Active Android Malware Analysis: An approach based on Stochastic Games

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ABSTRACT

Active Malware Analysis focuses on learning the behaviors and the intentions of a malicious piece of software by interacting with it in a safe environment. The process can be formalized as a stochastic game involving two agents, a malware sample and an analyzer, that interact with opposite objectives: the malware sample tries to hide its behavior, while the analyzer aims at gaining as much information on the malware sample as possible.

Our goal is to design a software agent that interacts with malware and extracts information on the behavior, learning a policy. We can then analyze different malware policies by using standard clustering approaches. In more detail, we propose a novel method to build malware models that can be used as an input to the stochastic game formulation. We empirically evaluate our method on real malware for the Android systems, showing that our approach can group malware belonging to the same families and identify the presence of possible sub-groups within such families.

CCS Concepts

•Security and privacy → Malware and its mitigation; Mobile platform security; •Computing methodologies → Multi-agent reinforcement learning; Adversarial learning; Stochastic games;

Keywords

malware analysis, active analysis, malware model generation, android systems

1. INTRODUCTION

The first line of defense in IT security is *threat detection*, and common antivirus or firewalls attempt this, by using some kind of known information. This is possible thanks to *threat analysis*, aiming at achieving a better understanding of something recognized as a threat. Nowadays, malware analysis is mostly done by human security experts aided by specific tools, often built ad hoc for each new malware sample detected into the wild. These tools help to identify how malware penetrate a system, how they propagate to other systems and what is the payload. This is a time consuming process, often requiring to manually analyze binary code by executing it and examining logs.

Automated techniques for threat analysis are valuable tools aiding human security experts. Specifically, such techniques can be broadly classified as *static* (i.e., techniques that inspect the source or object code), or *dynamic*, (i.e., techniques that execute the malicious program and analyze the execution traces). Static techniques include several approaches such as Eureka [16], BinJuice [13], and BinHunt [10], which are frameworks for analyzing malware code producing a possibly approximated representation of the control flow graph for code similarity analysis or as DroidMiner[21], a malicious Android app detection system that mines malicious program logic from known malware. On the other hand, dynamic analysis includes execution traces analysis and the attempt to classify them using various metrics, as discussed in [3, 4, 5, 18].

Notice that, all the mentioned automated techniques are *passive*, i.e., they do not interact with malware during execution. However, in most realistic settings, malicious behaviors on the infected systems are triggered by specific user actions. In this perspective, *active analysis* methods analyze malware by interacting with the malicious software in order to reveal the behavior. The first steps towards an *active* type of analysis, have been presented in [14], where authors discussed the existence of malware requiring specific inputs to show their malicious behaviors. Recently, active analysis has been applied to malware for smartphones [17]. In this approach the analyzer tries to reproduce very specific activation conditions in order to trigger malicious payloads, relying on stochastic models.

While previous approaches provide significant contributions to active malware analysis, they still rely on human expertise to decide which actions should be executed by the analyzer in order to gain the most possible information on malware behaviors. This important issue can be addressed by considering machine learning approaches and stochastic

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games. Specifically, in the context of active malware analysis, we have two interacting agents with opposite goals: the malware sample wants to hide its behavior from the analyzer and to perform malicious activities. In contrast, the analyzer aims at learning the maximum possible amount of information regarding the malware sample behaviors in order to build countermeasures for protecting the system. This interaction can be conveniently formalized using game theory, and more in detail, the uncertainty associated to the actions of malware can be captured by stochastic games. In a recent work (Williamson et al. 2012) [19] authors apply learning algorithms for stochastic games [7] so as to devise the most informative action that the analyzer should execute for reducing the uncertainty on a malware sample policy. However, the learning algorithms operate on models for malware behaviors which are manually designed by human security experts.

In this work, we follow a similar methodology, but we propose an automated technique for generating malware models and we apply such methodology to the Android operating system (whereas the work in [19] focuses on the Windows OS).

In more detail, this work provides the following contributions to the state of the art:

1. An *automated* method for generating Android malware models;
2. An Active Android Malware Analysis technique allowing us to automatically:
   (a) Safely execute malware in an isolated environment;
   (b) Driving the interaction with malware performing different actions using a strategy for the stochastic game and observing malware reactions on the system;
   (c) Extract information on malware behaviors, based on the executed actions on the system;
3. An experimental analysis of real Android malware, clustering the obtained policies in relation to malware families with centroid-based and hierarchical agglomerative clustering.

The remainder of the paper is organized as follows: in Section 2 we introduce a stochastic game model suitable for the active malware analysis, along with a heuristic method to learn malware behaviors in such model. In Section 3, we present an automated technique for building malware models using our framework. Section 4 describes our framework for the practical analysis of real Android malware. The malware policies obtained with our approach are analyzed in Section 5, where we apply clustering techniques to group malware in families. Finally, Section 6 concludes the paper and outlines possible future directions.

