Dual-task agent for run-time classification and killing of malicious processes

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Abstract—Malicious software (malware) is one of the key vectors for cyber criminal activity. New malware samples appear every minute. These new samples are distinct from previous examples because the precise file content is new though the software behaviour may not be new. For this reason, static detection methods perform poorly by comparison with methods using behavioural data. Behavioural analysis, however, is typically conducted in a sandboxed or emulated environment. The sandbox takes several minutes to analyse the file, whilst static detection takes seconds. Some malware behaves one way in a sandbox and differently on a target endpoint, risking the sample being misclassified.

Run-time malware analysis examines software behaviour as it executes on the target endpoint. This eliminates the time delay caused by sandbox analysis and ensures that the behaviour monitored is identical to the behaviour on the target endpoint. Malicious software is capable of causing damage within seconds of delivery, only an automated response is capable of acting quickly enough to mitigate its impact.

Previous run-time detection research has not considered real damage prevention to the endpoint. This paper proposes an agent for earlier run-time detection and killing of malware than has previously been presented. The agent uses a dual-task recurrent neural network trained both to maximise classification accuracy and to exercise caution in killing processes, as the latter action is irreversible. Real-time testing of the model found that it was able to detect 90% of fast-acting ransomware (ransomware which begins encryption within 30 seconds of launching) and reduce the number of files encrypted in the first 30 seconds by 50%.

I. INTRODUCTION

Malicious software (malware) evolves rapidly both to evade detection and take advantage of new vulnerabilities. In the first quarter of 2017, it is estimated that a new malware specimen appeared every 4.2 seconds [1]. Automatic detection techniques are necessary to cope with the rate at which new malware samples are being created. Traditional antivirus techniques are static, matching signatures from incoming files to known malware signatures. The same malware sample can easily produce a different signature using code obfuscation techniques such as encryption [2]. Behavioural analysis, by contrast, is dynamic meaning it is anchored in the activity of the malware as it executes. Behavioural activity is much more difficult to disguise as it is often closely linked to the essential functionality of the malware.

Dynamic analysis is more likely than static analysis to detect completely new malware variants [3], but it is rarely used as part of endpoint malware detection due to the time it takes to evaluate a single sample. Dynamic analysis entails executing the malware, which requires either (i) running in an isolated virtual environment and waiting for analysis results or (ii) live-analysis of the malware as it runs on the target endpoint. The former can mean a significant delay (several minutes) for the user, and more critically, malware may only execute under certain conditions such as when user activity is low or when the environment does not appear to be a virtual machine (VM) [4]. Conditional execution leads to different behaviour during analysis than on the target endpoint, potentially allowing malware to appear benign during analysis. The alternative is to employ run-time detection and analyze the file as it executes in its intended environment. This eliminates time delay for the user, and negates the problem of conditional execution.

However, running applications on the target endpoint introduces the risk that malware will be able to carry out unwanted behaviour on that machine. To mitigate the chances of this happening, malware should be detected and stopped as early as possible. A software-based model has been proposed by Sun et al. [5] which kills malicious processes, but real-time testing of the model required applications to run for several minutes, during which time malware can cause considerable damage [6]. Other hardware-based models (e.g. [7], [8], [9]) proposed may use short timescales but it is difficult to discern the precise timescales as the recording period is reported in volume of data rather than time; these authors do not investigate the impact of killing processes once they are deemed malicious. Further to this, hardware models are difficult to distribute and update (as new malware families and variants appear) by comparison with software models. In this paper we present a software-based model for quickly detecting and killing malicious processes.

This paper contributes to the field of run-time malware detection in the following ways:

- This is the first paper to detect and kill malicious processes within seconds of the processes beginning.

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• We create a realistic environment by comparison with previous works based on the typical hardware capabilities of a modern laptop (see Section III-D) and by running many applications at once as a user would. This is the largest set of concurrent applications (up to 35) for runtime data collection that has been researched up to this point.
• We quantify the impact of detecting and killing processes through tangible metrics, namely the number of files altered by ransomware with and without the detection system running, reducing the number of files compromised in the first 30 seconds by 50%.
• We conduct a comparison of behavioural features and find that the commonly-used system API calls (\cite{10}, \cite{11}, \cite{12}, \cite{13}, \cite{14}), give fewer accurate detections than continuous numeric machine activity metrics.

