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# Resilient and Adaptive Framework for Large Scale Android Malware Fingerprinting using Deep Learning and NLP Techniques

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**Abstract**—Android malware detection is a significant problem that affects billions of users using millions of Android applications (apps) in existing markets. This paper proposes **PetaDroid**, a framework for accurate Android malware detection and family clustering on top of static analyses. **PetaDroid** automatically adapts to Android malware and benign changes over time with resilience to common binary obfuscation techniques. The framework employs novel techniques elaborated on top of natural language processing (NLP) and machine learning techniques to achieve accurate, adaptive, and resilient Android malware detection and family clustering. **PetaDroid** identifies malware using an ensemble of convolutional neural network (CNN) on proposed Inst2Vec features. The framework clusters the detected malware samples into malware family groups utilizing sample feature digests generated using deep neural auto-encoder. For change adaptation, **PetaDroid** leverages the detection confidence probability during deployment to automatically collect extension datasets and periodically use them to build new malware detection models. Besides, **PetaDroid** uses code-fragment randomization during the training to enhance the resiliency to common obfuscation techniques. We extensively evaluated **PetaDroid** on multiple reference datasets. **PetaDroid** achieved a high detection rate (98-99% f1-score) under different evaluation settings with high homogeneity in the produced clusters (96%). We conducted a thorough quantitative comparison with state-of-the-art solutions MaMaDroid, DroidAPIMiner, MalDozer, in which **PetaDroid** outperforms them under all the evaluation settings.

## I. INTRODUCTION

Android OS’s popularity has increased tremendously since the last decade. It is undoubtedly an appropriate choice for smart mobile devices such as phones and tablets or the internet of things devices such as TVs due to its open-source license and the massive number of useful apps developed for this platform (about 4 Million apps in 2019 [2]). Nevertheless, malicious apps target billions of Android users through centralized app markets. The detected malicious apps increased by 40% in 2018-Q3 compared to the same period in 2017 [1]. Google Play [36] employs a vetting system named **Bouncer** to detect malicious apps through static and dynamic analyses. Despite these analyses, many malicious apps<sup>1</sup> were able to bypass **Bouncer** and infect several hundred thousand devices<sup>2</sup>. Therefore, there is a dire need for accurate, adaptive, yet resilient Android malware detection systems for the app market scale.

<sup>1</sup><https://tinyurl.com/y4qdtuy9>

<sup>2</sup><https://tinyurl.com/y4mckwxm>

### A. Problem Statement

In this paper, we identify the following gaps in the state-of-the-art solutions for Android malware detection:

**P1:** The accuracy of Android malware detection systems tends to decrease over time due to different factors: (1) variations in existing malware family, (2) new malware families, (3) and new Android APIs in benign and malicious apps. These factors are mostly reflected in the changes in Android API call sequences in malicious and benign apps. Nevertheless, these changes are incremental in most cases compared to the existing apps. In this context, we consider two problems: (1) The resiliency of the detection systems that use machine learning models [37] to changes over time, (2) and the possibility of automatic adaptation to the new changes [48].

**P2:** Android malware family attribution is an important problem in the realm of malware detection. The malware family attribution could be important essential to define the threats<sup>3</sup> of the detected malware [33]. However, few existing solutions [9], [50] provide Android malware family attribution. Furthermore, these solutions rely on supervised learning where prior knowledge of the families is required [16]. However, such knowledge is hard to get and not realistic in many cases, especially for new malware families<sup>4</sup>.

**P3:** malware developers employ various obfuscation techniques to thwart detection attempts. Obfuscation resiliency is a key requirement in modern malware fingerprinting that applies static analyses. Few solutions address the obfuscation issue in the context of Android malware detection, more specifically, the resiliency to common obfuscations and binary code transformations.

**P4:** Many existing solutions [8], [43], [11] rely on manual feature engineering to extract relevant malware patterns for classification. Despite the good detection performance, manual feature engineering is not scalable to the amount and the growth pace of Android malware. Therefore, there is a dire need for malware detection solutions that rely on automatic feature engineering to discover relevant malware patterns. Other solutions [37] utilize automated feature engineering but lack efficiency. The malware detection process’s efficiency is a paramount requirement due to the growing number of Android apps.

<sup>3</sup><https://tinyurl.com/yydg5vew>

<sup>4</sup><https://tinyurl.com/y8rc6q89>

## B. Proposed Solution

In this paper, we propose **PetaDroid**, an accurate, adaptive, resilient, and yet efficient Android malware detection and family clustering using natural language processing (NLP) and deep learning techniques on top of static analysis features. In **PetaDroid**, we aim to address the previously mentioned problems as follows:

1. Our fundamental intuition for time resiliency and adaptation is that Android apps are changing over time incrementally. Benign apps embrace new Android APIs, deprecations, and components gracefully to do not disturb the user experience. Malware developers aim to target the maximum devices by employing stable and cross-Android version APIs. We argue that **PetaDroid** can fingerprint malicious apps within a time window with high confidence because the application still contains enough patterns of similarity to known samples. In this period, we argue that those top confidence detection apps (malicious or benign) could extend our initial build dataset of **PetaDroid** to enhance the overall performance and keep up with the change over time. **PetaDroid** introduces an automatic and continuous dataset enrichment technique and machine learning model training to overcome the change over time.

2. **PetaDroid** goes a step further in the detection process by clustering the detected samples into groups with high similarity. We *exclusively* group highly similar samples, most likely of the same malware family. **PetaDroid** family attribution is found upon the assumption that malicious applications tend to have similar characteristics in the Android Dalvik bytecode code. For example, SMS malicious apps exploit the same Android APIs in a very similar manner. The similarity increases when malicious apps are from the same malware family. We leverage this assumption to build an automatic and unsupervised malware family tagging system using deep neural network auto-encoder for sample digest generation on top of *InstNgram2Bag* features (based on NLP bag of words). Using the DBScan [15] clustering algorithm, we cluster the *most similar samples* from the detected malicious apps.

3. **PetaDroid** introduces code fragments randomization during training and deployment phases to enhance the obfuscation resiliency. We artificially apply random permutations to change the order of code basic-blocks without altering the basic-block instructions. We consider a code basic-block as a possible micro-action in the app execution flows. Therefore, we randomize the app execution flows without affecting the micro-actions within the flow to emulate code transformation during the training and deployment phases. Code fragment randomization strengthens the obfuscation robustness of **PetaDroid**, as shown in Section V-D.

4. **PetaDroid** leverages deep learning techniques to achieve automatic feature engineering. Specifically, We employ an ensemble of CNN models on top of canonical instruction embeddings, namely *Inst2Vec*. Those embeddings are learned using word2vec [35], an NLP technique that translates latent patterns and semantics from raw word sequences into word embeddings. **PetaDroid** detection is very efficient due to its minimal preprocessing compared to state-of-the-art solutions [37].

## C. Contributions and Outline

The main contributions of this paper are:

- (1) We propose a novel adaptation technique for Android malware detection to automatically adapt the detection system. The proposed techniques rely on the confidence probability of the detection ensemble to collect extension training datasets from received samples during the deployment (Section II-C7).

- (2) We propose a novel fragment randomization technique to boost the detection system resiliency to common code-obfuscation techniques. In this technique, we randomize the order of code basic-blocks without affecting the basic-blocks instructions during the training and the deployment phases (Section II-C1).

- (3) We propose **PetaDroid**, an accurate and efficient malware detection and clustering framework based on code static analyses, NLP, and machine learning techniques. In **PetaDroid**, we propose an ensemble of CNN models on top of a code embedding model, namely *Inst2Vec*, to accurately detect malware with probability confidence (Section II-C). Besides, we propose an unsupervised family attribution by clustering malware family samples on top of *InstNgram2Bag* features generated using deep auto-encoders (Section II-D). We released the source code of **PetaDroid** to the community in <https://github.com/mouatez/petadroid>.

- (4) We extensively evaluate **PetaDroid** to assess its effectiveness and efficiency on different reference datasets of **PetaDroid** under various evaluation settings (Section II-B). To demonstrate the framework robustness against common obfuscation techniques, we evaluate **PetaDroid** on the obfuscated dataset generated using DroidChameleon [40] obfuscation tool and PRAGuard [31] dataset (Section V-D). We conduct an empirical comparison study between state-of-the-art solutions, namely MaMaDroid [37], DroidAPIMiner [3], and MalDozer [24] in which **PetaDroid** outperforms these solutions (Section VI).

## II. PETADROID

In this section, we detail **PetaDroid** methodology and its components. The general overview of **PetaDroid** is presented in Figure 1.

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### A. Methodology Summary

**PetaDroid** employs static analyses on Android Packaging (APK) to investigate the maliciousness of Android apps. **PetaDroid** starts by extracting raw static features from the Android Packaging, specifically the Dalvik bytecode. We develop a fast preprocessing phase to extract raw Dalvik assembly instructions. We generate, on the fly, the canonical form of the assembly instructions by substituting the value of constants, memory addresses with symbolic names. The output is a raw sequence of canonical assembly instructions of Dalvik virtual machine.

