m2vDroid: Attacking the HinDroid Malware Detector

INTRODUCTION

Over the past decade, malware has established itself as a constant issue for the Android operating system. In 2018, Symantec reported that they blocked more than 10 thousand malicious Android apps per day, while nearly 3 quarters of Android devices remained on older versions of Android. With billions active Android devices, millions are only a swipe away from becoming victims. Naturally, automated machine learning-based detection systems have become commonplace solutions as they can drastically speed up the labeling process. However, it has been shown that many of these models are vulnerable to adversarial attacks, notably attacks that add redundant code to malware to consfuse detectors.

First, we introduce a new model that extends the Hindroid detection system by employing node embeddings using metapath2vec which we call m2vDroid. We believe that the introduction of node embeddings will improve the performance of the model beyond the capabilities of HinDroid. Second, we attempt to attack these models with adversarial machine learning using a method similar to that proposed in the Android HIV paper. Specifically, we aim to find a way to add small changes to malware so that it may evade a detector. We hope that this will serve as a first step to determining the robustness of these models against adversarial attacks.

PREVIOUS WORKS

Hindroid

Hindroid is a malware detection system developed in 2017 by Hou, et al and is a significant inspriation for our model, m2vDroid. In it, they "represent Android apps, related APIs, and their rich relations as a hereogeneous information network" and was one of the first to apply this method for the detection of malware. To build their heterogeneous information network, they unpack and decompile Android apps into the readable `smali` format and extract information for each API call (Notably, their code block, package, and invoke method). With this data, they construct 4 matrices which serve as adjacency matrices for Apps and APIs in the heterogeneous information network:

Description of Each Matrix

G	Element	Description
A	$a_{i,j}$	If app_i contains API_j, then $a_{i,j} = 1$; otherwise, $a_{i,j} = 0$.
B	$b_{i,j}$	If API_i and API_j co-exist in the same block, then $b_{i,j} = 1$; otherwise, $b_{i,j} = 0$.
P	$p_{i,j}$	If API_i and API_j have the same package name, then $p_{i,j} = 1$; otherwise, $p_{i,j} = 0$.
I	$i_{i,j}$	If API_i and API_j have the same invocation type, then $i_{i,j} = 1$; otherwise, $i_{i,j} = 0$.

Using these relationships, they form metapaths between all apps. For example, the metapath $App \xrightarrow{contains} API \xrightarrow{contains^{-1}} App$ which is captured by the AA^T kernel. Other kernels they consider include ABA^T, APA^T, $ABPB^TA^T$, and $APBP^TA^T$. For n apps, this produces $n \times n$ matrices — for each metapath — where the value at index $[i, j]$ is the number of paths connecting App_i with App_j for that metapath. Therefore, each row in the matrix is the feature vector for an app with the number of metapaths between it and all other apps in the training set. Each matrix then forms a kernel for a support vector machine and with multi-kernel learning they were able to achieve performances ranging from a 0.948 F1-score to 0.988 with the multi-kernel model.

Android HIV

In this paper, the authors, Chen et al., introduce a framework for attacking malware detection models, specifically the MamaDroid and Drebin systems. To perform this, they modified two adversarial attack algorithms: a modified Carlini and Wagner (C&W) attack and a modified Jacobian Saliency Map Attack (JSMA). These modified algorithms were used to generate perturbations that were added into the features of an apps so that they were misclassified as benign all while keeping the app(s) as functional examples of malware. With these methods, they were able to reduce the performance of both the MamaDroid and Drebin malware from detection rates of more than 95% to 1%. In this paper, we adapt their methods in order to attack the HinDroid system and our model, m2vDroid.

METHODOLOGY

In this section, first, we will describe the details of our proposed model, m2vDroid, and then we will describe the method we used to attack each model in the Adversarial Attack section.

m2vDroid

m2vDroid is another malware detection model that we implemented that is largely based off HinDroid. However it uses node embeddings for the final vector representations of apps instead of the bag-of-APIs/commuting matrix solution that HinDroid applied.