The next section will discuss related work. The features used, model and environment are described in section III followed by the dataset and experimental results in section IV. Finally, section V will outline the limitations of the proposed model and the future experiments following on from these limitations.

II. RELATED WORK

A. Behavioural Malware Analysis

Behavioural or dynamic malware analysis uses data extracted from software whilst it is executing. Dynamic analysis contrasts with static analysis, which uses data collected without executing the software e.g. file signatures or byte frequencies from binaries. The same program behaviour can be written in an infinite number of ways; malware authors can easily change code and achieve the same functionality. Code obfuscation techniques such as encryption are common practice for evading static antivirus tools \cite{2}. For malware to successfully achieve its ends it must at least exhibit the behaviours that comprise those ends. It is difficult for malware authors to obfuscate behaviour as it is often intrinsic to the desired functionality, this helps to explain why dynamic malware approaches have outperformed static approaches in direct comparisons (\cite{15}, \cite{3}).

The most common data used in behavioural malware research are API calls made to the operating system (\cite{10}, \cite{11}, \cite{12}, \cite{13}, \cite{14}). API calls are the means by which any piece of software communicates with the operating system in order to execute. Other metrics include data collected from hardware as used by Syadi et al. \cite{7} and machine activity metrics such as CPU and RAM usage (\cite{16}, \cite{17}).

Machine learning techniques, and neural networks in particular have been widely used to distinguish benign and malicious software. Hansen et al. \cite{12}, used Random Forests trained with API calls and their input arguments achieving 0.996 AUC (Area Under the Curve) score with a dataset of 5,000 malware and 837 benignware samples. Tian et al. \cite{11} and Sami et al. \cite{14} also used Random Forest algorithms trained using API calls to score 97% accuracy and 0.98 AUC respectively. Huang and Stokes \cite{10} used API co-occurrence data with a feed-forward neural network to correctly detect 99.64% of samples tested on a very large dataset of 6 million samples. Whilst Tobiyama et al. \cite{18} used a combination of recurrent and convolutional neural networks with API calls to achieve 0.96 AUC with a dataset of 170 samples.

Each of these papers achieves a high detection accuracy but are using several minutes of (if not complete) behavioural traces to distinguish benign and malicious applications. Some progress has been made on early detection of malware. For instance, Rhode et al. \cite{16} were able to detect malware with 94% accuracy within 5 seconds of execution with a dataset of 4,631 samples. However, as a sandbox-based method, malware which is inactive for the first 5 seconds is unlikely to be detected with this approach. This paper seeks to use behavioural analysis for early-detection during run-time to avoid the risks of sandbox-aware malware and crucially, to react to detection quickly enough to prevent or mitigate malicious activity rather than needing to recover from it.

B. Run-time malware detection

Run-time malware detection is a specific subset of behavioural malware analysis. Behavioural malware analysis is typically conducted offline; the entire behavioural trace is collected, stored, and later processed in a non-time-sensitive context whereas run-time analysis processes data as it is emerges using a partial behavioural trace. Behavioural malware analysis often monitors activity in a virtual machine or emulator, whereas run-time analysis uses traces collected from the environment in need of protection. Some malware will exhibit different behaviour depending on its environment such that behaviour in an emulator is not indicative of behaviour on the target machine. Run-time analysis eliminates any disparity between behaviour on the target endpoint and other (virtualized) environments.

Run-time analysis can be grouped into software- and hardware-based approaches, with some using a combination of the two. Hardware-based approaches are attractive for the lower compute power required to collect data. Syadi et al. \cite{7} use high performance counters (HPC) as features to train ensemble learning algorithms and scored 0.94 AUC using a dataset of 100 each malicious and benign Linux software samples. Das et al. \cite{9} used an FPGA as part of a hybrid hardware-software approach to detect malicious Linux applications using system API calls which are then classified using a multilayer perceptron, the model is able to detect 46% of malware within the first 30% of its execution with a false-positive rate of 2% in offline testing. Ozsoy et al. \cite{8} use low-level architectural events to train a multilayer perceptron on the more widely used \cite{19} (and attacked) Windows operating system. The model was able to detect 94% of malware with a false positive rate of 7% using partial execution traces of 10,000 committed instructions. As far as we are aware, the hardware-based detection models proposed do not explore the automatic killing of malicious processes once detected to protect the system. Two questions follow: (i) Can run-time detection systems form
the basis of an automated response protocol, which will kill malicious processes faster than human security experts are able to react to an alert, thus reducing the time for which malware is running. (ii) What will be the impact in practice of an automated response? Killing or suspending a process also kills the child branches of the process tree (child processes). These questions have not been addressed by previous hardware-based malware detection research.

