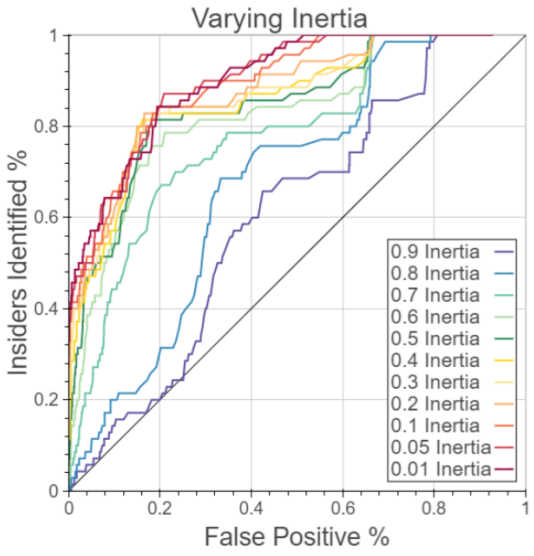


Figure 8: ROC Curve showing the effect of varying the inertia in Algorithm 2

used. A higher threshold corresponds with a lower probability (i.e., in order for a sequence to be classified as anomalous, the model's probability of generating that sequence must be lower when using a higher threshold). We observe that a lower inertia corresponds with a higher threshold for each point on the ROC curve. This implies that the values produced by our HMM are more spread out with a lower inertia. We hypothesise that this decreases the effect of small variances in our model's output, and hence allows the anomalous sequences to be better separated from the other sequences.

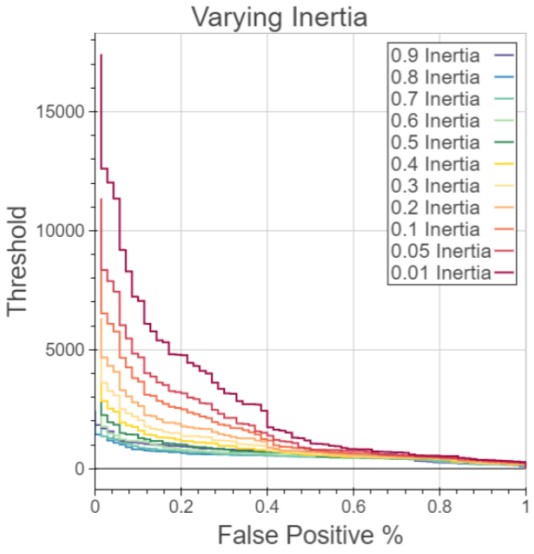


Figure 9: The value used for the Threshold vs. False Positive % for each point on the ROC curve

Using an inertia of 0.05 shows good performance on the dataset. An AUC of 0.830 indicates we are able to successfully identify the majority of insider threats, and in addition

the graphs show a 85% identification rate with a false positive rate of only 20%. If our system was combined with more signals of insider attacks (as in [1]), as well as more traditional security monitoring tools (e.g., flag up visits to certain websites), we hypothesise that potentially much better performance could be achieved. We believe that incorporating other approaches would provide complimentary indicators of an insider threat. This is because our approach is designed to capture deviations from a user's normal behaviour, whereas those other approaches capture other separate indicators of an attack.

4.2 Case Study

Dataset r4.2 contains 70 malicious insiders who execute one of three attacks. Now, we consider a brief case study with a single insider, User MCF0600, in more detail so that we can better understand how and why our model correctly classifies them as a threat. The attack carried out by this user is as follows: User MCF0600 begins to logon after hours, starts using a removable drive and then begins uploading data to *wikileaks.org*.

We will use the Simple feature set to simplify our visualisation, and run the model with 10 states and the following parameters: TRAIN($sequence, max\_iters = 20$, $\epsilon_{convergence} = 0.01$, $\epsilon_{restart} = 0.1$, $max\_restarts = 5$, $\lambda = 0.05$. Figure 10 shows the model's probability of generating each week's activities. We see a large spike at Week 39 which corresponds to the dates 20/9/2010 till 26/9/2010 in the dataset. This is the exact week which contains the malicious behaviour in which the user attacks the company by uploading data to wikileaks.org.