2. BACKGROUND

Williamson et al. [19] proposed a new approach to malware analysis. Analyzing malware behaviors can be seen as a process involving two agents: an *analysis agent* and a *malware agent*. The analysis agent wants to learn about the malware agent, while the latter tries both to penetrate the

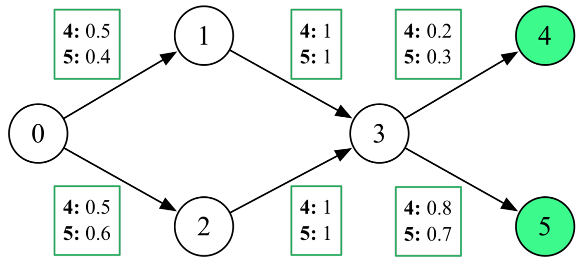


Figure 1: Malware model example

analyzed system and, maybe, to avoid the analysis. A possible method for achieving this goal, is to use the concept of probability embedded in stochastic games, to model uncertainty about a possibly unknown adversary policy. We made a few changes to the model used in [19] in order to conduct an analysis on malware execution traces based on function calls, instead than looking at the sequence of system components affected by execution. The active malware analysis (AMA) game is played on a model consisting in a weighted graph, where each vertex represents an action that can be executed. In particular, there are malware actions (the internal vertices in Figure 1) and trigger actions, performed by the analyzer (the leaves in Figure 1). Edges represent the transitions between actions and the weight on each edge is the transition probability (conditioned by analyzer current executed action) from the edge source vertex to the destination one. Those probability values are the *policy* of a malware sample, seen also as a behavioral signature. A malware model is a graph of the kind depicted in Figure 1, where malware starts from vertex 0, vertices 1-2-3 are the malware possible actions and vertices 4-5 are the possible actions of the analyzer. A path from the start vertex to a leaf represents a behavior (an execution trace) that malware exhibits and that the analyzer agent wants to learn.

The game is an interaction in which the analyzer chooses an action from its set of possible actions and then awaits for malware response. Once the malware sample execution ends (potentially reaching a destination leaf) then the analyzer updates the weights on the edges based on the observation of the malware sample behavior (updating the policy) and chooses another trigger action, repeating the process. The game continues till the analyzer stops. In order to trace complete behaviors we fix the maximal number of triggering actions that the analyzer can execute, while in [19] the termination of the analysis is limited by the number of timesteps (possibly interrupting the response before the end of it).

In the next part of the section we present a heuristic principle that can be used by the analyzer in order to select which action to play for triggering malicious behaviors, followed by two algorithms that we employed in the experiments for resolving stochastic games. The section is concluded with a brief explanation of the clustering techniques we applied for analyzing results.

2.1 Entropy as a Reward Function

The analyzer needs a strategy for choosing the next action to execute in order to trigger malicious behaviors and acquiring the maximum possible amount of information. As the goal of AMA is to learn about malware policies, this notion is incorporated in an information-centric reward function based on entropy. The learning process then, will try to minimize the entropy at each step, given the fact that lowering the entropy means acquiring new information about the policy.

A policy π is defined as the probability distribution over the edges towards the possible actions V^H, given the current analyzer executed action v^h and the malware position v^m. The aim is to learn this policy, based on the location of the analyzer current executed action $s \in V^H$. Malware initial probability of taking an edge $e_n \in E_{v_i}$ of vertex v_i is uninformative, meaning that each edge has the same probability of being taken.

$$Pr(e_n|s = v^h) = \frac{1}{|E_{v_i}|} \quad (1)$$

Malware historical frequency of taking an edge $e_n \in E_{v_i}$ of vertex v_i, is computed based on the observation of past interactions. Specifically, if a malware sample has visited vertex v_i for l times and an edge $e_n \in E_{v_i}$ has been taken m times, when the action executed by the analyzer was s, the malware historical frequency of taking the edge e_n becomes:

$$Pr(e_n|s = v^h) = \frac{1+m}{|E_{v_i}| + l} \quad (2)$$

By definition of probability, a vertex v_i with outgoing edges E_{v_i} must respect the invariant:

$$\sum_{e_n \in E_{v_i}} Pr(e_n|s = v^h) = 1 \quad (3)$$

A path can be defined as a sequence of edges $e_0, ..., e_k$ and the probability for malware of taking a path $p_i \in P^H$ is:

$$Pr(p_i|s = v^h) = \prod_{e_n \in p_i} Pr(e_n|s = v^h) \quad (4)$$

Finally, the entropy reward function for the policy π is the following:

$$U(\pi) = -\sum_{s \in V^H} \sum_{p_i \in P^H} Pr(p_i|s) log(Pr(p_i|s)) \quad (5)$$

The resolution of an AMA game can be automated using algorithms for playing stochastic games. The decision of which analyzer action to execute is taken selecting the one with highest associated reward, computed using equation 5, and the observation of malware response to that action, leads to an update of edges probabilities given by equation 2[19].

2.2 R-Max

Multi-agent learning within stochastic games, can be accomplished using R-Max[7] algorithm, which is capable of learning near-optimal policies of unknown agents and for this reason it can be used also within AMA games. The model is initialized optimistically: all actions in all states return the maximal possible reward. R-Max computes the expected reward associated to an action as the average of observed entropy gains of past executions of that action. The model then, is updated only if an action has been executed multiple times, in this way it is possible to retrieve a reasonable amount of information on the policy in a specific state. Indeed, the information acquired in a single action execution could be misleading, since the behavior of an agent could differ between same action executions, hence, doing many repetitions before updating the model can help to handle uncertainty.