Software-based approaches are not limited by the hardware configuration of the endpoint, which can vary significantly between machines, even those using the same operating system. Software-based antivirus systems are widely used commercially as they are cheaper to produce, distribute and update than hardware-based systems. Sun et al. [5] have proposed a software-based online detection system which automatically slows down and then kills malicious processes. The authors trained and tested traditional machine learning and deep learning models using 9,115 malware 877 benign samples. The machine learning model is invoked prior to the deep learning model, causing the process to be slowed down whilst the deep learning model conducts more computationally expensive analysis to decide whether or not to kill the process. In real-time analysis, the authors found that their model performed less well by comparison with the offline test set, hypothesising that fewer API calls were collected using their ‘on-the-fly’ API hooker, achieving 87% detection accuracy after 5 minutes of execution and 91% accuracy after 10 minutes of execution. Malware is capable of inflicting substantial damage in less than 5 minutes. One security vendor has found that Chimera ransomware can encrypt 70 MB worth of files (stored in 1,000 documents) in 18 seconds [6]. Though the encryption rate is dependent on the hardware features of the target (e.g. solid state drives allow ransomware to encrypt at a faster rate), it is likely that encryption begins before 5 minutes. This paper proposes a novel approach to detecting and killing malicious processes in seconds rather than minutes.

III. MODEL

The model proposed is a software-based agent designed to classify and kill malicious processes using much shorter time frames (several seconds) of behavioural data than has previously been investigated. These shorter time frames increase the chances of preventing damage to the target endpoint by reducing the running time of the malware. The proposed model consists of three parts: a monitor, a decision-maker and an actor. The monitor collects and stores data about running processes in buffers, the decision maker then parses a batch of buffer data relating to the current processes and sends decisions to the actor for which processes to kill. Figure 1 gives a high-level overview of the model analysing a single snapshot of data, snapshots of the running processes are taken every second.

Behavioural malware analysis typically examines entire applications, but application behaviour is dictated by individual processes. Each application can initiate multiple processes. One way to classify applications is by examining all of the subprocesses of an application and taking an average prediction as to whether the file is malicious but this requires queuing and storing process trees in memory. Quick processing is preferable to limit the time available to malicious software to carry out its aims, therefore the following model analyses individual processes which can be conducted asynchronously; introducing the added benefit that the model could be parallelised for further speed increases if multiple cores are available.

The experimental results section (Section IV) will refer to offline and online modes. In both modes the same monitor (see Figure 1) collects the data but in online mode the data is stored to a log file for later use in training and testing the RNN model, whereas in online mode the data is stored in buffers and fed to the RNN at one second intervals.

A. Features

The data collected are numeric machine activity metrics, these continuous data can represent a wider range of states in fewer features than discrete events such as API calls are able to. 34 features are used, these were dictated by the attributes available using the Psutil [20] python library. The machine activity metrics collected were: system CPU usage; user CPU usage; memory use; swap use; the number of child processes...
running; and the maximum process ID of any child processes; number of threads; number of connections currently open; read, write and other I/O operations bytes on disk; read, the number of write and other I/O operations on disk; number of command line arguments passed to process; process priority; I/O process priority; number of handles currently used by process; number of TCP packets sent and received, number of UDP packets sent and received, and the counts of the statuses of the ports opened by the process.

For comparison with other proposed malware detection models we also collected API call data. Though API calls have been used in a number of high-accuracy malware detection models (as described in Section II-B), there are several reasons to prefer machine activity metrics: (i) API calls are a set of (hundreds of) possible function calls, only some of which are invoked by a given piece of software. This means that any API call appearing during inference which was not present during training will be disregarded by the model. The machine activity metrics collected on the other hand are almost always activated at some point during execution by every application, meaning that during inference the model is able to make use of all data relative to the data it was trained with. (ii) API calls from an executed process are captured using hooking, this entails redirecting every instance of monitored API calls from and then back to the running process, thus slowing the process down. As we cannot know how many times an API call will be made, it is difficult to estimate the overhead of collecting this data by comparison with the time-based polling proposed here, which could be adjusted to reduce data collection overheads if necessary.