**PetaDroid** maintains a logical separation among the software component of an Android app. We keep track of methods' instruction sequences within the app global instruction sequence. It is a natural breakdown because an Android app

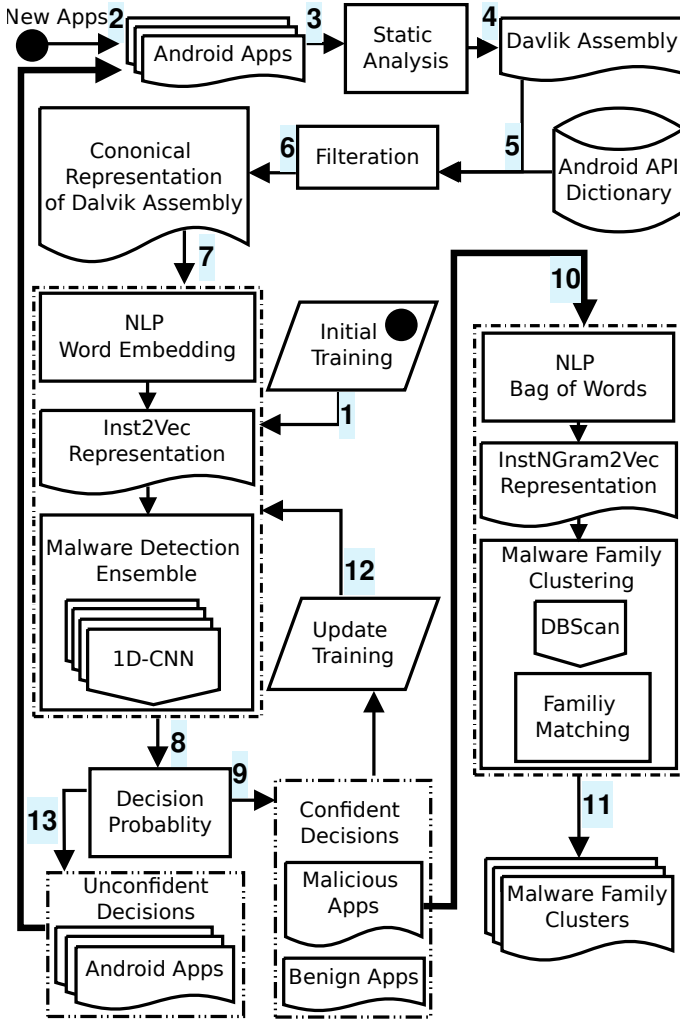


Fig. 1: PetaDroid Architecture Overview

is a set of classes, and a class is a set of methods and attributes. In the context of Android apps, we consider the class's methods as our basic-block codes, which we keep unaltered when applying the fragment randomization technique. Our tests for granularity beyond methods (i.e. code basic-blocks of the method' Control Flow Graph (CFG)) results in very small code basic-blocks (one instruction in many cases). The global app execution sequence is composed of a list of micro-execution paths (instruction sequences of the methods), through which the execution proceeds during runtime. The extracted canonical instruction sequences (described in the next section) help preserve the underlying micro-execution paths while not emphasizing the global execution order.

Previous solutions [37] apply heavy and complex preprocessing to construct a global call graph to simulate runtime execution using static analyses. In contrast, our extraction approach is lightweight because we consider only the class's methods. This allows swift preprocessing in commodity hardware while maintaining the intended granularity. Furthermore, and in contrast with previous solutions [8], [3], we adopt granular features using a canonical instruction followed by representation learning. We propose custom code modeling

techniques for representation learning inspired by advanced NLP techniques. Specifically, we design and develop *Inst2Vec* and *InstNGram2Bag* code modeling techniques to model and discover latent information. In a nutshell, PetaDroid detection process has the following main components:

(1) **Representation Learning for Classification:** PetaDroid learns latent representations in an unsupervised manner using the word2vec technique [35] on raw Dalvik canonical instruction sequences and produces embeddings.

(2) **Malware Detection:** PetaDroid employs neural network models for automatic features engineering from the embedding representation. During the training phase, the training dataset automatically guides the feature engineering to discover relevant malware patterns. PetaDroid detection system rests on the CNN models ensemble that consumes *Inst2Vec* embedding features and produces maliciousness probability likelihood.

(3) **Model Adaptation:** PetaDroid collects Android apps that are detected with high confidence, whether malicious or benign, to extend the PetaDroid primary labeled dataset (used to build the current detection ensemble). Periodically, PetaDroid employs the collected datasets (primary and extensions) to build new model ensembles to adapt to new benign and malware patterns overtime automatically.

(4) **Code Representation for Clustering:** In contrast with classification, the malware family clustering requires another representation that squashes a canonical instruction sequence into one feature vector instead of a sequence of embeddings for a given malware sample to fit with our clustering system. For each detected malware sample, we produce feature vectors using a bag of words (N-grams) NLP model and the feature hashing technique [42] on top of the canonical instruction sequences. We call the outcomes *InstNGram2Bag* vectors, one *InstNGram2Bag* vector for each detected malware.

(5) **Digest Generation:** we produce malware digests by applying deep neural auto-encoders [18] on the *InstNGram2Bag* vectors to produce even more compact embedding or a digest for each malware sample.

(6) **Malware Family Clustering:** PetaDroid clusters the flagged malicious apps into groups with high inter-similarity between their digests, and most likely of the same malware family. PetaDroid clustering system is based on DBScan [15] clustering algorithm.

## B. Android App Representation

In this section, we present the preprocessing of Dalvik code and its representation into a canonical instruction sequence. We seek the preservation of the maximum information about apps' behaviors while keeping the process very efficient. The preprocessing begins with the disassembly of an app bytecode to Dalvik assembly code, as depicted in Figure 2.

We model the Dalvik assembly code as code fragments where each fragment is a class's method code in the Dalvik assembly. It is a natural separation because Dalvik code  $D$  is composed of a set of classes  $D = \{C_1, C_2, \dots, C_s\}$ . Each class  $C_i$  contains a set of methods  $C = \{M_1, M_2, \dots, M_k\}$ , where we find actual assembly code instructions. We preserve the order of Dalvik assembly instructions within methods while

```

// Object Creation
new-instance v10, java/util/HashMap
// Object Access
invoke-direct v10, java/util/HashMap
if-eqz v9, 003e
...
// Method Invocation
// * = Android/telephony
invoke-virtual v4, */TelephonyManager.getDeviceId()java/lang/String
move-result-object v11
// Method Invocation
invoke-virtual v4, */TelephonyManager.getSimSerialNumber()java/lang/String
move-result-object v13
// Method Invocation
invoke-virtual v4 */TelephonyManager.getLine1Number()java/lang/String
move-result-object v4
...
// Object Creation
new-instance v20, java/io/FileReader
const-string v21, "/proc/cpuinfo"
invoke-direct/range v20, v21, java/io/FileReader.init()java/lang/String)
new-instance v21, java/io/BufferedReader
...
move/from16 v2, v20
// Field Access
// * = Android/content/pm
iget-object v0, v0, */ApplicationInfo.metaData Android/os/Bundle
move-object/from16 v19, v0

```

Fig. 2: Android Assembly from a Malware Sample

ignoring the global execution paths. Method execution is a possible *micro-behavior* for an Android app, while a global execution path is a likely *macro-behavior*. An Android app might have multiple global execution paths based on external events. In contrast, Android malware tends to have one crucial global execution path (malicious payload) and other ones to distract malware detection systems. The malware could produce variations for the payload global execution path. However, it still depends on the micro-behavior to produce another global one. PetaDroid assembly preprocessing produces a multiset of sequences  $P = \{S_1, S_2, \dots, S_h\}$  where each sequence  $S$  contains an ordered instruction sequence  $S = \langle I_1, I_2, \dots, I_v \rangle$  of a class's method. In other words,  $P$  contains instruction sequences  $P = \{\langle I_1, I_2, \dots \rangle_1, \langle I_1, I_2, \dots \rangle_2, \dots, \langle I_1, I_2, \dots \rangle_h\}$  where the order is only preserved inside individual sequences  $S_i$  (the methods instructions). Thus, a sequence  $S$  defines a possible micro-execution (or behavior) from the Android app's overall runtime execution.

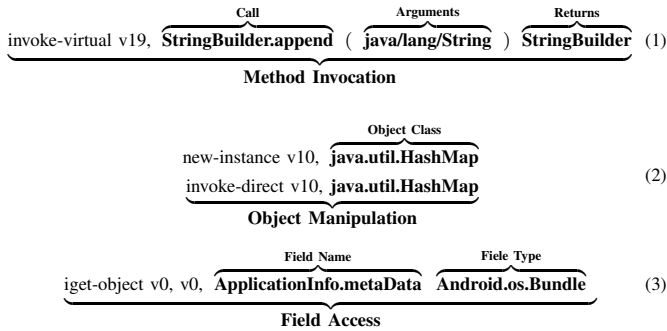


Fig. 3: Canonical Representation of Dalvik Assembly

As shown in Figure 2, the Dalvik assembly is too sparse. We want to keep the assembly instruction skeleton that reflects

```

java/util/HashMap
java/util/HashMap
...
Android/telephony/TelephonyManager.getDeviceId()
java/lang/String
Android/telephony/TelephonyManager.getSimSerialNumber()
java/lang/String
Android/telephony/TelephonyManager.getLine1Number()
java/lang/String
...
java/io/FileReader
java/io/FileReader.init()
java/lang/String
java/io/BufferedReader
...
Android/content/pm/ApplicationInfo.metaData
Android/os/Bundle

```

Fig. 4: Flatten Canonical Representation

possible runtime behaviors with less sparsity. In PetaDroid, we propose a canonical representation for Dalvik assembly code, as shown in Figure 3. The key idea is to keep track of the Android platform APIs and objects utilized inside the method assembly. To fingerprint malicious apps, the canonical representation will mostly preserve the actions and the manipulated system objects, such as sending SMS action or getting (setting) sensitive information objects. PetaDroid canonical representation covers three types of Dalvik assembly instructions, namely: *Method invocation*, *object manipulation*, and *field access*, as shown in Figure 3. In the method invocation, we focus on the method call, *Package.ClassName.MethodName*, the parameters list, *Package.ClassName*, and the return type, *Package.ClassName*. In object manipulation, we capture the class object, *Package.ClassName*, that is being used. Finally, we track the access to system fields by capturing the field name, *Package.ClassName.FieldName*, and its type, *Package.ClassName*. Our manual inspections of Dalvik assembly for hundreds of malicious and benign samples shows that these three forms cover the essential of Dalvik assembly instructions.