2.3 MYOPIC

R-Max assumes the near-optimal policy will be learnt in polynomial time. In a real environment this is not feasible, since executing a particular action on the system could take seconds. As a result, the interest is no more in obtaining the optimal policy, but in learning the most possible about a malware sample in very few interactions. The concept is applied in an extension of R-Max algorithm called MYOPIC[19], in which the entropy reward equation 5 is used as a 1-step look-ahead action selection function. The heuristic suggests that the higher is the entropy, the higher is the information to be acquired, so choosing an action following this principle gives good results most of the times. MYOPIC then, selects the action with the current highest entropy value, ignoring past observations. The downside of this approach is that MYOPIC drops the near-optimal guarantee of R-Max.

2.4 Clustering

Analyzing a malware sample gives insights on how it works and what are its behaviors, but there is often an additional step to be done. Knowing how different samples are related to others, measuring how similar they are to existing families, allows to classify them into one or more categories. Clustering comes in help with this task, since it is used for partitioning a given set of datapoints into a set of groups which are as similar as possible.

2.4.1 K-Medoids

K-Medoids is a known method to perform centroid-based clustering. To use this algorithm it is necessary to know a priori the exact number of clusters the data is partitioned into. The goal is to minimize the distance between datapoints of the same cluster and the datapoint designated as representative of that cluster. The representative of a cluster is called *medoid* and it is defined as the datapoint of a cluster, whose average dissimilarity from all other datapoints in the same cluster is minimal. That makes the medoid the most centrally located point of a cluster[12]. We will use K-Medoids with the purpose of allocating malware samples belonging different families, to the most related ones.

2.4.2 Hierarchical Agglomerative Clustering

Hierarchical clustering is employed when there is the necessity of keeping track of the history of the clusters construction. The dendogram is a tree that embeds this concept of *merge history*. Unlike centroid-based clustering, there is no need to know a priori the number of clusters the data is partitioned into, since the process will end up with just one cluster. The agglomerative approach is bottom up, starting off with the individual datapoints and successively merging the two closest clusters in order to create a dendogram[1]. We will use Hierarchical Agglomerative Clustering so as to dissect the composition of the malware families, finding the possible existence of subfamilies composed by variations of the same malware.

3. MODEL GENERATION

The starting point of the AMA game is always the model: its construction technique is fundamental in order to obtain a good solution. The generation of such model, though, depends on many factors and there exists not a well defined technique, moreover, different models can give different results in terms of computed policies. In the following we present one of our main contributions: the development of an automated technique for generating malware models to be used in the AMA game. We will use our generated model for a specific malware kind in order to test if other unknown samples are somehow related to that model (using clustering).

3.1 Model Structure

In the model, graph cycles are avoided because the game requires the computation of entropy for all possible paths towards every leaf vertex, hence, cycles make this computation imprecise. Moreover, we need to be able to associate a sequence of malware actions to a sequence of edges of the model, retrieving a path. The correspondence is obtained labeling vertices with function calls and sequentially build a path reading the execution log, starting from the initial vertex.

3.2 Manual Generation

Williamson et al. [19] use a fixed model manually generated by a security expert that knows exactly which system components to monitor. This kind of model could miss malicious behaviors if the actions taken by malware do not influence system components that are being observed.

In our approach we monitor function calls and the model can be manually generated executing a malware sample inside the framework, manually performing interactions with the system, selecting the actions from a defined input set. After each interaction, the log is read and the sequence of function calls we consider important to define a malicious behavior is converted into a path. The process is repeated multiple times, since a behavior triggered by an action could differ because of multiple factors, thus, an action should be tested more than once for being sure of capturing all the possible paths. This results in small and fine tuned models containing as much information as required. Indeed, useless function calls can be discarded, lowering the number of edges and vertices of the model, multiple equivalent vertices can be merged into a single one and many other considerations can be done.

3.3 Automated Generation

As opposed to the manual generation, an automated one can be employed to speed up the process. This solution builds bigger models, because it can not discard edges and vertices based on the knowledge that a function call is "useless" at certain times, but not at others. For this reason a model could contain information not strictly needed, but this is not a game breaking problem. An automated generation can indeed be helpful even if not used "as is", because it can be just manually refined instead of being built completely by hand. Automated generation requires the subset of function calls to track in order to restrict the field only to the ones we are interested into, since observing all of them can generate much useless information.