Preliminaries

There are a few concepts that we should introduce before we get into details:

- *Definition 1)* A **Heterogeneous Information Network (HIN)** is a graph in which its nodes and edges have diferent types.
- *Definition 2)* A **Metapath** is a path within a HIN that follows certain node types. For example, let us define a HIN with a set of node types T and a path $P = n_1 \longrightarrow n_2 \longrightarrow \ldots \longrightarrow n_N$ of length N. P follows metapath $M_P = t_1 \longrightarrow t_2 \longrightarrow \ldots \longrightarrow t_N$ if $type(n_i) = t_i$ for all $i \in [1, 2, \ldots, N]$.

Feature extraction

Our ETL pipeline begins with Android apps in the form of APK files. These APKs are unpacked using Apktool to reveal the contents of the app, but we are primarily concerned with `classes.dex`, the app's bytecode. We decompile the bytecode using Smali into readable `.smali` text files. From here we extract each API call, the app and method it appears in, and the package it is from. This is done for every API in an app and for every app in the dataset, forming a table with the information needed for the next step.

HIN Construction

Using the data extracted previously, we construct a heterogeneous information network using the Stellargraph library. Our HIN contains 4 types of nodes which we define as:

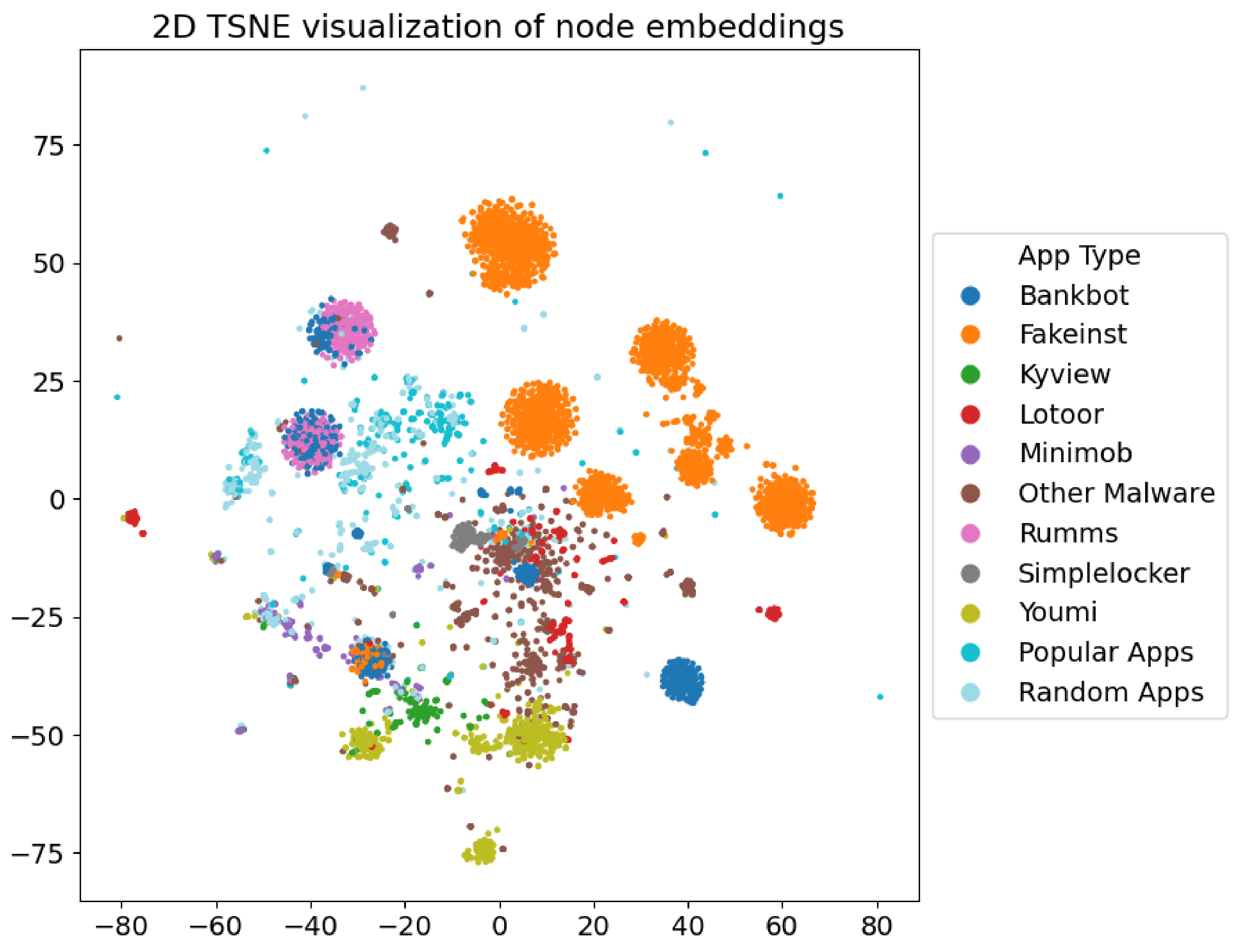
- $Apps$: Android apps determined by name or md5, i.e. `com.microsoft.excel` or `09d347c6f4d7ec11b32083c0268cc570`.
- $APIs$: APIs determined by their smali representation, i.e. `Lpackage/Class;->method();V`
- $Packages$: the package an API originates from, i.e. `Lpackage`.
- $Methods$: Methods (or "functions") that API calls appear in, i.e. `LclassPackage/class/method();V`.