PetaDroid instruction parser keeps only the canonical representation and ignores the rest. For example, our experiments show that Dalvik opcodes add a lot of sparsity without enhancing the malware fingerprinting performance. On the contrary, it could negatively affect overall performance, which is shown in previous solutions [34]. The final step in preprocessing a method  $M$  (see Figure 2) is to flatten the canonical representation of a method into a single sequence  $S$  (see Figure 4). We keep only the Android platform related assets like API, classes, and system fields in the final method's sequence  $S$ . We maintain a vocabulary dictionary (key: value) in the form of  $(Androidassets : identifier)$  (for example  $(Android/telephony/TelephonyManager : 439)$ ) of all Android OS assets (all versions) to filter and map Android assets to unique identifiers (unique integer for a given Android assets) for the method instruction sequence during the preprocessing. The output of the app representation phase is a list of sequences  $\hat{P} = \{S_{c1}, cS_{c2}, \dots, cS_{ch}\}$ . Each sequence is an ordered canonical instruction representation of one method.

In the following, we summarize the notations used in the rest of the paper:

TABLE I: Notation Summary

Notation	Description	Format
$D$	Dalvik assembly code of one Android App	Raw text
$C$	Dalvik Java Class	Raw text
$M$	Dalvik Java Method	Raw text
$S$	Sequence of extracted instructions of one Dalvik Java Method $M$	List of Dalvik raw text instructions
$P$	Multiset of methods' sequences $S$	Multiset of sequences
$S_c$	Sequence of canonical instructions generated from $S$ using $V$	List of canonical instruction IDs
$\hat{P}$	Multiset of methods' sequences $S_c$	Multiset of sequences
$P_c$	The result of shuffling and concatenating of all $S_c$	Sequence of canonical instructions
$F$	Fragment is a truncated portion from $P_c$	List of canonical instructions
$CNNModel$	Classification model based on Convolutional Neural Network (CNN)	Deep learning model
$\Phi$	Ensemble of classification models $\Phi = \{CNNModel_1, CNNModel_2, \dots, CNNModel_\phi\}$	Set of deep learning models
$y$	Dataset label	Malware or not
$\hat{y}$	Prediction likelihood of the classification models $\hat{y} = \Phi(F)$	Probability
$\zeta$	Detection threshold for the general decision strategy	Probability threshold
$\eta$	Detection threshold for the confidence decision strategy	Probability threshold

$$\hat{P} = \{S_{c1}, S_{c2}, S_{c2}\} \quad (4)$$

$$\{ \underbrace{S_{c3}, S_{c1}, S_{c2}}_{\text{Shuffled sequences}} \} \quad (5)$$

$$\overbrace{\langle I_1, I_1, \dots, I_{|S_{c3}|} \rangle_3, \langle I_1, I_1, \dots, I_{|S_{c1}|} \rangle_1, \langle I_1, I_1, \dots, I_{|S_{c2}|} \rangle_2}^{\text{while preserving the order inside sequences}} \quad (6)$$

$$\hat{P}_c = \underbrace{\{ I_{3,1}, I_{3,1}, \dots, I_{3,|S_{c3}|}, I_{1,1}, I_{1,1}, \dots, I_{1,|S_{c1}|}, I_{2,1}, I_{2,1}, \dots, I_{2,|S_{c2}|} \}}_{\text{Fragment truncation}} \quad \text{Rest} \quad (7)$$

$$F = \underbrace{\{ I_{3,1}, I_{3,1}, \dots, I_{3,|S_{c3}|}, I_{1,1}, I_{1,1}, \dots, I_{1,|S_{c1}|}, I_{2,1} \}}_{\text{on fragment size } |F|} \quad (8)$$

Fig. 5: Example of Fragment Generation

### C. Malware Detection

In this section, we present the PetaDroid malware detection process using CNN on top of *Inst2Vec* embedding features. The detection process starts from a multiset of discretized canonical instruction sequences  $\hat{P} = \{S_{c1}, S_{c2}, \dots, S_{ch}\}$ . Notice that  $\hat{P}$  is a multiset and not a set since it might contain duplicated sequences. The duplication comes from having the same Dalvik method's code in two (or more) distinct Dalvik classes. PetaDroid CNN ensemble produces a detection result together with maliciousness and benign detection probabilities for a given sample. To achieve automatic adaptation, we leverage the detection probabilities to automatically collect an extension dataset that PetaDroid employs to build new CNN ensemble models.

1) *Fragment Detection*: Fragment-based detection is a key technique in PetaDroid. A fragment  $F$  is a truncated portion from the beginning of the concatenation  $P_c$  of  $\hat{P} = \{S_{c1}, S_{c2}, \dots, S_{ch}\}$  as shown in Figure 5. The size  $|F|$  is the

number of canonical instructions in the fragment  $F$ , and it is a hyper-parameter in PetaDroid. Our grid search for the best  $|F|$  hyper-parameter result  $|F| = 10k$  for the current version of PetaDroid. For a sequence  $S_{ci}$ , the order of canonical instructions is preserved within a method. In other words, we guarantee the preservation of order inside the method sequence or what we refer to as a *micro-action*. However, no specific order is assumed between methods' sequences or what we refer to as *macro-action* (or behavior). On the contrary, before we truncate  $P_c$  into size  $|F|$ , we apply random permutations on  $\hat{P}$  to produce a random order in the macro-behavior. The randomization happens in every access, whether it is during training or deployment phases. Each Android sample has  $\frac{h!}{(h-k)!}$  possible permutations for the methods' sequences  $\hat{P} = \{S_{c1}, S_{c2}, \dots, S_{ch}\}$ , where  $h$  is the number of methods' sequence in a given Android app, and  $k$  is the number of sampled sequences. The concatenation of the sampled  $k$  sequences must be greater than  $|F|$ .

The intuition behind fragment detection is the abstraction of Android apps behavior into very small *micro-actions*. We consider each method canonical instruction sequence  $S_c$  as possible *micro-actions* for an Android app. In a fragment, we keep the possible micro-actions intact and discard the app flow graph. We argue that this will force pattern learning, during the training, to focus on only micro-actions, which allows better generalization. Fragment-based detection has many advantages in the context of malware detection. First, it challenges the machine learning model and its training process to learn dynamic patterns at every training epoch. It also focuses the model on robust, distinctive patterns from a sample of random micro-actions of methods. Second, we argue that our fragment-based detection improves the overall resiliency of the malware detection model against conventional obfuscation techniques and code transformation. Third, in the deployment phase, PetaDroid infers the maliciousness of a given sample by applying PetaDroid CNN on multiple fragments from a single sample to obtain a detection decision.

*These fragments are entirely different since we apply the randomization technique for every fragment generation. Furthermore, each code fragment  $F$  produces a different view*

angle of the Android app for the machine learning model and brings new information by considering a new  $S_{ci}$  list in the truncation. Finally, the fragment detection happens on a single CNN model transparently to the ensemble.

2) *Inst2Vec Embedding*: *Inst2Vec* is based on *word2vec* [35] technique to produce an embedding vector for each canonical instruction in our sequences. *Inst2Vec* is trained on instruction sequences to learn instruction semantics from the underlying contexts. This means that *Inst2Vec* learns a dense representation of a canonical instruction that reflects the instruction co-occurrence and context. The produced embeddings capture the semantics of instructions (interpreted by geometric distances). Furthermore, embedding features show high code fingerprinting accuracy and resiliency to common obfuscation techniques [14]. *Word2vec* [35] is a vector space model to represent the words of a document in a continuous vector space where words with similar semantics are mapped closely in the space. *word2vec* functionality could be replaced with recent representation learning models based on *Transformer* such as [39], [13]. From a security perspective, we want to map our features (canonical instructions in a code fragment) to continuous vectors where their semantics is translated to a distance in the vector space [6].

*Word2vec* is a neural probabilistic model that is trained using the maximum likelihood concept. More precisely, given sequence of words:  $w_1, w_2, \dots, w_T$ , at each position  $t = 1, \dots, T$ , the model predicts a context of sequence within a window of fixed size  $m$  given center word  $w_j$  (illustrated in Equation 9), where  $m$  is the size of the training context [35].

$$L(\theta) = \prod_{t=1}^T \prod_{-m \leq j \leq +m, j \neq 0} P(w_{t+j}|w_t; \theta) \quad (9)$$

The objective function [35]  $J(\theta)$  is the negative log likelihood, as shown in Equation 11. The probability  $P(w_{t+j}|w_t; \theta)$  is defined in Equation 13, where  $v_w$  and  $v'_w$  are the input and the output of the embeddings of  $w$ .

$$J(\theta) = -\frac{1}{T} \log L(\theta) \quad (10)$$

$$= -\frac{1}{T} \sum_{t=1}^T \sum_{-m \leq j \leq +m, j \neq 0} \log P(w_{t+j}|w_t; \theta) \quad (11)$$

$$P(w_O|w_I) = \text{softmax}(\hat{v}_{w_O}^T v_{w_I}) \quad (12)$$

$$= \frac{\exp(\hat{v}_{w_O}^T v_{w_I})}{\sum_{w=1}^W \exp(\hat{v}_w^T v_{w_I})} \quad (13)$$

We train the embedding model by maximizing log-likelihood as illustrated in Equation 15.

$$J_{ML} = \log P(w_O|w_I) \quad (14)$$

$$= (\hat{v}_{w_O}^T v_{w_I}) - \log \left( \sum_{w=1}^W \exp\{\hat{v}_w^T v_{w_I}\} \right). \quad (15)$$

3) *Classification Model*: Our single CNN model takes *Inst2Vec* features, which are a sequence of embeddings; each embedding captures the semantics of an instruction. The temporal CNN [28], or 1-dimensional CNN [51], is the working

TABLE II: PetaDroid Single CNN Model

#	Layers	Options
1	ID-Conv	Filter=128, Kernel=(5,5), Stride=(1,1), Padding=0, Activation=ReLU
2	BNorm	BatchNormalization
3	Global Max Pooling	/
4	Linear	#Output=512, Activation=ReLU
5	Linear	#Output=256, Activation=ReLU
6	Linear	#Output=1, Activation=ReLU

core component in the PetaDroid single classification model. Table II details the architecture of our CNN single model.