Algorithm 1 builds a model starting from a set of func-

Algorithm 1 Model Generator

```
Require:
    $F$ - set of function calls to observe
    $A$ - set of actions to execute
    $repetitions$ - number of times an action has to be executed
Ensure:
    Model

 1: $root \leftarrow MakeVertex(\emptyset)$
 2: $N \leftarrow [\emptyset]$    ▷ Matrix of semantically equivalent vertices
 3: for all $a \in A$ do
 4:     for $i \leftarrow 1$ to $repetitions$
 5:         Start malware sample in the framework
 6:         $log \leftarrow Exeutea(a)$    ▷ Log after action execution
 7:         Stop framework
 8:         $c \leftarrow root$
 9:         for all calls $f \in log$ do
10:             if $f \in F$ then    ▷ If it's a call to observe
11:                 if $f \in N$ then    ▷ If previously observed
12:                     $added \leftarrow False$
13:                     for all vertices $n \in N_f$ do
14:                         $link(c, n)$    ▷ Create edge
15:                         if $ExistsCycle(root)$ then
16:                             $unlink(c, n)$    ▷ Avoid cycles
17:                         else
18:                             $added \leftarrow True$
19:                             break
20:                     if $added = False$ then    ▷ Create new
21:                         $n \leftarrow MakeVertex(f)$
22:                         $N_f \leftarrow N_f + n$
23:                         $link(c, n)$    ▷ Create edge
24:                 else    ▷ Create first vertex for this call
25:                     $n \leftarrow MakeVertex(f)$
26:                     $N \leftarrow N + [n]$
27:                     $link(c, n)$    ▷ Create edge
28:                 $c \leftarrow n$
    return root
```

tion calls to observe, for a varying level of abstraction, and an action set to execute for triggering malicious behaviors. The creation of redundant vertices is avoided when possible, trying to create only one copy of a vertex associated to the same function call. Each action is repeated for a *repetition* number of times, starting the malware sample in the framework, executing the action and then retrieving the log (lines 5-7). The execution log is parsed and for each function call, if comprised in the set of those to be observed, a semantically equivalent vertex is linked to the previous parsed one. If this creates a cycle in the model, the link is undone and another vertex is tried. If a cycle is created at every linking attempt, a new vertex is generated, linked and added to the lists of semantically equivalents (lines 13-23). Appendix A reports a brief example of the application of this algorithm for the generation of a fictitious malware model.

3.4 Model Merging

Executing the AMA game on a single malware model can give hints on *samples* of the same family. It can show a family decomposition into different subfamilies or if a malware sample is not related to any other one belonging to that family. Nevertheless, it may be useful to execute even a more sophisticated analysis, where the model analyzed is the composition of multiple malware families, with the aim of allocating samples to the correct belonging family. Starting from single malware family models, they have to be merged into a single one. We investigated two different strategies for this purpose: *plain merge* and *semantic merge*.

3.4.1 Plain Merge

The plain merge strategy is straightforward. It simply takes each single malware family model and merges their initial vertex into a new one. Each single model will continue to exist in the result, maintaining all of its vertices and edges, along with the original semantics. At the end, in the model there can be redundant vertices representing the same function call.

3.4.2 Semantic Merge

The semantic merge strategy, tries to keep only one copy of a vertex if there are multiple copies of it across the single models (the check is done comparing vertex labels). This results in a smaller model, maintaining the original semantics, plus additional possible behaviors generated by new paths that were not present in the single models. Indeed, an edge of a single model might be redirected to a new vertex having outgoing edges coming from other single models, obtaining paths that did not exist before the merge.

This kind of merge can be obtained starting from the single models and performing a slight variation of algorithm 1, in which there is no need to execute any malware. Each single model is analyzed, acquiring the action vertices directly from the model (instead of parsing an execution log) and linking them using the same approach of avoiding cycles.

4. ANALYSIS FRAMEWORK

The analysis framework built is based on the existing open source sandbox project *Cuckoo*[8] that we have extended with the required functionality of the AMA game. The emulator used runs an operating system which base is the Android image version 4.1.2, compiled for ARM architecture. The Host runs the core component modules of the sandbox

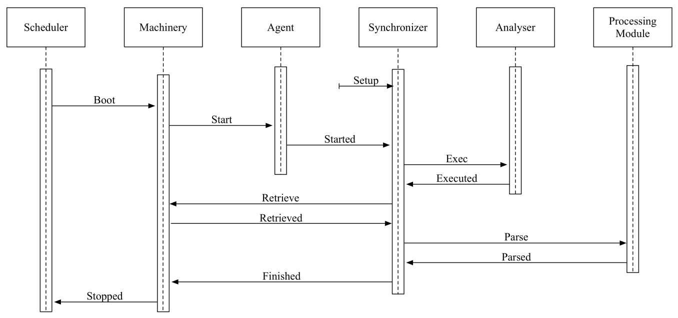


Figure 2: Analysis pipeline

that manage the whole analysis process, while the Guest is the isolated environment where the malware samples get actually safely executed and analyzed. Additionally, a collection of anti-detection techniques are installed for hiding the Android emulator from malware.

We modified the sandbox Machinery module in order to be able to execute the AMA game. Specifically, we added functions for: pausing/resuming the emulator and retrieving the malware execution log. Moreover, we built an extendable set of “actuators”, for executing analyzer actions on the system: send/receive an SMS, make/receive a call, add/remove contacts, touch the screen, read/write a file, open an URL. We chose to work with those high level set of actions, since they are the most common user interactions in a mobile environment. Communication between modules of the framework inside the Host and the Guest makes us of Python RPC. We created two additional modules: a Synchronizer for the correct scheduling of an analysis and a log Parser, for retrieving a model path from a sequence of function calls in the execution log. The analysis execution pipeline for one analyzer action is visible in figure 4, where time flows from top to bottom.