The distinct nodes for each type correspond to the distinct values of their column in the API data table described earlier. $Apps$ and $APIs$ share an edge if an API is used within an App. Likewise $APIs$ and $Methods$ share an edge if a $Method$ contains an API. $Packages$ and $APIs$ share an edge if an API orginates from a $Package$.

Metapath2vec

To generate our features, we apply the metapath2vec algorithm on the App nodes of our HIN . That is we 1) perform a random-walk leveraging Stellargraph's `MetaPathRandomWalk` algorithm starting from each app. We follow designated metapaths to generate a "corpus" consisting of nodes in our HIN, then we 2) pass this corpus into the gensim implmentation of the word2vec model to transform each App into a vector.

After running this ETL on our data, we observed clear clustering after plotting a TSNE transformation of the vectors we generated. For the most, part it seems that this method is able to distinguish between not only malware and non-malware, but can also distinguish between different classes of malware to a reasonable extent. Notably, we have not tested the node2vec or metapath2vec++ algorithms for generating our random walk.



EDA of Clusters

Looking at these node embeddings, we have several clusters with seemingly random apps in the middle. We will discuss what makes it hard to differentiate these apps, and why there might be clusters overlapping with these apps.

Malware Descriptions:

- **BankBot:** a mobile banking trojan that steals banking credentials and payment information, by presenting an overlay window which looks identical to a bank app's login page,
- **RuMMs:** a distributed through SMS phishing, and in some cases initiate transactions by contacting financial institutions.
- **Simplelocker:** a ransomware that encrypts the users data, which includes a pop up window that requests a fee to recover data.
- **Lotoor:** a trojan that tries to manage the data on the system and change the settings on the device.
- **FakeInst:** portrays itself as the real instagram app but will actualy send premium SMS text messages once the user installs it. It evolved into many different variations over the years, so the numerous clusters we see are likely due to the similar versions of it clustering together.

The are two distinct BankBot and RuMMs clusters may be explained by them both targeting banking data, as RuMMs initiates transactions and BankBot steals a user's banking information. Rumms and Bankbot are the same type of malware, as they are both considered trojans. Then there is the general malware cluster defined mostly by the Other Malware catergories. What may be contributing the these apps clustering together is that they might share many of the common APIs used in creating malware, such as those that require root access of the device, which is required to gather sensitive information such as their phone number to text them, opening a popup window, as well as locking them out of their phone.