We choose to build our classification models based on CNN architecture over recurrent neural networks (RNN) such as LSTM or GRU. Due to the efficiency of CNN during the training and the deployment compared to RNN [17]. **In the training phase**, the CNN models take on average 0.05 second per batch (32 samples), which is five times faster than RNN models in our experiments. The CNN model converges early (starting from 10 epochs) compared to the RNN model (starting from 30 epochs). **In the deployment phase**, the CNN model's inference is, on average, five times faster than RNN models. Both neural network architecture gives very similar detection results in our experiments. However, our automatic adaptation technique will benefit from the efficiency of CNN models to rapidly build new models using large datasets. The non-linearity used in our model employ the rectified linear unit (ReLU)  $h(x) = \max\{0, x\}$ . We used Adam [17] optimization algorithm with a 32 mini-batch size and a  $3e - 4$  learning rate for 100 epochs in all our experiments. The chosen hyper-parameters are the results of empirical evaluations to find the best values.

4) *Dataset Notation*: In this section, we present the notations used in the next sections.

$X = \{\langle P_0, y_0 \rangle, \langle P_1, y_1 \rangle, \dots, \langle P_m, y_m \rangle\}$ :  $X$  is the global dataset used to build ensemble models and report PetaDroid performance on various tasks, where  $m$  is the number of  $\langle \text{sample}, \text{label} \rangle$  records in the global dataset  $X$ .

$X = \{X_{build}, X_{test}\}$ : We use a build set  $X_{build}$  to train and tune the hyper-parameters of PetaDroid models. The test set  $X_{test}$  represents Android apps that the system will receive during the deployment. The test set  $X_{test}$  is used to measure the final performance of PetaDroid, which is reported in the evaluation section.  $X$  is split randomly into  $X_{build}$  (50%) and  $X_{test}$  (50%).

$X_{build} = \{X_{train}, X_{valid}\}$ : The build set,  $X_{build}$ , is composed of a training set  $X_{train}$  and a validation set  $X_{valid}$ . It is used to build PetaDroid single CNN models for the CNN ensemble. For each single CNN model, we tune the model parameters to achieve the best detection performance on  $X_{valid}$ . The build set  $m_{build} = m_{train} + m_{valid}$ : is the total number of records used to build PetaDroid. The training set takes 80% of the build set  $X_{build}$  and, 20% of  $X_{build}$  is used for the validation set  $X_{valid}$ .

5) *Detection Ensemble*: PetaDroid detection component relies on an ensemble  $\Phi = \{CNNModel_1, CNNModel_2, \dots, CNNModel_\phi\}$ . Ensemble  $\Phi$  is composed of  $\phi$  single CNN models.

The number of single CNN models in the ensemble  $\phi$  is a hyper-parameter. We choose to be  $\phi = 6$ , which is a trade-off of between maximum effectiveness on malware detection with the highest efficiency possible base on our evaluation experiments.

As mentioned previously, PetaDroid trains each CNN model for the number of epochs ( $epochs = 100$ ). In each epoch, we compute  $Loss_T$  and  $Loss_V$ , the *training* and *validation* losses, respectively, and save a snapshot of the single CNN model parameters.  $Loss_T$  and  $Loss_V$  are the log loss across training and validation sets:

$$p = CNNModel_{\theta}(y = 1|F)$$

$$loss(y, p) = -(y \log(p) + (1 - y) \log(1 - p)),$$

$$Loss_T = \frac{-1}{m_{train}} \sum_{i=1}^{m_{train}} loss(y_i, p_i),$$

$$Loss_V = \frac{-1}{m_{valid}} \sum_{i=1}^{m_{valid}} loss(y_i, p_i),$$

Where  $p$  is the maliciousness likelihood probability given a fragment  $F$  (a truncated concatenation of canonical instructions  $P_c$ ) and model parameters  $\theta$  (Section II-B). PetaDroid selects the top  $\phi$  models automatically from the saved model snapshots that have the lowest *training* and *validation* losses  $Loss_T$  and  $Loss_R$ , respectively.

$$\hat{y} = \Phi(x) = \frac{1}{\phi} \left( \sum_i^{\phi} CNNModel_i(x) \right) \quad (16)$$

PetaDroid CNN ensemble  $\Phi$  produces a maliciousness probability likelihood by averaging the likelihood probabilities of multiple CNN models, as shown in Equation 16.

6) *Confidence Analysis*: PetaDroid ensemble computes the maliciousness probability likelihood  $Prob_{Mal}$  given a fragment  $F$ , as follows:

$$\hat{y} = \Phi(F), \quad Prob_{Mal} = \hat{y}, \quad Prob_{Ben} = (1 - \hat{y})$$

Previous Android malware detection solutions, such as [37], [24], [11], utilize a simple detection technique (we refer to it as a *general decision*) to decide on the maliciousness of Android apps. In the *general decision*, we compute the general threshold  $\zeta \in [0, 1]$  that achieves the highest detection performance on the validation dataset  $X_{valid}$ . In the deployment phase (or evaluation in our case on  $X_{test}$ ), The general decision  $D_{\zeta}$  utilize the computed threshold  $\zeta$  to make detection decisions:

$$D_{\zeta} = \begin{cases} Malware & Prob_{Mal} > \zeta \\ Benign & Prob_{Mal} \leq \zeta \end{cases}$$

PetaDroid employs f1-score as a detection performance metric to automatically select  $\zeta$  and to report the general detection performance on the test set  $X_{test}$  during our evaluation, in Section V. We choose f1-score as our detection performance metric due to its simplicity, and its measurement reflects the reality under unbalanced datasets. *The general decision* provides a firm decision for every sample. However, security practitioners might prefer dealing with decisions that

have associated confidence values and filter out less-confident decisions for further investigations. In a real deployment, we want as many detection decisions with high confidence and filter out the few uncertain apps with low confidence probability. Unfortunately, the *general decision* strategy that has been used by most previous solutions does not provide such functionality. For this purpose, we propose the **confidence decision strategy**, a mechanism to automatically filter out apps with uncertain decisions. PetaDroid computes a confidence threshold  $\eta$  that achieves a high detection performance (f1-score) and a negligible error rate (false negative and false positive rates) in the validation dataset. In other words, we add the error rate constraint to the system that computes the detection threshold  $\eta$  from  $X_{valid}$ . In the deployment, we make the confidence-based decision as follow:

$$D_{\eta} = \begin{cases} Uncertain & Prob_{Mal} < \eta \wedge Prob_{Ben} < \eta \\ Malware & Prob_{Mal} \geq \eta \wedge Prob_{Mal} > Prob_{Ben} \\ Benign & Prob_{Ben} \geq \eta \wedge Prob_{Ben} > Prob_{Mal} \end{cases}$$

For example, we could fix the error rate to  $< 1\%$  and automatically find  $\eta$  that achieves the highest f1-score in the validation set. Our goal is to maximize confidence detection decisions during the deployment, which we called the *detection coverage performance* and minimize alerts for uncertain ones that require further analyses (such as dynamic analyses). In our case, the *detection coverage performance* is the percentage of confidence decisions from  $X_{test}$ . In Section V, we conduct experiments where we report the *general detection performance* metric to compare with existing solutions such as [37], [24], [11]. Besides, we report *confidence detection performance* and *detection coverage performance* metrics, which we believe are suitable for real-world deployment. The *confidence decision strategy* is key for automatic adaptation in PetaDroid, as will be explained next.

7) *Automatic Adaptation*: In this section, we describe our mechanism to adapt to Android ecosystem changes over time automatically. The key idea is to re-train the CNN ensemble on new benign and malware samples periodically to learn the latest changes. To enhance the automatic adaptation, we leverage the confidence analysis to collect an extension dataset that captures the incremental change over time. Initially, we train PetaDroid ensemble using  $X_{build} = \{X_{train} + X_{valid}\}$ . Afterward, PetaDroid leverages the *confidence detection strategy* to build an extension dataset  $X_{exten}$  from test dataset  $X_{test}$  from high-confidence detected apps. In a real deployment,  $X_{test}$  is a stream of Android apps that needs to be checked for maliciousness by the vetting system. The test dataset  $X_{test} = \{X_{Certain}, X_{Uncertain}\}$  is composed of apps having a high-confidence decision ( $X_{Certain}$  or  $X_{exten}$ ) and apps having uncertain decisions  $X_{Uncertain}$ . In the deployment, PetaDroid accumulates from high-confidence apps over time to form  $X_{exten}$  dataset. Periodically, PetaDroid utilizes the extension dataset  $X_{exten}$  to extend the original  $X_{build}$  and later updates the CNN ensemble models. In our evaluation, and after updating the CNN ensemble, we report **updated general performance** and **updated confidence-based performance**, respectively the general and confidence-based performance of the new trained CNN ensemble on  $X_{test}$ . These metrics answer the question: what would be the detection performance on  $X_{test} = \{X_{Certain}, X_{Uncertain}\}$  after we build the ensemble on  $X_{NewBuild} = \{X_{Certain}, X_{build}\}$ ? In other words,



PetaDroid reviews previous detection decisions using the new CNN ensemble and drives new general and confidence-based performance.

In a deployment environment, PetaDroid is continuously receiving new Android apps, whether benign or malware, which is figuratively our  $X_{test}$ . PetaDroid employs the extension dataset  $X_{exten}$  to automatically overcome pattern changes, whether malicious or benign. Our approach is based on the assumption that Android apps patterns change incrementally with slow progress. Therefore, starting from a relatively small  $X_{build}$  dataset, PetaDroid could learn new patterns from new  $X_{exten}$  datasets progressively over time. PetaDroid ensemble update is an automatic operation for every period. Our evaluation (Section V-F) shows the effectiveness of our automatic adaptation strategy.