5. EXPERIMENTS AND RESULTS

The main goal of the experiments was to highlight the difference in learning between R-Max, MYOPIC and an additional Random algorithm for benchmark purposes (which randomly chooses the next analyzer action to execute), applied to AMA in a constrained time limit. We also investigated the two different strategies adopted for merging malware models: plain and semantic. Results of the analysis have been processed with K-Medoids[12] clustering algorithm, in order to allocate a malware sample policy into its most related family, and with Hierarchical Agglomerative Clustering[1], so as to dissect a family composition into possible subfamilies. Analysis have been conducted on models generated by the automated technique presented in section 3.

Active analysis is especially effective in analyzing malware showing malicious behaviors only if triggered by some actions, such as spywares or bots. For this reason, to conduct our experiments, we chose four existing Android malware families categorized as spywares (or private data stealers) and bots: ZSone, GoldDream, SMSReplicator and TigerBot. The malware samples have been downloaded from [20], which is an online malware repository for research purpose.

5.1 Clustering Evaluation

To make use of clustering of malware policies obtained from analysis, it is necessary to define a distance metric between policy π_a and policy π_b, by means of L_1 norm as follows:

$$distance(\pi_a, \pi_b) = \sum_{s \in V^H} \sum_{p \in P^H} |Pr_a(p|s) - Pr_b(p|s)| \quad (6)$$

The metric computes the sum of the distance for each transition in all states, to give a measure over the entire policy that becomes a multi-dimensional datapoint to be used in clustering[19].

Results of centroid-based clustering process must be evaluated using some reference parameters. There are two main measures that can be used: *Purity* and *Inverse Purity*. In the explanation of these measures we will refer to C as the set of clusters to be evaluated, to F as the set of families (reference distribution) and to N as the total number of malware samples.

5.1.1 Purity

Purity focuses on the frequency of the most common category in each cluster. It is computed by taking the weighted average of maximal precision values:

$$Purity = \sum_{C_i \in C} \frac{|C_i|}{N} \max_{F_j \in F} Precision(C_i, F_j) \quad (7)$$

where the precision of a cluster C_i for a given family F_j is defined as:

$$Precision(C_i, F_j) = \frac{|C_i \cap F_j|}{|C_i|} \quad (8)$$

Purity penalizes the noise in a cluster, but it does not reward grouping samples from the same family together[2].

5.1.2 Inverse Purity

Inverse Purity focuses on the cluster with maximum recall for each family. It is computed by taking the weighted average of maximal recall values:

$$InversePurity = \sum_{F_i \in F} \frac{|F_i|}{N} \max_{C_j \in C} Recall(F_i, C_j) \quad (9)$$

where the recall of a family F_i for a given cluster C_j is defined as:

$$Recall(F_i, C_j) = \frac{|F_i \cap C_j|}{|F_i|} \quad (10)$$

Inverse Purity rewards grouping items together, but it does not penalize mixing samples from different families[2].

5.2 Empirical Methodology

The dataset for the experiments was composed by 40 malware samples, 10 for each family. Hence, we had a knowledge of which was the belonging family of each analyzed sample. The K-Medoids clustering process has been evaluated using *purity* and *inverse purity* measures, based on *precision* and *recall* respectively[2]. To compute K-Medoids centroid-based clustering, since the result could vary depending on the choice of initial medoids, we repeated the process multiple times, keeping the best result in terms of purity. From that, we computed the inverse purity of the partitioning. Each malware sample analysis has been repeated 10 times, obtaining the average as the final result.

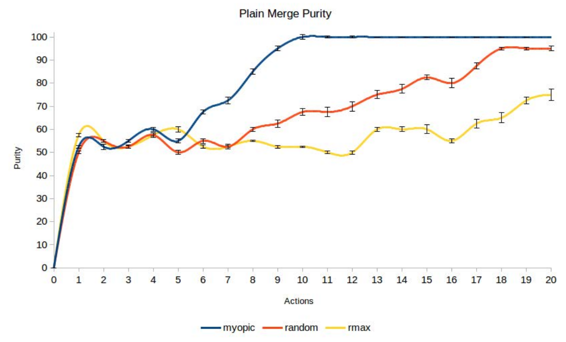


Figure 3: Plain merge purity analysis benchmark

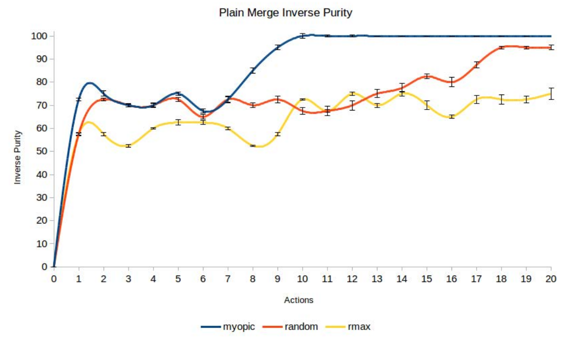


Figure 4: Plain merge inverse purity analysis benchmark

5.3 Plain Merge Experiments

Figure 3 and 4 show the curves of purity and inverse purity respectively of the 3 tested algorithms. It is clear that MYOPIC has an advantage over the others, when the number of actions to play is constrained.