ADVERSARIAL ATTACK

Our adversarial attack follows many of the techniques applied by Chen, et al. (2018) to attack the MaMaDroid and Drebin models. To perform our attack on HinDroid, we simulated their *Scenerio FB* which can be described as having blackbox access to a malware classifier and the feature set of this classifier. This will allow us to query the classifier as we create examples. The feature set will be the set of distinct APIs derived from our training apps. In our case, the input vector will be the one-hot-encoded set of APIs for the example app. To perform the attack, we modified a Carlini and Wagner (C&W) attack with the following objective function.

$$\begin{aligned} &min_{\delta} \|\delta\|_2^2 + c \cdot f(X+\delta) \\ &s.t.\, X+\delta \in \{0,1\}^n \\ &\text{and } X_i + \delta_i \neq 1 \text{ if } X_i = 1 \end{aligned} \tag{1}$$

and an unchanged loss function defined as

$$f(x') = \max\{0, (\max_{i \neq t} Z(x')_i - Z(x')_t) \cdot \tau + \kappa\} \tag{2}$$

The goal is to have the adversarial model add APIs to an example until it is misclassified or we reach a maximum. We will also avoid removing any APIs as that will likely result in making the example inoperable.

The C&W implementation we used also took advantage of the *tanh trick* that the original authors used. This trick creates a new variable w such that $\delta_i = \text{a}(\tanh(w_i))$ where a rescales the output from $\tanh(x) \in (-1,1)$ to $(0,1)$. We optimize over this variable instead of optimizing δ in order to avoid creating extreme regions where the model may get stuck when performing gradient decent. However, being that we are working with one-hot-encoded values, i.e. the values 0 and 1, and not continuous values like the probabilities used in Android HIV, we introduce a scalar λ such that $\delta_i = \text{a}(tanh(w_i)/\lambda)$ so that it is unlikely that the model considers values are not approximately equal to 0 or 1. As a final check, we also modified the algorithm to verify that the example generated still misclassifies after the values are rounded.

We summarize the algorithm below:

`model` is a substitute model, `X` is the input example, `t` is the ground truth label, `X*` is the correspooning adversarial example, `perts` is the perturbations we apply to the input, `Y` is the output label from the substitute, `c` is constant balancing the distorition and the adversarial loss, `c_max` is the upper bound for `c`, `max_iter` is max number of gradient update iterations, `lr` is the learning rate