B. Preprocessing

Preprocessing in the proposed model is minimal to reduce overall time from data collection to model decision, though some normalization is necessary to avoid over-weighting features with higher absolute values. The test, train and validation sets (x) are all normalized by subtracting the mean (μ) and dividing by the standard deviation (σ) of each feature in the training set: \( \frac{x - \mu}{\sigma} \). This sets the range of input values largely between -1 and 1 for all input features, avoiding the potential for some features to be weighted more important than others during training purely due to the scalar values of those features.

C. Dual-task RNN

This paper builds on our previous work in [16], which demonstrated better results with a recurrent neural network over other machine learning algorithms for detecting malware in its early execution stages. Neural networks are mappings from inputs to outputs, recurrent neural networks (RANNS) map time-series inputs to outputs. A RNN uses information about the way in which features are changing over time as well as the raw values.

In the same way that a feed forward neural network (Figure 2) feeds data from input to output nodes through intermediate “hidden” layers of nodes, the recurrent neural network also does this temporally, such that historic data from the input features are fed into the network. In the hidden layer of the RNN, the time series neurons feed information along weighted paths to the next neuron in the series. Bidirectional RNNs also communicate backwards in time, as illustrated in Figure 3.

Historically, RNNs were difficult to train for long sequences as the gradients of the error term with respect to the change in weights, used to update the weight values between neurons tended to explode or vanish (the exploding / vanishing gradient problem [21]). In 1997 Schmidhuber and Hochreiter [22] developed the Long-Short Term Memory (LSTM) cell which made use of gating mechanisms, enabling RNNs to learn over longer time series without the gradients exploding or vanishing. Chung et al. [23] have subsequently developed a variant of the LSTM cell, Gated Recurrent Units (GRUs), which are computationally more efficient due to using one fewer gating mechanism whilst generally maintaining the accuracy of LSTMs on most datasets [24], these are the RNN cells used in this paper.

In our previous work [16] we found that a recurrent neural network performed better than other machine-learning algorithms for malware detection when using time-series data. Hyperparameter selection can be crucial to the success of a neural network. The hyperparameters for the dual task model are taken from our previous extensive random hyperparameter search in [16]. For reproducibility, these are: a bidirectional RNN with GRU units, in 3 hidden layers of 74 neurons each. The network weights are adjusted using the “Adam” weight update rule following each batch of 64 samples during training for 53 epochs. Further to these hyperparameters, for run-time analysis it is necessary to select the length of the window of data to be used for classification. Section IV-C details the experiments to determine the window size.

A dual-task model is proposed to accommodate the irreversible action of killing a process. Killing a process removes...
the chance to re-classify that process (and its children) later in execution. From the perspective of accuracy metrics, killing a process is equivalent to labelling it as malicious for all future time points. This contrasts with sequential malware analysis models, which may analyze a file for 5 minutes, making multiple predictions during analysis; if the predictions are malicious only 8% of the time, the file is deemed benign. Over a time period $T$, with model predictions $p_1...p_T$, where $p = 1$ is malicious and $p = 0$ is benign. An analysis model takes the mean of the set of predictions, $\frac{1}{T} \sum_{t=0}^{T} (p_t)$, whereas a run-time detection model takes the maximum of the prediction set: $\max_{t=0}^{T} (p_t)$.

The dual task model aims to accurately predict whether a process is malicious as its first task. The second task was devised to combat the inherent bias in machine learning algorithms to achieving mean accuracy across the training set. We will refer to the two tasks as “prediction” and “caution”, which correspond to the “p” and “c” outputs in Figure 1.

