**Abstract**

A Practical Application of Machine Learning-Based Classification Techniques to Proactively Identify Insider Threats

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Insider incidents are on the rise, just like the high-profile security breaches such as Snowden, thousands of insider-perpetrated security breaches occur in United States businesses every day. While current commercial software can monitor, log, and prevent access to designated files and directories, it remains difficult to predict and prevent unauthorized insider usage. Due to the gaps in research in this area, the focus of this study is to more accurately predict insider threats within a terminal environment.

Linux was chosen specifically because of its ubiquity on commercial servers around the globe. Amazon’s Machine Learning (AML) service has been selected to analyze the data, reduce the necessary computing power, and to minimize human factors considerations in the design of the machine learning architecture. AML uses multinomial logistic regression for multi-class classification and uses the stochastic gradient descent optimization technique.

The method adapted is to utilize the AML software, it will be trained on a dataset comprised of normal user situations, crafted mistakes, and malicious activity. After providing the training dataset, the software will be instructed to make predictions against similar datasets to verify accuracy. It will then be tested against a human actor that will simulate multiple different roles, and test predictions in a high-fidelity simulation.

In result, should it be demonstrated that ML software can accurately identify and predict insider threats, this research could be a foundation for future cyber security software architectures. Other opportunities for research in this area would include ML applications in intruder and malware detection.

**Data** **Gathering**

There are three main sources of data used for the machine learning model. The first is an un-edited history file from the test system. Second is a list of commands assembled during this research. The third is the UNIX User Dataset from Purdue University. Simple programs were developed to remove unnecessary lines and markup from the two gathered datasets.

**Methods**

The method utilizes the Amazon Machine Learning software. It will be trained on a dataset comprised of normal user situations, crafted mistakes, and simulated malicious activity. The software will use the training dataset, to make predictions against similar datasets to verify accuracy. It will then be tested against a human actor to test predictions in a high-fidelity simulation. A testing dataset of 100 commands will be given to the model for batch prediction and will be evaluated for statistical accuracy. The python timeit module will be used to test for latency between the user entering their command and when it executed. Four categories will be analyzed; code only, execution only, code + execution, and code + execution + AML. To have a baseline for the network speed, the pings against the AML endpoint will be analyzed.

**Results**

The batch predictions have shown that the model is 100% accurate at predicting normal use and has a 30% rate of false negatives for malicious and mistake commands.

The results of the high-fidelity simulation indicate that the software is partially effective at capturing all input. The participants were able to escape it and after that became untraceable to the system. This indicates that further work is needed in this area.

In the latency tests, results show a small discrepancy of and additional ~0.25ms between the combined times of code only and execution only, compared with the code + execution time. There is a major difference between the network speed, execution, and the time it takes to interact with the AML of over ~440ms.

Overall the process has indicated that a prototype like this can capture near 80% of the commands and suggests that further work on this model can produce far more reliable results.

**Conclusions**

The results of the test indicate the model isn't sufficiently accurate in detecting ~~intrusion~~ malicious and mistake activity even when given special weighting. This is likely due to the lack of data in ~~the malicious and mistake~~ those categories.

Future research in the area needs more open data. One solution is to ask organizations to publish the cleaned logs after an attack.

This study also indicated that further improvements are needed to the program to accurately capture information from a live terminal. While the program created a fake prompt, it was severely limited in what it could capture and that skewed the data from the simulation.

There are a few factors that come into account with the timing. One is that most of the code in the `evaluate()` function was commented out and the `get\_prediction()` and `get\_input()` functions were not called at all.

While the high-latency is understandable, this is within range of unacceptable latency and would be highly noticeable to all users. In the future, using a white-list of commands that don’t need evaluation would reduce time. Another option would be to allow command execution before getting results from AML, eliminating the issue altogether.

Future research is needed in order to determine how to best approach the problem of practical proactive

intruder detection. As other researchers have indicated, larger datasets comprising of more points such as time-stamps and keyboard information would help better track user behavior in an attempt to establish recognizable patterns by neural networks. This and other research indicate that more data is needed.

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**Source Code & Materials are available at:** <http://github.com/Skraelingjar/cyberml>

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