#### D. Malware Clustering

In this section, we detail the family clustering system. PetaDroid clustering aims to group the previously detected malicious apps (Section II-C) into highly similar malicious apps groups, which are most likely part of the same malware family. PetaDroid clustering process starts from a multiset of discretized canonical instruction sequences  $P = \{S_{c1}, S_{c2}, \dots, S_{ch}\}$  of the detected malicious apps. We introduce the *InstNGram2Vec* technique and deep neural network auto-encoder to generate embedding digests for malicious apps. Afterward, we cluster malware digests using the DBScan [15] clustering algorithm to generate malware family groups.

1) *InstNGram2Vec*: Notice that our clustering system (DB-Scan [15]) requires to represent malware samples by one feature vector for each sample instead of a list of embeddings as in *Inst2Vec* for PetaDroid classification. For this reason, we introduce *InstNGram2Vec* technique that automatically represents malware samples as feature vectors without an explicit manual feature selection. *InstNGram2Vec* is a technique that maps concatenated instruction sequences to fixed-size embeddings employing NLP bag of words (N-grams) [4] and feature hashing [42] techniques.

a) *Common N-Gram Analysis (CNG)*: The common N-gram analysis (CNG) [4], or simply N-gram, has been extensively used in text analyses and natural language processing in general and related applications such as automatic text classification and authorship attribution [4]. N-gram computes the contiguous sequences of  $n$  items from a large sequence. In the context of PetaDroid, we compute canonical instructions N-grams on concatenated sequence  $P_c$  by counting the instruction sequences of size  $n$ . Notice that the N-grams are extracted using a forward-moving window (of size  $n$ ) by one step and incrementing the counter of the found features (instruction sequence in the window) by one. The window size  $n$  is a hyper-parameter; we choose  $n = 4$  based on our experiments. We notice that using  $n > 4$  will affect the efficiency considerably if feature vector generation. Using  $n < 4$  affects the effectiveness of the clustering. N-gram computation takes place simultaneously with the feature hashing in the form of a pipeline to prevent and limit computation and memory overuse due to the high dimensionality of N-grams.

b) *Feature Hashing*: PetaDroid employs Feature Hashing (FH) [42] along with N-grams to vectorize  $P_c$ . The feature

hashing algorithm takes as an input  $P_c$  N-grams generator and the target length  $L$  of the feature vector. The output is a feature vector with components  $x_i$  and a fixed size  $L$ . In our framework, we fix  $L = |V|$ , where  $V$  is the vocabulary dictionary (Section II-B). We normalize  $x_i$  using the euclidean norm (also L2 norm). Applying *InstNGram2Vec* on a detected malicious app  $P_c$  produces a fixed size hashing vector  $hv$ . Therefore, the result is  $HV = \{hv_0, hv_1, \dots, hv_{DMal}\}$ , and hashing vector  $hv$  for  $DMal$  detected malicious apps.

$$L2Norm(x) = \|x\|_2 = \sqrt{x_1^2 + \dots + x_n^2} \quad (17)$$

The feature hashing algorithm takes as an input  $P_c$  N-grams generator and the target length  $L$  of the feature vector. The output is a feature vector  $x_i$  with a fixed size of  $L$ . In our framework, we fixed  $L = |V|$ , where  $V$  is the vocabulary dictionary (Section II-B) to prevent collusion problems. We normalize  $x_i$  using the euclidean norm. As shown in Formula 17, the euclidean norm is the square root of the sum of the squared vector values. Previous researches [46], [42] shows that the hash kernel approximately preserves the vector distance and grows linearly with the number of samples. Applying *InstNGram2Vec* on a detected malicious app  $P_c$  produces a fixed size hashing vector  $hv$ . Therefore, the result is  $HV = \{hv_0, hv_1, \dots, hv_{DMal}\}$ , a hashing vector  $hv$  for  $DMal$  detected malicious apps.

2) *Auto-Encoder*: We develop a deep neural auto-encoder through stacked neural layers of encoding and decoding operations, as shown in Table III. The proposed auto-encoder learns the latent representation of Android apps in an unsupervised way. The unsupervised learning of the auto-encoder is done through the reconstruction (Table III) of the unlabeled hashing vectors  $HV = \{hv_0, hv_1, \dots, hv_{DMal}\}$  of random Android apps. Notice that we do not need any labeling during the training of PetaDroid auto-encoder, off-the-self Android apps are sufficient.

TABLE III: PetaDroid Neural Auto-Encoder

#	Layers	Options
01	Linear	#Output= $ V $ , Activation=Tanh
02	Linear	#Output=512, Activation=Tanh
03	Linear	#Output=256, Activation=Tanh
04	Linear	#Output=128, Activation=Tanh
05	Linear	#Output=64, Activation=Tanh
06	Linear	#Output=64, Activation=Tanh
07	Linear	#Output=128, Activation=Tanh
08	Linear	#Output=256, Activation=Tanh
08	Linear	#Output=512, Activation=Tanh
10	Linear	#Output= $ V $ , Activation=Tanh

The training goal is to make the auto-encoder learn to efficiently produce a latent representation (or digest) of an Android app  $hv$  that keeps the discriminative patterns of malicious and benign Android apps. Formally, the input to the deep neural auto-encoder [18] network is an unlabeled hash vector  $HV = \{hv_0, hv_1, \dots, hv_{DMal}\}$ , denoted  $\mathbf{x}' \in \mathcal{U}$  on which operates the encoder network  $f_{enc} : \mathbb{R}^{|V|} \rightarrow \mathbb{R}^p$ ,  $p = 64$  as shown in Table III (parameterized by  $\Theta_{enc}$ ) to produce the latent representation  $\mathbf{z}_{\mathbf{x}', \Theta_{enc}}$ , i.e.

$$\mathbf{z}_{\mathbf{x}', \Theta_{enc}} = f_{enc}(\mathbf{x}'; \Theta_{enc}) \quad (18)$$

The produced digest, namely  $z_{x', \Theta_{\text{enc}}} \in \mathbb{R}^p$ , is used by the decoder network  $f_{\text{dec}} : \mathbb{R}^p \rightarrow \mathbb{R}^{|V|}$  to rebuild or reconstruct the *InstNGramBag2Vec* feature vector. The training loss of the auto-encoder network given the unlabeled *hv*  $x'$  is,

$$\tilde{x}' = f_{\text{dec}}(z; \Theta_{\text{dec}}) \quad (19)$$

$\tilde{x}' \in \mathbb{R}^{d \times w}$  denotes the generated reconstruction.

$$\mathcal{L}_{\text{auto}}(x'; \Theta_{\text{enc}}, \Theta_{\text{dec}}) = \|x' - f_{\text{dec}}(z_{x', \Theta_{\text{enc}}}; \Theta_{\text{dec}})\|^2 \quad (20)$$

In the training phase, the gradient-based optimizer minimizes the objective reconstruction function on the *InstNGram-Bag2Vec* feature vectors of unlabeled Android apps.

$$(\Theta_{\text{enc}}^*, \Theta_{\text{dec}}^*) = \arg \min_{\Theta_{\text{enc}}, \Theta_{\text{dec}}} \sum_{i=1}^{N_1+N_2} \mathcal{L}_{\text{auto}}(x'_i; \Theta_{\text{enc}}, \Theta_{\text{dec}}) \quad (21)$$

Notice that *PetaDroid* auto-encode is trained only once during all the experimentation due to its general usage. To this end, *PetaDroid* employs a trained encoder  $f_{\text{dec}}$  to produce digests  $Z = \{z_0, z_1, \dots, z_{DMal}\}$  for the detected malicious apps.

3) *Family Clustering*: *PetaDroid* clusters the detected malware digests  $Z = \{z_0, z_1, \dots, z_{DMal}\}$  into groups of malware with high similarity and most likely belonging to the same family. In *PetaDroid* clustering: **First**, we use an **exclusive** clustering mechanism. The clustering algorithm only groups highly similar samples and tags the rest as non-clustered. This feature could be more convenient for real-world deployments since we might not always detect malicious apps from the same family, and we would like to have family groups only if there are groups of the sample malware family. To achieve this feature, we employ the *DBScan* clustering algorithm. **Second**, as an optional step, we find the best cluster for the non-cluster samples, from the clusters produced previously by computing the euclidean similarity between a given non-cluster sample and a given cluster samples. We call this step the *family matching*, as shown in Figure 1. In the evaluation, we report *homogeneity* and *coverage* metric for the clustering before and after applying this optional step. *DBScan*, in contrast with clustering algorithms such as *K-means*, produces clusters with high confidence. The most important metrics in *PetaDroid* clustering is the homogeneity of the produces clusters.

### III. IMPLEMENTATION

We build *PetaDroid* using *Python* and *Bash* programming languages. We use *dexdump*<sup>5</sup> to disassemble the DEX bytecode into Dalvik assembly. The tool *dexdump* is a simple and yet very efficient tool to parse APK file and produce disassembly in a textual form. We develop python and bash scripts to parse Dalvik assembly to produce sequences of canonical instructions. Notice that there is no optimization in the preprocessing; in the efficiency evaluation, we only use

a single thread script for a given Android app. We implement *PetaDroid* neural networks, CNN ensemble, and auto-encoders, using *PyTorch*<sup>6</sup>. For clustering, we employ official *hdbscan*<sup>7</sup> implementation. We evaluate the efficiency of *PetaDroid* on a commodity hardware server (Intel(R) Xeon(R) CPU E5-2630, 2.6GHz). For training, we use *NVIDIA 8 x Titan RTX* Graphic Processing Unit (GPU).

### IV. DATASET

Our evaluation dataset contains 10 million Android apps as sampling space for our experiments (over 100TB) collected across the last ten years from August 2010 to August 2019, as depicted in Table IV. The extensive coverage in size (10 M), time range (06-2010 to 08-2019), and malware families (+300 family) make the result of our evaluation quite compelling.