Machine learning algorithms typically take the mean error across predictions, and adjust parameters to minimize this error during training. Here, the caution task is heavily biased against killing benign processes, and is unconcerned by leaving malicious processes alive. The predictive task is interested in minimizing overall error but we have introduced a scaling factor to account for the fact that killing a process with children labels those processes as malicious too; this should result in a larger penalty if the software was benign and a larger reward if it was malicious. The loss function for the predictor is a squared error term scaled proportionally to the number of children a process has. The “caution” loss function then adds an additional binary cross-entropy error term to those benign processes classified as malicious. Let $p, c, y, y^*, k$ indicate the predicted value of a sample, the caution predictor value, the true class (benign or malicious), and whether or not the prediction was correct, and the number of child processes of the sample respectively. The total loss over $N$ predictions is:

$$\frac{1}{N} \sum_{n=0}^{N} ((y-p)^2(k+1) - ((1-y)(1-y^*) \log(1-c)))$$  

During inference, the caution task is used to temper the predictive task outputs. If the sum of these outputs is greater than some threshold $\theta$, the process will be killed. We explain the derivation of $\theta$ in Section IV-D.

D. Environment

The environment describes the machine used to test the proposed model. The following experiments were conducted using a virtual machine (VM) running with Cuckoo Sandbox for ease of collecting data and restarting between experiments. To emulate the capabilities of a typical machine, we took the modal hardware attributes of the top 10 “best seller” laptops according to a popular internet vendor, and used these attributes to set up the machine. This resulted in a VM with 4GB RAM, 128GB Storage and dual-core processing running Windows 7 64-bit. Though new PC laptops are typically packaged with Windows 10, Windows 7 is still the most widely used operating system globally.

In typical machine use, multiple applications run simultaneously. This is not reflected by behavioural malware analysis research in which which samples are injected individually to the virtual machine for observation. The environment used for the following experiments launches multiple applications on the same machine. Human interaction with the application is simulated by a Cuckoo Sandbox package. The human interaction module affirmatively accepts dialogue box options, and performs some clicking within the application. The module also sleeps for periods as some malware is programmed to wait until the user is idle to begin its activity. Though accepting dialogue boxes is crucial to get many applications to run, it does not mimic full human interaction, future work will test the model with live interaction from humans.

Compute overheads are a concern for run-time models. As the proposed model monitors individual processes, the model’s workload increases with the number of running processes. Security software can be vulnerable to flooding attacks if it easily reaches some resource limit. Figure 4 shows the mean polling time to collect data, parse the data with the RNN and killing process time. The polling and killing each use a for-loop with $O(n)$ complexity, whereas the RNN model conducts inference in batches second with $O(1)$ complexity, where $n$ is the number of running processes. Taking the sum of the time delay graphs, Figure 4 shows that the model takes longer than the 1 second polling period once 35 processes or more are being analysed. To test whether this limit introduces performance issues for the model, each malware is launched with a manageable number (1-3) and a larger number (3-35) benign applications. Since each application may launch multiple processes, those malware with 35 benign applications running will at least reach the limit indicated by Figure 4. Section IV-D reports the results of having multiple processes running Windows 7 64-bit. Though new PC laptops are typically packaged with Windows 10, Windows 7 is still the most widely used operating system globally.

This was conducted before the experiments in the next section by randomly initializing a network to mimic the complexity of the RNN that would be used in reality.
running on the speed of killing malicious processes. From the existing run-time analysis literature, only Sun et al. \[5\] run up to 5 applications at the same time. We could not find up to date user data on the number of simultaneous applications running on a typical desktop, so have chosen to launch up to 36 applications (35 benign + 1 malicious) at once to test the limits of the model, which is the largest number of simultaneous apps for run time data collection to date.

IV. EXPERIMENTAL RESULTS

A. Preliminaries

1) Samples: The software samples used in this paper are all Windows portable executables, these are the most commonly seen file types submitted to VirusTotal [29], a free malware analysis service. We use 3,603 benign and 2,876 malicious samples, with 3,313 for training and 3,946 for testing, this is consistent with previous run-time detection dataset sizes \([6]\) uses 168 malicious, 370 benign; \([7]\) uses over 100 each benign and malicious; \([8]\) uses 1,087 malicious and 467 benign; \([5]\) uses 9,115 malicious, 877 benign.

Overall there are 57,981 processes in the training, testing and validation datasets together. The benign samples comprise files from VirusTotal [30], from free software websites (later verified as benign with VirusTotal), and from a fresh Windows 7 installation. The malicious samples were collected from two different VirusShare [31] repositories. The dataset is split in half with the malicious samples in the test set coming from the more recent VirusShare repository, and those in the training set from the earlier repository. This is to increase the chances of simulating a real deployment scenario in which the malware tested contain new functionality by comparison with those in the training set.