As can be seen, there is a progress in the purity and inverse purity values at the increase of the actions limit. MYOPIC is the best in learning celerity, thanks to its entropy reducing heuristic associated to a 1-step look-ahead strategy. R-Max is the slowest in learning, because of the need of more actions to compute a policy, even though it aims to a near-optimal one.

5.4 Semantic Merge Experiments

Figure 5 and 6 show the curves of purity and inverse purity respectively of the 3 tested algorithms. It is clear again that MYOPIC has an advantage over the others, when the number of actions to play is constrained, whereas R-Max is again the slowest.

MYOPIC is still the fastest learning algorithm, but all three learn faster compared to the plain merge strategy. As mentioned before, this is due to the fact that, with this merging technique, more paths become available to be followed compared to the single models. For this reason, even

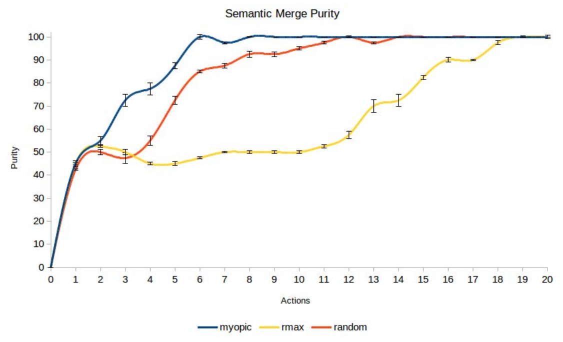


Figure 5: Semantic merge purity analysis benchmark

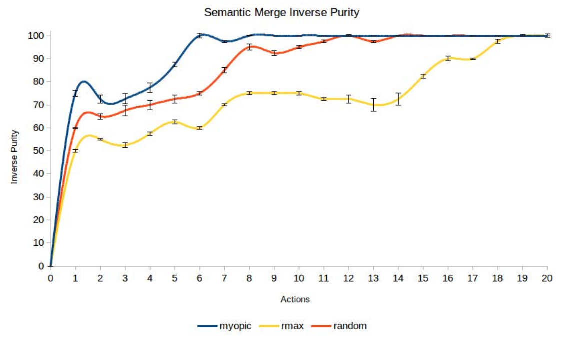


Figure 6: Semantic merge inverse purity analysis benchmark

if the action played is not specific of the malware sample being tested, there is a greater chance that it will move on the graph anyway, because there might exists a new corresponding path available.

The semantic merge strategy embeds more information in the resulting model compared to the plain one. As can be seen from the purity in figure 7, the Random algorithm (which uses no reward function nor heuristics) has a strong advantage in learning rate using the semantic merge strategy, because the model used is more informative by itself. The same stands for inverse purity and the other tested algorithms too.

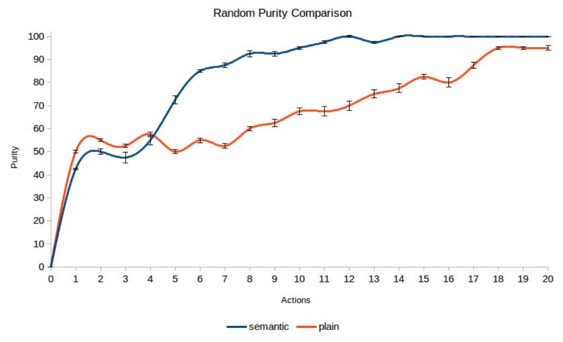


Figure 7: Random purity rates comparison

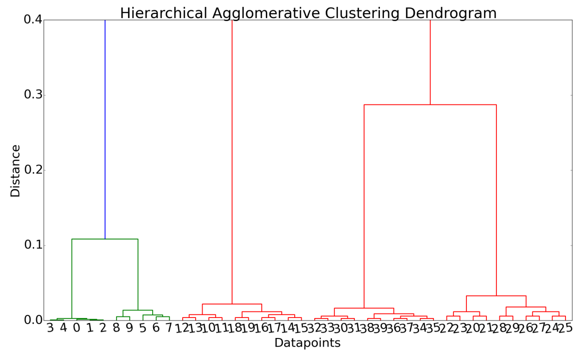


Figure 8: MYOPIC semantic merge subfamilies dendogram

5.5 Dendogram for the Subfamilies

Dendogram in figure 8, in which 4 clusters are clearly distinguished, shows the families composition obtained by Hierarchical Agglomerative Clustering for the semantic merge model in combination with MYOPIC. It is visible that ZSone (green lines) is composed of two main subfamilies, along with the other three main families in red. The figure has been zoomed on its lower end for a better visibility.

5.6 Multi-Behavioral Malware

During the analysis, if an analyzer action with multiple paths leading to it is tried too few times, the resulting policy could differ between samples of the same malware. MYOPIC though, overcomes this problem with its entropy reducing heuristic: multiple paths toward an action vertex, mean higher entropy, because of the branches between vertices. The algorithm, by construction, tries an action multiple times in order to lower its entropy level, until enough information about it has been acquired.