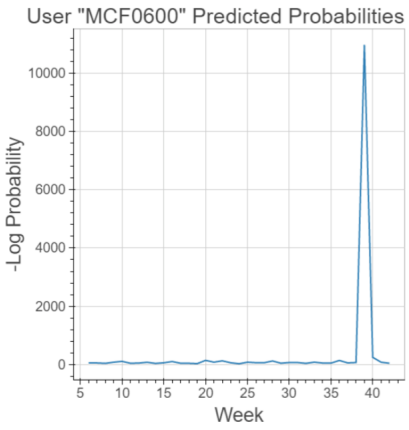


Figure 10: User MCF0600's predicted probabilities for each week

Figure 11 shows a visualisation of the model at Week 38, which is used to predict the likelihood of the actions taking place in Week 39. It shows the model learns the user frequently visits websites, and occasionally sends emails throughout the day. Notably there is an absence of removable drive usage and the downloading of files. In detail, the Starting probabilities for each state are concentrated on State 9 ($P(X_0 = State9) = 1$), represented by the purple arrow. Similarly, the emission probabilities for each state are concentrated on a single symbol, hence only that symbol is shown for each state. The transition probabilities are more varied, hence we only show those > 0.2 otherwise the diagram quickly becomes too noisy. Note that State 5 is not shown in the diagram, because there is no significant probability (> 0.2) of transitioning to it from any other state.

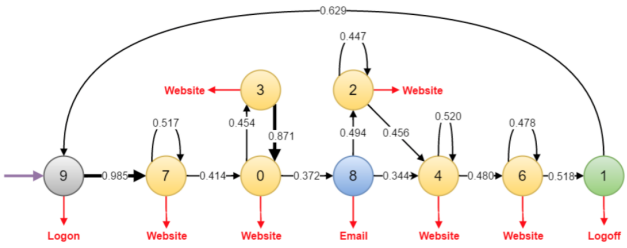


Figure 11: The Hidden Markov Model after week 38 for User MCF0600

More generally, a sample from the first day of the week with malicious activity is:

['*Logon*', '*Connect*','*File*', '*Disconnect*', '*Connect*', '*File*', '*File*', '*File*', '*Disconnect*', ...].

It is clear that this does not conform to the user's normal behaviour due to the marked increased usage of a removable drive, and the downloading of files. Contrast this sequence with another normal day for this user which is modelled almost perfectly by the model:

['*Logon*'; '*Website*'; '*Website*'; '*Website*'; '*Email*'; ['*Website*' $\times$ 7]; '*Logoff*']

From our case study we see promising indicators that our model effectively *learns* a user's behaviour, and then can accurately use that to determine deviations from it. We should note that it is the features identified from our literature review to be characteristic of insider threats that enable the HMM algorithms to flag anomalies relevant to insider activities. Therefore, a deeper understanding of how insiders act and which characteristics can be identified in their malicious activities is of significant importance for our detection system since they can more accurately profile the behaviour of an insider. For the needs of the CERT case study and given the limited number of different types of logs in the dataset, we emphasised in providing features for detecting suspicious activity related to intellectual property theft.

5. CONCLUSIONS

In this paper we have examined the problem of insider threat detection, by framing it as a machine learning task. Our main contribution is the development and testing of a novel method of using Hidden Markov Models to learn a user's normal behaviour in order to identify deviations from it, which may be indicative of a threat (or at least behaviour worth following-up).

From our results we can see that our system is able to detect insider threats with a reasonable false-positive rate. Furthermore, our case study of user MCF0600 shows that the HMM is able to learn a user's behaviour and determine when the user deviates from that behaviour. In addition, the use of a HMM allows us to visualise the model, and thus

to determine what the model deems as normal behaviour which allows us to understand why a particular sequence of actions is classified as anomalous. This is extremely pertinent information, since there are severe repercussions when an employee is flagged as a potential threat to an organisation. By allowing a human security analyst the chance to investigate the offending behaviour we can provide valuable insight into why an attack took place, and also to allow false positives to be identified as such.