The training and validation sets are created from the same set of samples, but the test set is generated from a distinct set of benign and malicious applications. The same applications are run multiple times within the same sets, because each malware is executed with a small number of benign applications and then a large number of benign applications in order to test the limits of the model, as determined by the findings shown in Figure 4. Though the behavioural traces included in each set are mutually exclusive, Figure 5 illustrates the dataset generation for clarity.

In practice, a user will launch the same benign application again and again. The proportion of benign applications which are completely new to the system will only represent a small proportion of all benign applications executed due to the repeated use of installed applications (e.g. browsers, email clients, word processors). Though the same applications are used again and again, their behavioural traces may be slightly different, such that a detection model may have seen a behavioural trace for application \('X'\) before but has not seen it behave in the specific way it is acting now. This is analogous to a model which has learned how to recognise objects from images, but it may not have seen a learned object from a particular perspective or angle before.

Fig. 5: Generation of train (T), validation (V) and test (X) sets from the mutually exclusive sets of training samples (A) and testing samples (B). The samples in A and B have the potential to produce produce much larger sets of possible execution traces, \(A'\) and \(B'\) respectively, from which the training, validation and testing sets are drawn. The sets satisfy the following conditions: \(A \cap B = \emptyset\); \(A' \cap B' = \emptyset\); \(T \subset A'\); \(V \subset A'\); \(X \subset B'\); \(T \cap V = \emptyset\); \(X \cap V = \emptyset\); \(T \cap X = \emptyset\)

The validation set represents this group of use cases. To generate the validation set, benign samples from the training set are run again to generate new unseen behavioural traces. Malicious samples are not included in the validation set as a malicious application is likely only execute once on a given endpoint. Once a piece of malware is known to the security community, it will be caught by signature-based antivirus filters. It is important that the model does not kill benignware that it has seen before, but that it does kill unseen malware.

2) Data Collection: Data collection used the Psutil \([20]\) python library to collect machine activity data for running processes and to kill those processes deemed malicious. The RNN was implemented using the Pytorch \([32]\) python library. The model runs with high priority to make sure the polling is maintained when compute resources are scarce. Cuckoo Sandbox was used to collect the API calls.

B. Metrics

The false positive and false negative rates are important indicators of the accuracy of a malware detection model. In this paper the false positive and false negative rates do not indicate the proportions of wrongly classified benignware and malware by the RNN, but the false positive and false negative rates of the agent that kills the processes. The false positive and false negative rates in this paper indicate the proportions of wrongly classified benignware and malware by the RNN, but the false positive and false negative rates of the agent that kills the processes. The false positive and false negative rates in this paper indicate a benign process being killed at any point during execution and a malicious process being left to run for its entire duration respectively. If a benign process executes for 60 seconds with two child processes launched at 15 and 30 seconds, and the parent process is predicted malicious once during that time at 10 seconds into execution, it is treated as a false positive along with the child processes that would have executed were that process not killed. The false positive rate for the model with
Fig. 6: A shows the total number of processes running for 50 seconds when 1 malicious and 3 benign applications are randomly launched. B gives the total number of processes running when an RNN agent is able to kill processes, the dashed line. C, D, E and F are all normalised to show every process starting from 0 and the total number relative to the maximum possible of each benign and malicious. C and D have the same false positive and false negative rates but C allows both the benign and malicious processes to run for longer. E and F evaluate different time frames (50 vs. 45 seconds) which impacts the false positive and false negative area scores despite the agent behaving exactly the same.

this example dataset is 100% (3/3) rather than 00.07% (1/(60 + 45 + 30)) for the RNN alone.

False positives and false negatives are useful summary metrics, but do not reflect the advantage of killing malicious processes after 10 seconds over 10 minutes. Additional metrics are required to compare the speed with which models kill malicious processes. The earlier a process is killed, the less chance it has had to carry out malicious objectives. The temporal metrics introduced here are “false negative area” which quantifies the opportunity cost of leaving a malicious process running and “false positive area” which measures program execution time lost by killing a benign program.