Figure 9, is the result of the semantic merge analysis performed by Random algorithm. It is visible that the samples belonging to TigerBot family (last group of datapoints on the right) are more far from each other, since the algorithm is not capable of figuring out that they are part of the same family, because of the described multi-behavioral responses to actions. The figure has been zoomed on its lower end for a better visibility. For MYOPIC instead, as visible in figure 8, TigerBot samples are closer to each other, thanks to the algorithm entropy reducing heuristic that allows it to insist on actions triggering different malware responses.

6. CONCLUSIONS

Experiments confirmed that the theoretically near-optimal algorithm R-Max, does not give acceptable solutions in a real environment with a low number of actions to be executed. The random based algorithm instead, gives much better results considering a constrained time limit. The best and capable of handling multi-behavioral malware responses to specific actions though, has been recognized to be MYOPIC, the R-Max extension for a fast learning. It does not give the theoretical guarantee of finding the near-optimal policy, but it works very well for real Android malware analysis.

In more detail, we examined computed policies with two different clustering algorithms. The first, K-Medoids, cor-

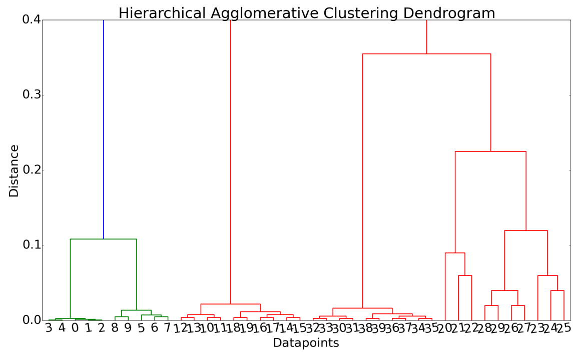


Figure 9: Random multi-behavioral clustering

rectly grouped the majority of the policies associated to malware belonging to the same family. Notice that some of those malware were variations of others, forming subfamilies within our main family groups. The second, Hierarchical Agglomerative Clustering, clearly displayed the presence and the composition of those subfamilies.

We proposed an automated technique for generating malware models and we also investigated two different strategies for merging those models: plain and semantic. Experiments have shown that both are suitable for active malware analysis, but the second one gives better results in terms of learning rate with a constrained number of actions to be played. Specifically, the semantic merge strategy embeds more information in the model, helping less sophisticated algorithms (such as Random) to reach better results with a less number of actions.

Future work includes a deeper study on the malware model to be used, starting from its generation. The use of static analysis could be investigated as a different approach to create such model. A particularly interesting future direction is to apply the stochastic game approach to self-modifying malware. This would allow us to extract signatures of metamorphic malware as policies, in this case applied to code transformation, therefore bypassing dynamic obfuscation strategies employed by malware[9]. In particular, the idea of merging malware models may become useful also in this context, where different versions of the same malware can be merged to obtain a *metamorphic malware model*. There might also be different and better techniques to merge malware families, other than the semantic and plain ones employed in the experiments. Another enhancement could be the investigation of the possibility to analyze a malware "on the fly", generating its model during the analysis execution, without the need of a pre-built one. This alternative would change the way policies are compared, because malware belonging to the same family might have different models that would have to be related somehow.
Finally, we observe that the existence of triggering conditions is not the only way malware interacts with the user or the environment for protecting itself. Malware may try to avoid analysis by exploiting environment detection tricks allowing them to understand whether they are emulated or not. These techniques are called anti-emulation checks[11, 15]. If an anti-emulation check detects the presence of a virtual environment, the malware sample changes its behavior showing only harmless executions. Most of the actual frameworks do not provide the possibility to dynamically customize the configuration of the virtual machine, making easy for malware to detect the virtual environment [6]. We believe that an active approach could be employed also to discover and bypass anti-emulation checks.

APPENDIX

A. AUTOMATED MODEL GENERATION EXAMPLE

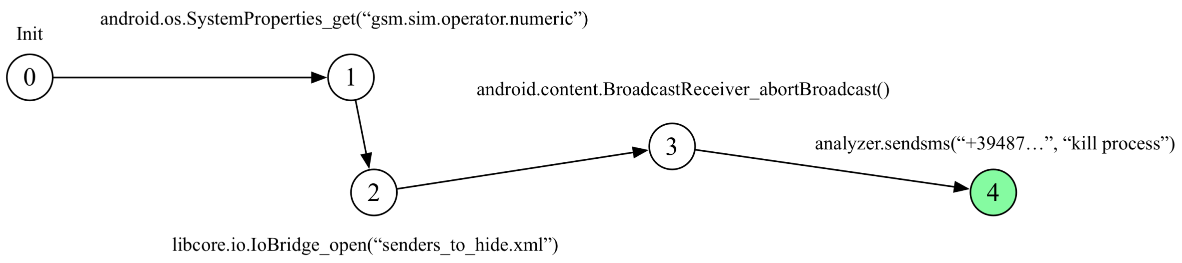
In this appendix we present a brief example of the application of algorithm 1 for the automated generation of a model. Specifically, we consider a synthetic malware sample we created, which hides the messages received if the sender appears in a given *hide-list*. We chose to illustrate the execution of the algorithm on a synthetic sample for the sake of clarity, resulting in a small model easy to read. In our example, the analyzer executes three triggering actions, simulating incoming SMS from two different mobile numbers: the first and the last SMS are sent by the same number and will be hidden to the user, since the sender appears in the *hide-list*. The model is generated in three steps, one for each of the actions executed by the analyzer. Below, we report the sequences of function calls observed in each step and the resulting paths.