In section V-B and V-C, to evaluate *PetaDroid* detection and family clustering, we leverage malware from reference Android malware datasets, namely: *MalGenome* [53], *Drebin* [8], *MalDozer* [24], and *AMD* [45]. Also, we collected Android malware from *VirusShare*<sup>8</sup> malware repository. In addition, we use benign apps from *AndroZoo* [5] dataset (randomly sampling from 7.4 Million benign samples in each experiment). In the family clustering evaluation (section V-C), we use only malware samples from the reference datasets.

TABLE IV: Evaluation Datasets

Name	#Samples	#Families	Time
MalGenome [53]	1.3K	49	2010-2011
Drebin [8]	5.5k	179	2010-2012
MalDozer [24]	21k	20	2010-2016
AMD [45]	25k	71	2010-2016
VirusShare <sup>9</sup>	33k	/	2010-2017
MaMaDroid [37]	40k	/	2010-2017
AndroZoo [5]	9.5M	/	2010- Aug 2019

In the comparison (Section VI) between *PetaDroid*, *MaMaDroid* [32], [37], and *DroidAPIMiner* [3], we apply *PetaDroid* on the same dataset (benign and malware) used in *MaMaDroid* evaluation<sup>10</sup> to measure the performance of *PetaDroid* against state-of-the-art Android malware detection solutions.

To assess *PetaDroid* obfuscation resiliency (Section V-D), we conduct an obfuscation evaluation on *PRAGuard* dataset<sup>11</sup>, which contains 11k obfuscated malicious apps using common obfuscation techniques [31]. Besides, we generate over 100k benign and malware obfuscated Android apps employing *DroidChameleon* obfuscation tool [40] using common obfuscation techniques and their combinations.

To assess the adaptation of *PetaDroid* (Section V-F), we employ the whole *AndroZoo*<sup>12</sup> [5] dataset (until August 2019), which contains 7.4 million benign apps and 2.1 million malware apps, by randomly sampling a dataset (100k malware and benign) in each experiment. We rely on *VirusTotal* detection of multiple anti-malware vendors in (metadata provided by

<sup>6</sup><https://pytorch.org>

<sup>7</sup><https://hdbscan.readthedocs.io>

<sup>8</sup><https://VirusShare.com>

<sup>10</sup>[https://bitbucket.org/gianluca\\_students/mamadroid\\_code/src/master/](https://bitbucket.org/gianluca_students/mamadroid_code/src/master/)

<sup>11</sup><http://pralab.diee.unica.it/en/AndroidPRAGuardDataset>

<sup>12</sup><https://androzoo.uni.lu/>

<sup>5</sup><https://tinyurl.com/y4ze8nyy>

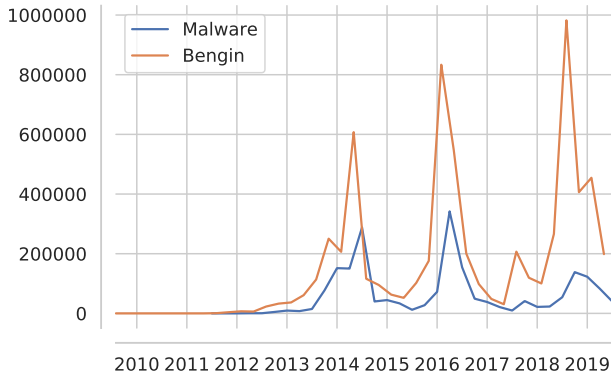


Fig. 6: PetaDroid Dataset Distribution Over Time

AndroZoo repository) to label the samples. The dataset covers more than ten years span of Android benign and malware apps [5].

## V. EVALUATION

In this section, we evaluate PetaDroid framework through a set of experiments and settings involving different datasets.

We aim to answer questions such as: *What is the detection performance of PetaDroid on small and large training datasets (Section V-B)? What is the effect of PetaDroid ensemble and build dataset sizes on the overall performance (Section V-B2)? What is the performance of family clustering (Section V-C)? How efficient is PetaDroid in terms of runtime on commodity hardware (Section V-G)? How robust is PetaDroid against common obfuscation techniques (Section V-D)?*

### A. Evaluation Metrics

The evaluation results are presented in terms of *precision*, *recall*, and *f1 score*. We use *homogeneity* [41] and *coverage* metrics to measure the family clustering performance. The homogeneity metric scores the purity of the produced family clusters. A perfect homogeneity means each produced cluster contains samples from only one malware family since PetaDroid clustering aims only to generate groups with confidence while ignoring less certain groups. The coverage metrics score the percentage of the clustered dataset with confidence.

*Precision (P)* is the percentage of positive prediction, i.e., the percentage of the detected malware out of all sample apps; formally,  $P = \frac{TP}{TP+FP}$ . *Recall (R)*. It is the percentage of correctly detected malicious apps out of all malware samples, formally,  $R = \frac{TP}{TP+FN}$ . *True positives (TP)* measures the number of correctly detected malicious apps. *False negatives (FN)*: measures the number of incorrectly classified malicious apps. *False positives (FP)*: measures the number of incorrectly classified benign apps. *f1-Score (F1)* is the harmonic mean of precision and recall, formally,  $f1 = 2 \times \frac{P \times R}{P + R}$ .

### B. Malware Detection

In this section, we report the detection performance of PetaDroid and the effect of hyper-parameters on malware detection performance.

1) *Detection Performance*: Table V shows PetaDroid *general* and *confidence-based* performance in terms of f1-score, recall, and precision metrics on the reference datasets. In the general performance, PetaDroid achieves a high f1-score 96 – 99% with a low false-positive rate (precision score of 96.4 – 99.5% in the general detection). The detection performance is higher under confidence settings. The f1-score is 99% and a very low false-positive rate with a recall score of 99.8% on average. The confidence-based performance causes the filtration of 1–8% low confidence samples from the testing set. In all our experiments, the confidence performance flags  $\approx 6\%$  on average, as uncertain decisions, which is a small and realistic value in a deployment with low false positives.

TABLE V: General and Confidence Performances on Various Reference Datasets

Name	General (%)			Confidence (%)		
	F1	P	R	F1	P	R
Genome	99.1	99.5	98.6	99.5	100.	99.0
Drebin	99.1	99.0	99.2	99.6	99.6	99.7
MalDozer	98.6	99.0	98.2	99.5	99.7	99.4
AMD	99.5	99.5	99.5	99.8	99.7	99.8
VShare	96.1	96.4	95.7	99.1	99.7	98.6

2) *Dataset Size Effect*: In Table VI, there is a small change in the detection performance when the build set percentage drops from 90% to 50% from the overall dataset. Note that the build dataset is already composed of 80% training and 20% validation set  $X_{build} = \{X_{train}, X_{valid}\}$ , which makes the model trained on a smaller dataset. However, PetaDroid detection still performs well under these settings. Notice that in all our experiments, we use 50% from the evaluation dataset as a build dataset.

Build Dataset Size (%)	General (F1 %)			Confidence (F1 %)		
	50%	70%	90%	50%	70%	90%
Genome	98.8	99.1	98.8	100.	99.5	99.1
Drebin	98.2	99.1	99.1	99.6	99.6	99.8
MalDozer	98.3	98.6	98.7	99.6	99.5	99.6
AMD	99.3	99.5	99.5	99.7	99.8	99.7
VShare	95.6	96.1	96.4	99.0	99.1	99.1

TABLE VI: Effect of Building Dataset Size on the Detection Performance

3) *Ensemble Size Effect*: Another important factor that affects PetaDroid malware detection performance is the number of CNN models in the detection ensemble. Table VII depicts PetaDroid performance under different ensemble sizes. We notice the high detection accuracy using a single CNN model (95 – 99% f1-score). In addition to the strength of CNN in discriminating Android malware, fragment detection adds a significant value to the overall performance even in a single CNN model. In the case of MalGenome (Table VII), the ensemble size adds no value to the detection performance due to the small size of MalGenome dataset (1.3k malware + 12k benign randomly sampled from AndroZoo [5]). In the case of VirusShare (Table VII), augmenting the ensemble size enhanced the detection rate. Our empirical tests show that  $\phi = 6$  as the ensemble size gives the best detection results while keeping the system’s efficiency.

#Model	General (F1 %)				Confidence (F1 %)			
	1	5	10	20	1	5	10	20
MalGenome	99.5	99.3	99.3	99.1	99.5	99.5	99.5	99.5
Drebin	99.0	99.1	99.0	99.1	99.4	99.6	99.6	99.6
MalDozer	98.0	98.6	98.4	98.6	99.0	99.5	99.5	99.5
AMD	99.3	99.5	99.5	99.5	99.5	99.8	99.7	99.8
VShare	95.0	96.0	96.1	96.1	98.1	99.0	99.2	99.1

TABLE VII: Effect of Ensemble Size on Detection

### C. Family Clustering

In this section, we present the results of PetaDroid family clustering on reference datasets (only malware apps). Malware family clustering phase comes after PetaDroid detects a considerable number of malicious Android apps. The number of detected apps could vary from  $1k$  (MalGenome [53]) to  $+20k$  (Maldozer [24]) samples depending on the deployment. We use *homogeneity* [41] and *coverage* metrics to measure the family clustering performance. The homogeneity metric scores the purity of the produced family clusters. A perfect homogeneity means each produced cluster contains samples from only one malware family. By default, PetaDroid clustering aims only to generate groups with confidence-based while ignoring less certain groups. The coverage metrics score the percentage of the clustered dataset with confidence. We also report the clustering performance after applying the *family matching* (optional step) to cluster all the samples in the dataset (100% coverage).