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```
    while c < c_max and Y = t:
        while iter < max_iter:
            grads = compute_gradients()
            perts = perts + lr * grads
            X* = X + perts
            Y = F(X*)
        c = c * 10
    return X*
```

EXPERIMENT

To evaluate our methods we conducted two tests: The first evaulating the performance of HinDroid vs m2vDroid and second evaluating the strength the our adversarial attack.

m2vDroid Experiment

To test our models, we used a dataset of 6,451 apps. 5,516 of these apps have been deemed malicious through other methods. We will use this set the malware set. For the benign set, we selected 2 categories of apps: popular apps and random apps. Popular apps were selected from the popular category of apkpure.com, a Android app marketplace. Random apps were selected at random from the site. While popular apps are unlikely to be malicious, the same cannot be said for random apps. Some estimates believe that up to 5% of the apps could contain malware. Nevertheless, we use the apps to bolster the benign app set as not doing so would make the benign app set negligibly small compared to the malware set. In total, we used 905 apps for the benign set, with 324 popular apps and 581 random apps. Between these apps, there were 6,495,974 distinct API calls, 653,742 packages, and 6,945,506 distinct method declarations.

We then created a training set with one third of the apps, with the remainder becoming the test set, being sure to keep the proportion of each category of app equal. The result is that the training set had a total of 2,535,703 distinct API calls, 273,241 packages, and 2,674,056 distinct method declarations. With these sets, we will compare the performance of m2vDroid against 5 of Hindroid's best performing single-kernel models (AA^T, ABA^T, APA^T, $ABPB^TA^T$, $APBP^TA^T$).

m2vDroid Parameters

For the metapath walk, we specified a walk length of 60, walking on each of the following metapaths 3 times per App node:

- $App \rightarrow Api \rightarrow App$
- $App \rightarrow Api \rightarrow Method \rightarrow Api \rightarrow App$
- $App \rightarrow Api \rightarrow Package \rightarrow Api \rightarrow App$
- $App \rightarrow Api \rightarrow Package \rightarrow Api \rightarrow Method \rightarrow Api \rightarrow App$
- $App \rightarrow Api \rightarrow Method \rightarrow Api \rightarrow Package \rightarrow Api \rightarrow App$

We chose these metapaths as they are similar to the set formed by the 5 single kernel models of HinDroid that we will be considering.

For word2vec, we used a skip-gram model trained over 10 epochs. We used a window size of 7 so that 2 connected apps could appear in the window even in the longest metapaths. The `min_count` parameter was set to `0` so that all nodes in the metapath walk were incorporated. We also were sure to include negative sampling as part of the process, as negative samples would help further distinguish nodes the are not associated with each other. For this we specified `negative=5` for a final output vector of length 128.

Adversarial Experiment

To test the adversary, we trained a substitute model on the AA^T kernel for HinDroid. Using this model, we generated examples for 500 apps selected at random from our entire app dataset. We then took these examples and their original inputs and ran them through the each kernel of HinDroid classifier. This would help use determine how well the examples generalize to attacking other the other kernels as well as shed insight into the inner workings of HinDroid itself.

As for the parameters of the attack, we used a lambda of 10000, a confidence of 0.0, a c_range of (0.1, 1e10), using 5 binary search steps, and max_iter of 1000. We also set the learning rate to be 0.01. We initialize the perturbations in tanh-space randomly setting approximately 5% of these values to 1. To clarify, this is not equivalent to randomly adding APIs. We found that the algorithm was never succeeded if we left the perturbations at 0. Adding these small changes gives inertia to the algorithm and was the key to generating successful examples.

RESULTS

HinDroid vs m2vDroid

With the final results, we can see that our while we still achieved some respectable numbers, m2vDroid struggled to keep up with the HinDroid kernels' performances and it had a pronounced issue with false positives. This may simply be the case that m2vDroid is not as effetive as HinDroid or that we may need to further tune the parameters of it. However, considering that some other kernels faced the same issue, albiet with a smaller magnitute, this may the result of the heavy bias in our dataset. This could also be due to the inclusion of random apps. Recall that a small percentage of these apps may actually be malware but we may have mislabeled them as benign by assuming all random apps were benign to begin with. It may be worth the effort to perform the test again by either excluding random apps or filtering possible malware using another method.

	ACC	TPR	F1	TP	TN	FP	FN
m2vDroid	0.950	1.000	0.973	3676	169	202	1
AAT	0.986	0.999	0.992	3674	316	55	3
ABAT	0.976	0.990	0.987	3642	310	61	35
APAT	0.979	0.998	0.989	3670	294	77	7
ABPBTAT	0.986	0.999	0.992	3672	320	51	5
APBPTAT	0.976	0.992	0.987	3647	303	68	30

Adversarial Attack

After testing the adversarial examples we generated, we were returned the following results. Being that we trained against the AA^T kernel for the test, it is not surprising we see that that the attack was most successful against this kernel, achieving a evasion rate of 97.2%. Malware examples were also able to evade the APA^T and $APBP^TA^T$ kernels with a success rate >99%. Malware example were fairly inneffective when it came to the APA^T and $ABPBTAT$ kernels. It may be that these kernels are more broad with their definition of malware, making it harder for malware examples to evade them. The inverse might be said for the $APBP^TA^T$ where benign examples struggled to evade the classifier. Overall, we believe these results are incredibly promising for our method and would like to expand them to other kernels as well as our model in the future.

	AAT	**ABAT**	**APAT**	**ABPBTAT**	**APBPTAT**	**Support**
Original AAT Label						
Benign	80.0%	96.4%	58.2%	96.4%	5.5%	55
Malware	99.3%	1.1%	99.1%	0.2%	99.3%	445
Total	97.2%	11.6%	94.6%	10.8%	89.0%	500

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- PyTorch implementation of Carlini-Wanger's L2 attack. https://github.com/kkew3/pytorch-cw2
- Imbalanced Data Sampler by ufoym. https://github.com/ufoym/imbalanced-dataset-sampler

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