5.1 Limitations

In the exploration into the utility of HMM to insider-threat detection, we have made many assumptions that could limit the effectiveness of our approach in certain scenarios. We enumerate the most important of these, and the possible effect they could have on our system below.

Insider attacks are anomalous: The most significant assumption we have made is that all insider attacks are examples of anomalous behaviour. This precludes us from recognising situations where a user systematically attacks an organisation over an extended time-framework (e.g., downloading sensitive files over months), or situations where our features are not sufficient to distinguish an attack from a user's normal behaviour.

Training on the first 5 weeks: In order to apply our model, we must first ensure that it is able to distinguish a user's normal behaviour from anomalous behaviour. This then means that we must train on some sample of a user's behaviour in order for the model to learn normal behaviour. Hence we are not looking for insider threats in that training set, which in our specific case means that we do not consider that a user might attack in the first 5 weeks. This could significantly hamper our ability to detect insider threats amongst short-term users (contractors for instance), which are a real threat [11].

Features: Our approach is only able to make use of the information that it is provided, and hence depends on the features that it is supplied with. This requires domain knowledge and manual feature engineering and experimentation in order to produce useful features. Our approach would therefore need to be adapted somewhat depending on application cases.

Choosing Hyperparameters: As is the case with many machine learning systems, our approach involves many different hyperparameters which must be set. Our results show that some of these (the inertia λ particularly) have a significant effect on the final results of the model, and hence these must be chosen carefully. This could lead to decreased performance on a real dataset where we would not have the benefit of knowing *a priori* who the insiders are. However, the hyperparameters can be changed whilst running the system, or we can initialise them based on results from other datasets.

5.2 Future Research

Our modular approach to the design of our systems means that each of the components could be replaced without affecting the others. This allows us to make changes to each of the individual parts without re-thinking the entire system. As this paper aimed to explore the utility of HMMs to detect insidrer threats, we discuss some areas that would be interesting for follow-on research below.

In our approach we have grouped a user's actions into week long sequences. Experimenting with different time-frameworks, such as day long sequences, could provide better performance. Using shorter sequences could allow specific events to be pinpointed as the source of concern, and could also allow the model to build a more accurate picture of a user's day-to-day behaviour. However, it could also prevent the model from observing longer-term trends in behaviour (e.g., on Friday a user sends fewer emails), so would have to be properly considered.

We have focussed on using a HMM for the task of learning a user's behaviour and then outputting how likely a particular sequence of actions is with respect to the user's past behaviour. We could replace the HMM with a more complex model such as a Long Short-Term Memory Recurrent Neural Network (LSTM) [7], in order to learn a richer representation of a user's behaviour. A LSTM does not make the Markov assumption, and hence is able to use longer-term dependencies in order make a more informed decision about the current action a user might take. This could stem from the inability of a HMM to use many bits of information about the past, without an exponentially large number of states (a HMM needs around $2k$ states to model k bits of information), whereas a LSTM can make use of potentially all the information it has seen. However, a LSTM could require significantly more training data in order to be effective; as with all techniques there are pros and cons.

Our current procedure for determining if a particular sequence is anomalous or not is to compare the probability of our model generating it with a threshold. This requires us to manually set a threshold value, which is another hyperparameter of our system that significantly affects the results. However, we could consider the task of determining which sequence is anomalous with respect to their probabilities as an anomaly detection problem itself. Hence, we could apply frequency-based anomaly detection techniques (e.g., [19]) on the sequences of probabilities generated by our model. This allows us to avoid having to manually set a threshold parameter, and also allows us to be more selective in flagging up sequences as anomalous. Moreover, it could help in the case where our model is unable to determine a user's normal behaviour accurately (or if the user's behaviour is erratic). Since in this scenario the majority of sequences will be unlikely with respect to the model, we would only want to classify as anomalous those as that are significantly more unlikely.

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