TABLE VIII: The Performance of the Family Clustering

Clustering Metrics	DBSCAN Clustering		After Family Matching	
	Homogeneity	Coverage	Homogeneity	Coverage
Genome	90.00%	— 37%	79.67%	— 100%
Drebin	92.28%	— 49%	80.48%	— 100%
MalDozer	91.27%	— 55%	81.58%	— 100%
AMD	96.55%	— 50%	81.37%	— 100%

Table VIII summarizes the clustering performance in terms of *homogeneity* and *coverage* scores before and after applying the *family matching*. **First**, PetaDroid can produce clusters with high *homogeneity* 90 – 96% while keeping an acceptable *coverage*, 50% on average. At first glance, 50% *coverage* seems to be a modest result, but we argue that it is satisfactory because: (i) we could extend the coverage, but this might affect the quality of the produced clusters. In the deployment, high confidence clusters with minimum errors and acceptable coverage might be better than perfect coverage (in the case of K-Means clustering algorithm) with a high error rate. (ii) The evaluation datasets have long tail malware families, meaning that most families have only a few samples. This makes the clustering very difficult due to the few samples (less than five samples) in each malware family in the detected dataset. In a real deployment, we could add non-cluster samples to the next clustering iterations. In this case, we might accumulate enough samples to cluster for the long tail malware families. **Second**, after applying the family matching, PetaDroid clusters all the samples in the dataset (100% coverage) and homogeneity decreased to 80 – 82%, which is acceptable.

### D. Obfuscation Resiliency

In this section, we report PetaDroid detection performance on obfuscated Android apps. We experiment on: (1) PRAGuard

obfuscation dataset [31] ( $10k$ ) and (2) obfuscation dataset generated using DroidChameleon [40] obfuscation tool ( $100k$ ). In the PRAGuard experiment, we combine PRAGuard dataset with  $20k$  benign Android apps randomly sampled from the benign apps of AndroZoo repository. We split the dataset equally into build dataset  $X_{build} = \{X_{train}, X_{valid}\}$  and test dataset  $X_{test}$ . Table IX presents the detection performance of PetaDroid on different obfuscation techniques. PetaDroid shows high resiliency to common obfuscation techniques by having an almost perfect detection rate, 99.5% f1-score on average.

TABLE IX: PetaDroid Obfuscation Resiliency on PRAGuard Dataset

ID	Obfuscation Techniques	General Performance (%)		
		F1 (%)	P (%)	R (%)
1	Trivial	99.4	99.4	99.4
2	String Encryption	99.4	99.3	99.4
3	Reflection	99.5	99.5	99.5
4	Class Encryption	99.4	99.4	99.5
5	(1) + (2)	99.4	99.4	99.4
6	(1) + (2) + (3)	99.4	99.3	99.5
7	(1) + (2) + (3) + (4)	99.5	99.4	99.6
<b>Overall</b>		99.5	99.6	99.4

In the DroidChameleon experiment, we evaluate PetaDroid on other obfuscation techniques, as shown in Table X. The generated dataset contains obfuscated benign ( $5k$  apps randomly sampled from AndroZoo) and malware samples (originally from Drebin). In the building process of CNN ensemble, we only train with one obfuscation technique (Table X) and make the evaluation on the rest of the obfuscation techniques. Table X reports the result of obfuscation resiliency on DroidChameleon generated dataset. The results show the robustness of PetaDroid. According to this experiment, PetaDroid is able to detect malware obfuscated with common techniques even if the training is done on non-obfuscated datasets. We believe that PetaDroid obfuscation resiliency comes from the usage of (1) Android API (canonical instructions) sequences as features in the machine learning development. Android APIs are crucial in any Android app. A malware developer cannot hide API access, for example *SendsSMS*, unless the malicious payload is downloaded at runtime. Therefore, PetaDroid is resilient to common obfuscations as long as they do not remove or hide API access calls. (2) The other factor is fragment-randomization, which makes PetaDroid models robust to code transformation and obfuscation in general. We argue that training machine learning models on dynamic fragments enhances the resiliency of the models against code transformation.

### E. Change Over Time Resiliency

An important feature in modern Android malware detection is the resiliency to change over time [32], [37], [24]. We study the resiliency of PetaDroid over the last seven-year (2013-2019). We randomly sample from AndroZoo repository a number of  $10k$  Android apps ( $5k$  malware and  $5k$  benign apps) for each year (2013-2019). As result, we have  $70k = 35k_{Mal} + 35k_{Ben}$ . We build the CNN ensemble using year  $Y_x$  samples and evaluate on the other years  $Y_{1..N}$  samples. Figure 7(a) shows the general and the confidence performances of PetaDroid, for models trained on 2013 samples,

TABLE X: Obfuscation Resiliency on DroidChameleon Dataset

Obfuscation Techniques	General Performance		
	F1 (%)	P (%)	R (%)
No Obfuscation	99.7	99.8	99.6
Class Renaming	99.6	99.6	99.5
Method Renaming	99.7	99.7	99.7
Field Renaming	99.7	99.8	99.7
String Encryption	99.8	99.8	99.7
Array Encryption	99.8	99.8	99.7
Call Indirection	99.8	99.8	99.7
Code Reordering	99.8	99.8	99.7
Junk Code Insertion	99.8	99.8	99.7
Instruction Insertion	99.7	99.8	99.7
Debug Information Removing	99.8	99.8	99.7
Disassembling and Reassembling	99.8	99.8	99.7

in terms of f1-score on 2014-2019 samples. As shown in Figure 7(a), PetaDroid, trained on 2013 dataset, achieved 98.17%, 96.10%, 93.01%, 70.60%, 54.82%, 55.59% f1-score on 2014, 2015, 2016, 2017, 2018, and 2019 datasets respectively. PetaDroid sustains a relatively good performance over the first few years. In 2018 and 2019, the performance drops considerably. In comparison to MaMaDroid [37], PetaDroid shows a higher time resiliency over seven years, while MaMaDroid drops considerably in year three (40% f1-score on year four). Figure 7(b) shows the training is on 2014 samples, which shows a performance enhancement over the overall evaluation period. The overall performance tends to increase as we train on a recent year dataset as depicted in Figure 7(c), 7(d), and 7(e). In Figure 7(f) and 7(g), training is on samples from 2018 and 2019 respectively, PetaDroid performance slightly decreases on old samples from 2013 and 2014. Our interpretation is that old and deprecated Android APIs are not present in new apps from 2018 and 2019, which we use for the training and this influences the detection performance negatively. We take from this experiment that PetaDroid is resilient to change over time for years  $t \pm 2$  when we train on year  $Y_t$  samples. PetaDroid covers about five years  $\{Y_{t-2}, Y_{t-1}, Y_t, Y_{t+1}, Y_{t+2}\}$  of Android app change.

#### F. Automatic Adaptation

PetaDroid automatic adaptation goes a step further beyond time resiliency. PetaDroid employs the confidence performance to collect an extension dataset  $X_{extend}$  during the deployment. PetaDroid automatically uses  $X_{extend}$  in addition to the previous build dataset as a new build dataset  $X_{build(t)} = X_{build(t-1)} \cup X_{extend}$  to build a new ensemble at every new epoch. Table XI depicts PetaDroid performance with and without automatic adaptation. PetaDroid achieves very good results compared to the previous section. PetaDroid maintains an f1-score in the range of 83 – 95% during all years. Without adaption, PetaDroid f1-score drops considerably starting from 2017. Table XI shows the performance of revisiting detection decisions on previous Android apps  $X_{test}$  (benign and malware) after updating PetaDroid ensemble using  $X_{build} \cup X_{extend}$ ,  $X_{extend} \subseteq X_{test}$ , where the samples in  $X_{extend}$  have been removed from  $X_{test}$ . The update performance is significantly enhanced in the overall detection during all years. Revisiting malware detection decisions is common practice in app markets (periodic full or partial scan the market’s apps), which empowers the use case of PetaDroid automatic adaptation feature and the update metric.

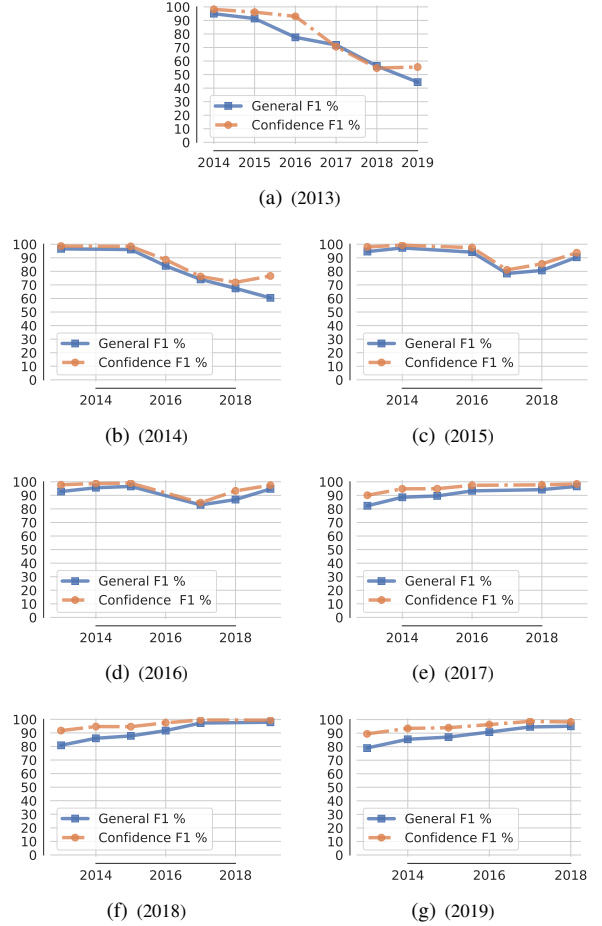


Fig. 7: PetaDroid Resiliency to Changes over Time

TABLE XI: Performance of PetaDroid Automatic Adaptation

Year	No Update(F1%)	General(F1%)	Confidence(F1%)	Update(F1%)
2014	98.2	97.0	97.9	99.7
2015	96.1	95.8	96.7	97.5
2016	93.0	93.3	94.8	96.4
2017	70.6	83.9	84.2	95.4
2018	54.8	87.6	91.6	93.8
2019	55.6	96.3	98.7	99.1

#### G. Efficiency

In this section, we present the average time of PetaDroid detection process. The detection process includes disassembly, preprocessing, and inference time. PetaDroid spends, on average, 4.0 seconds to fingerprint an Android app. The runtime increases for benign apps, 5.5 seconds, because their package sizes tend to be larger compared to malicious ones. For malware apps, PetaDroid spends, on average, 3.0 seconds for fingerprinting on the app.