1. `Trigger: sms from` +39487...:
   `SystemProperties_get("sim.operator.numeric")[1],`
   `IoBridge_open("senders_to_hide.xml")[2]),`
   `BroadcastReceiver_abortBroadcast()[3]`

2. `Trigger: sms from` +39561...:
   `SystemProperties_get("sim.operator.numeric")[1],`
   `IoBridge_open("senders_to_hide.xml")[2]`

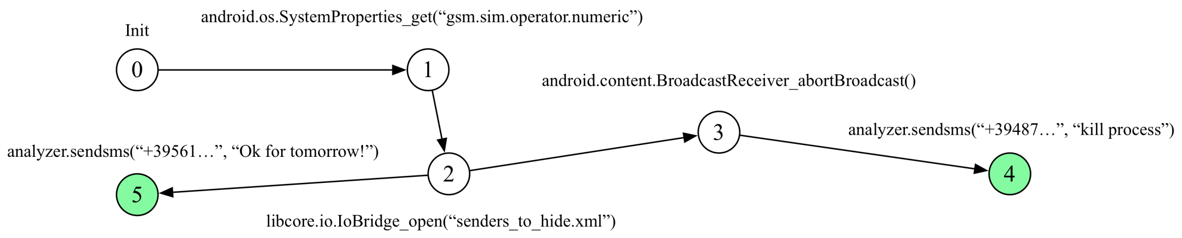
3. `Trigger: sms from` +39487...:
   `SystemProperties_get("sim.operator.numeric")[1],`
   `IoBridge_open("senders_to_hide.xml")[2],`
   `BroadcastReceiver_abortBroadcast()[3],`
   `IoBridge_open("senders_to_hide.xml")[6]`

Figures 10, 11 and 12 show the model structure after each triggering action executed by the analyzer. Notice that, in figure 12, vertices 2 and 6 are semantically equivalent, but they are not merged in order to avoid cycles (see Section 3).



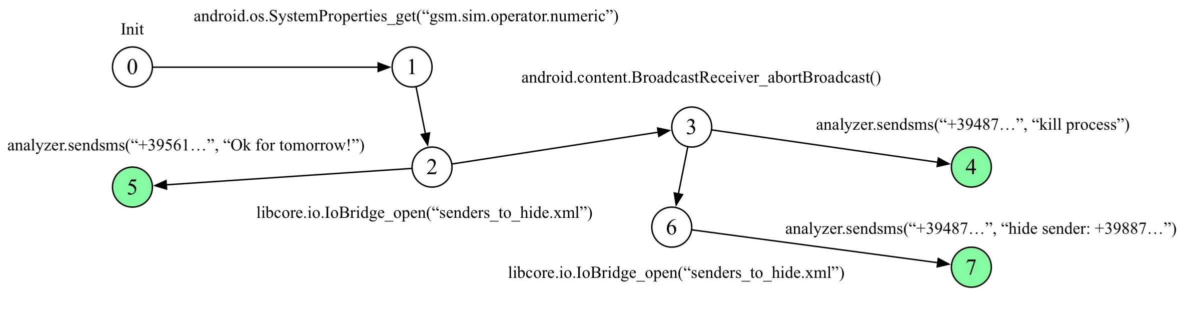
Init
android.os.SystemProperties_get(“gsm.sim.operator.numeric”)
android.content.BroadcastReceiver_abortBroadcast()
analyzer.sendsms(“+39487…”, “kill process”)
libcore.io.IoBridge_open(“senders_to_hide.xml”)
0
1
2
3
4

Figure 10: Model generation step 1, Trigger: sms from +39487...



Init
android.os.SystemProperties_get(“gsm.sim.operator.numeric”)
android.content.BroadcastReceiver_abortBroadcast()
analyzer.sendsms(“+39561…”, “Ok for tomorrow!”)
analyzer.sendsms(“+39487…”, “kill process”)
libcore.io.IoBridge_open(“senders_to_hide.xml”)
0
1
2
3
4
5

Figure 11: Model generation step 2, , Trigger: sms from +39561...



Init
android.os.SystemProperties_get(“gsm.sim.operator.numeric”)
android.content.BroadcastReceiver_abortBroadcast()
analyzer.sendsms(“+39561…”, “Ok for tomorrow!”)
analyzer.sendsms(“+39487…”, “kill process”)
libcore.io.IoBridge_open(“senders_to_hide.xml”)
analyzer.sendsms(“+39487…”, “hide sender: +39887…”)
libcore.io.IoBridge_open(“senders_to_hide.xml”)
0
1
2
3
4
5
6
7

Figure 12: Model generation step 3, Trigger: sms from +39487...

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