Figure C shows the number of benign and malicious processes running when one malicious and 3 benign applications are executing. The dashed line (graphs B - F) shows the number of processes without the intervention of a model killing processes and the solid line with intervention. In graphs C and D, the false positive and negative rates are the same but D kills the malware and benignware earlier. To quantify the disparity between C and D we use the difference between the definite integrals of the solid lines and the perfect preferred graphs. A perfect graph for malware is a flat line along the y-axis, the prefect graph for benignware is coincident to the total number of benign processes running without intervention (the dashed blue line).

To calculate these metrics, let $B$ be the number of benign processes running without agent intervention and $B_{agt}$ and $M_{agt}$ the total number of processes running when the agent is acting for benign and malicious processes respectively. For a monitoring period, $T$, the false positive area, ($Area_{FP}$) and false negative area ($Area_{FN}$) are:

$$Area_{FP} = \int_0^T (B - B_{agt})$$

(2)

$$Area_{FN} = \int_0^T M_{agt}$$

(3)

In practice we used the trapezoid rule to calculate the finite integrals from the data points.

The false positive and false negative areas are sensitive to the monitoring period, $T$, as demonstrated by panels E and F in Figure 6 which show exactly the same model measured over different time periods, giving the same false positive and negative rates but different false positive and negative areas. Hence both metrics are used in the following experiments.

C. Window length and feature sets

The window length determines the amount of historical data to be used for analysing running processes. A fixed window length prevents the volume of data consuming excessive memory as processes can run for many hours. The following experiments look at the trade-off between a short window length, which consumes less memory, and a longer window, expected to yield greater accuracy as it contains more data.

The shortest window size that an RNN can take advantage of has a length of two (otherwise there is no time series), this corresponds to two snapshots of data taken one second apart.

Table I shows the accuracy metrics from a window size of 2 to 10 seconds. The table also documents the accuracy for different feature input sets: machine activity data only (MA), API calls only (API) and both machine activity and API calls (MA, API). As the dataset is imbalanced due to the multiple benign applications running at the same time as malicious applications, the f-score gives a balance-adjusted accuracy metric. As Figure 7 shows, API call features consistently have lower accuracy rates and higher misclassification rates than the machine activity or combined feature sets. Combining the two feature sets does not improve the accuracy of the machine activity feature set alone. API calls are commonly used in behavioural malware research but for short sequences of 10 seconds or less we find that API calls give worse accuracy than machine activity data.

The highest accuracy and f-scores result from a 5 second window length. This may seem counter-intuitive because longer windows contain more data, which is usually linked to higher accuracy. We hypothesise that the higher accuracy for a shorter window size is because some processes only execute
for a few seconds as a child of another process. Or perhaps, for malicious processes, early detection may kill the parent process such that the child processes are never launched. These results indicated that a window size of 5 seconds gave optimal performance on the training set so it the window size used by the dual-task RNN.

### D. Dual-Task RNN

The dual-task model is designed to accommodate the irreversible nature of killing a benign process. Each task (predictive and cautious) addresses a slightly different optimisation problem with most network weights shared by both tasks. The predictive output is skewed by the number of children a process has whilst the cautious output task is heavily skewed in favour of not killing benign processes. If the sum of the predicted output and cautious output exceeds a threshold, $\theta$, the process will be terminated. For a normal binary classification problem, $\theta = 0.5$. In the proposed model $\theta$ is the lowest threshold for which the false positive rate on the validation set is within one percentage point of the false positive rate on the training set, effectively when the model is as unlikely to kill a behavioural trace it has seen in training as it is to kill a behavioural trace not seen in training but generated by one of the samples from the training set. This requirement biases the model not to kill installed applications, as this would create particularly poor user experience. This is first achieved when $\theta = 1.3$, equivalent to the mean of the outputs being greater than 0.65, to terminate a process.

Table II and Figures (8, 9, 10) illustrate the difference between a threshold of 1 (mean outputs > 0.5) and of 1.3 (mean outputs > 0.65) on the training, test, and validation sets. At 1.3 both the overall accuracy and f-score metrics are higher for the training (91% accuracy) and test (77% accuracy) sets.

Adjusting for the recorded time delays (presented in Figure 4), there is a maximum delay of 0.8 seconds, when 29 processes are killed in a single snapshot. This impacts accuracy metrics by a maximum of 0.01 percentage points. The maximum number of processes captured during a single snapshot was 95.

Killing a process impedes the (crucial) functionality of an application. Killing any application’s process hinders some functionality but we do not know the precise functionality of the different processes in the dataset, so it is difficult to measure the malicious activity prohibited by the 39% reduction in malicious process run-time. Ideally it would be
possible to quantify the damage caused by malware with and without the agent operating. Therefore for the online testing of the model we chose to use ransomware because it is possible to closely approximate the damage caused at any given time during execution.

### E. Online Testing: Ransomware Detection

Ransomware is a the broad term given to malware that prevents access to user data (typically by encrypting files) and holds the means for retrieving the data (usually a decryption key) from the user until a ransom is paid. It is possible to quantify the damage caused by ransomware using the number of encrypted/missing files as Scaife et al. [33] have done in developing a ransomware detection system. From 2000 VirusShare ransomware portable executables it was possible to identify 155 which begin modifying files within the first 30 seconds of execution. These are of particular interest for the proposed model because the payload is executed very shortly after delivery, representing one of the scenarios for which it was developed.

The ransomware was only allowed to execute for 30 seconds, once with the dual-task model running and killing processes, the other without. Of the 155 samples, the model was able to detect 141 (90.97%) within the 30 seconds. 24,259 files were modified without the model, and 12,119 with the model running, a 50.04% reduction in the number of files compromised.

### V. Discussion and Future Work

Behavioural malware analysis papers using machine learning regularly report >95% classification accuracy (e.g. [10], [11]) and are able to detect malware families unseen during training (eg. [16]). Though useful for analysts, behavioural detection should be deployed at run-time as part of the frontline defence against malware to leverage the full benefits of the analysis model. Malware is able to cause damage within seconds of delivery, since humans are unable to react to alerts within such a short time frame, automated responses are a necessary complement to run-time detection.

The model presented in this paper correctly identified 91.27% of completely unseen benign applications and 97.99% of previously seen benign applications, preventing 39.1% of the unseen malware from executing. This represents a first step towards a real-time software-based malware detection model, which we demonstrated was able to reduce file encryption in the case of ransomware by up to 50%. Previous run-time analysis research has not considered the importance of blocking malicious processes as early as possible. Sun et al. [5] are able to detect 87% of samples correctly after 5 minutes but in many cases this is too late to prevent the malicious payload from executing, as illustrated in Section IV-E. Hardware models require specific hardware configurations, and do not speak to the real-world security market in which most solutions are software-based for price, widespread use of operating system and ease of remote updates.

Future work will seek to improve the accuracy of the model using more granular labels, test accuracy when faced with real human computer use data and further test the robustness of the model under capacity strain.

- The precise accuracy of the model is difficult to tell without process-wise labelling of subprocesses. Future work could train the model with individually labelled processes. This is likely to improve accuracy results and give a better indication of how much damage is being prevented.
- The behaviour of the applications could be made more realistic by recording real human interaction with the machines as the malware is injected, this will probably give a much more diverse spectrum of behaviours for the
benign applications and could make it more difficult for the model to learn.

- The capacity limits of the model were not reached with 35 injected applications (95 processes). Future experiments should test the robustness of this model to find if there is a breaking-point after which accuracy severely diminishes. Does running 100 applications make the data snapshots so far apart that the RNN can no longer make as accurate predictions?

VI. CONCLUSIONS

Behavioural malware detection is a well-established research field with little translation into software models for run-time behavioural detection. In this paper we have demonstrated that for early-stage detection within the first ten seconds of execution, numeric machine activity data gives better detection accuracy than the commonly used system API calls for distinguishing malicious and benign software.

The dual-task model presented in this paper, aiming to both predict accurate labels and minimise false positives, performed better than a single-task prediction recurrent neural network. As far as we are aware this is the first software-based run-time detection system attempting to kill malicious processes on a timescale shorter than 10 seconds, during which time malware is capable of initiating damaging processes on the target machine.

The dual-task model does not yet achieve the detection accuracies of state of the art behavioural analysis models, but these models typically use the full post-execution trace of malicious behaviour and delaying classification until post-execution negates the principal advantages of run-time detection. However, the proposed model is able to translate from simulation to online deployment without a reduction in malware detection rate and a negligible time lag, indicating that this work can form the basis of future research into fast run-time detection with automated responses. Run-time automatic agents will become increasingly necessary for antivirus software to keep pace with the threat landscape of malicious software.

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