## VI. COMPARATIVE STUDY

In this section, we conduct a comparative study between PetaDroid and state-of-the-art Android malware detection systems, namely: MaMaDroid [32], [37], DroidAPIMiner [3], and MalDozer [24]. Our comparison is based on applying

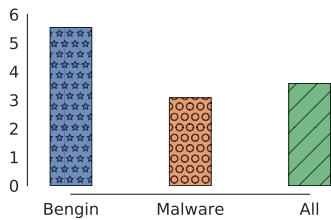


Fig. 8: PetaDroid Runtime Efficiency

PetaDroid on the same dataset (malicious and benign apps) and settings that MaMaDroid used in the evaluation (provided by the authors in [37]). The dataset is composed of 8.5K benign and 35.5K malicious apps in addition to the Drebin [8] dataset. The malicious samples are tagged by time; malicious apps from 2012 (Drebin), 2013, 2014, 2015, and 2016 and benign apps are tagged as oldbenign and newbenign, according to MaMaDroid evaluation.

#### A. Detection Performance Comparison

Table XII depicts the direct comparison between MaMaDroid and PetaDroid different dataset combinations. In PetaDroid, we present the general and the confidence performance in terms of f1-score. For MaMaDroid and DroidAPIMiner, we present the original evaluation result [37] in terms of f1-score, which are equivalent to the general performance in our case. Notice that we present only the best results of MaMaDroid and DroidAPIMiner as reported in [37].

TABLE XII: Detection Performance of MaMaDroid, PetaDroid, and DroidAPIMiner

	Peta (F1%) General-Confidence	MaMa (F1%)	Miner (F1%)
drebin&oldbenign	<b>98.94 - 99.40</b>	96.00	32.00
2013&oldbenign	<b>99.43 - 99.81</b>	97.00	36.00
2014&oldbenign	<b>98.94 - 99.47</b>	95.00	62.00
2014&newbenign	<b>99.54 - 99.83</b>	99.00	92.00
2015&newbenign	<b>97.98 - 98.95</b>	95.00	77.00
2016&newbenign	<b>97.44 - 98.60</b>	92.00	36.00

As depicted in Table XII, PetaDroid outperforms MaMaDroid and DroidAPIMiner in all datasets in the general performance. The detection performance gap increases with the confidence-based performance. Notice that the coverage in the confidence-based settings is almost perfect for all the experiments in Table XII.

#### B. Efficiency Comparison

In Table XIII, we report the required average time for MaMaDroid and PetaDroid to fingerprint one Android app. PetaDroid takes  $03.58 \pm 04.21$  seconds on average for the whole process (DEX disassembly, assembly preprocessing, CNN ensemble inference). MaMaDroid, compared to PetaDroid, tends to be slower due to the heavy preprocessing. MaMaDroid preprocessing [37] is composed of the call graph extraction, sequence extraction, and Markov change modeling, which require  $25.40 \pm 63.00$ ,  $1.73 \pm 3.2$ ,  $6.7 \pm 3.8$  seconds respectively for benign samples and  $09.20 \pm 14.00$ ,  $1.67 \pm 3.1$ ,  $2.5 \pm 3.2$  seconds respectively for malicious samples. On

average, PetaDroid ( $3.58s$ ) is approximately eight times faster than MaMaDroid.

TABLE XIII: MaMaDroid and PetaDroid Runtime

	PetaDroid (seconds)	MaMaDroid (seconds)
Malware	$02.64 \pm 03.94$	$09.20 \pm 14.00 + 1.67 \pm 3.1 + 2.5 \pm 3.2$
Benign	$05.54 \pm 05.12$	$25.40 \pm 63.00 + 1.73 \pm 3.2 + 6.7 \pm 3.8$
Average	$03.58 \pm 04.21$	$\approx 23s$

#### C. Time Resiliency Comparison

MaMaDroid evaluation emphasizes the importance of time resiliency for modern Android malware detection. Table XIV depicts the performance with different dataset settings, such as training using an old malware dataset and testing on a newer one. PetaDroid outperforms (or obtains a very similar result in few cases) MaMaDroid and DroidAPIMiner in all settings. Furthermore, the results show that PetaDroid is more robust to time resiliency compared to MaMaDroid [37].

#### D. PetaDroid and Maldozer Comparison

In this section, we compare PetaDroid with MalDozer [24] to check the effectiveness of the proposed approach. Specifically, we evaluate the performance of both detection systems on raw Android datasets without any code transformation. Afterward, we evaluate the systems on randomized code transformation. Table XV shows the effectiveness comparison between the detection systems. **First**, PetaDroid outperforms MalDozer in all the evaluation dataset without code transformation. One major factor to this result is the usage of the machine learning model ensemble to enhance the detection performance. **Second**, this gap significantly increases when we use code transformation in the various evaluation datasets. PetaDroid preserves the high detection performance due to the fragment randomization technique used in the training phase. As depicted in Table XV, the evaluation result shows the enhancement that the fragment randomization technique adds to the Android malware detection overall to enhance the resiliency.

## VII. CASE STUDIES

In this section, we conduct market-scale experiments on AndroZoo dataset (9.5 million Android apps). We argue that these experiments reflect real world deployments due to the dataset size, time distribution (2010-2019), and malware family diversity. We report PetaDroid's overall performance and overtime performance using our automatic adaptation feature in terms of general confidence.

#### A. Large Scale Detection

In this experiment, we employ 8.5 out of 10 million samples from AndroZoo dataset. The used dataset is composed of 1.0 million malicious samples and 7.5 millions benign sample. We filter out app samples that do not correlate with VirusTotal, or they have less than five maliciousness flags in VirusTotal. In our experiments, we randomly sample  $k$  samples as build dataset  $X_{build}$  and use the rest  $8.5M - k$  as  $X_{test}$ . We use different  $k$  sizes,  $k \in \{10k, 20k, 50k, 70k, 100k\}$ , and

TABLE XIV: Classification performance of MaMaDroid, PetaDroid, DroidAPIMiner.

Testing Sets	drebin & oldbenign			2013 & oldbenign			2014 & oldbenign			2015 & oldbenign			2016 & oldbenign		
	Miner	MaMa	Peta	Miner	MaMa	Peta	Miner	MaMa	Peta	Miner	MaMa	Peta	Miner	MaMa	Peta
drebin&oldbenign	32.0	96.0	<b>99.4</b>	35.0	95.0	<b>98.6</b>	34.0	72.0	<b>77.5</b>	30.0	39.0	<b>44.0</b>	33.0	42.0	<b>47.0</b>
2013&oldbenign	33.0	94.0	<b>97.8</b>	36.0	97.0	<b>99.6</b>	35.0	73.0	<b>85.4</b>	31.0	37.0	<b>59.3</b>	33.0	28.0	<b>56.6</b>
2014&oldbenign	36.0	92.0	<b>95.8</b>	39.0	93.0	<b>98.6</b>	62.0	95.0	<b>99.4</b>	33.0	78.0	<b>91.4</b>	37.0	75.0	<b>88.9</b>
Training Sets	drebin & newbenign			2013 & newbenign			2014 & newbenign			2015 & newbenign			2016 & newbenign		
	Miner	MaMa	Peta	Miner	MaMa	Peta	Miner	MaMa	Peta	Miner	MaMa	Peta	Miner	MaMa	Peta
2014&newbenign	76.0	98.0	<b>99.3</b>	75.0	98.0	<b>99.7</b>	92.0	99.0	<b>99.8</b>	67.0	85.0	<b>91.4</b>	65.0	81.0	<b>82.1</b>
2015&newbenign	68.0	97.0	<b>97.1</b>	68.0	97.0	<b>97.8</b>	69.0	<b>99.0</b>	98.9	77.0	95.0	<b>99.0</b>	65.0	88.0	<b>95.4</b>
2016&newbenign	33.0	<b>96.0</b>	95.6	35.0	98.0	<b>98.2</b>	36.0	<b>98.0</b>	97.9	34.0	92.0	<b>95.2</b>	36.0	92.0	<b>98.3</b>

TABLE XV: PetaDroid and MalDozer Comparison

	PetaDroid (F1 %)		MalDozer (F1 %)	
	Raw	- Randomization	Raw	- Randomization
MalGenome	99.6	- 99.3	98.1	- 92.5
Drebin	99.2	- 99.1	97.4	- 91.6
MalDozer	98.5	- 98.6	95.2	- 89.3
AMD	99.4	- 99.5	96.1	- 90.1
VShare	95.8	- 96.0	94.2	- 88.1

we repeat each experiment ten times to compute the average detection performance.

#Samples	General (F1 %)	Confidence (F1 %)
10k	95.34	97.88
20k	96.17	98.01
50k	96.50	98.10
70k	96.76	98.11
100k	97.04	98.17

TABLE XVI: PetaDroid Market-Scale Detection Performance

In Table XVI, we report the detection performance in terms of f1-score of PetaDroid on AndroZoo dataset. PetaDroid shows a high f1-score for all the experiments, 95 – 97% f1-score. We achieved 95.34% f1-score when the build set is only 10k. We argue that fragment randomization plays an important role in achieving these detection results because it acts as a data augementer during the training phase.

### B. Large Scale Automatic Adaptation

In this experiment, we put the automatic adaptation feature on mega-scale test using 5.5 million samples from AndroZoo dataset (2013-2016) on 25 training epochs (every three-months). We initiate PetaDroid on only 25k build dataset collected between 2013 – Jan – 01 and 2013 – Jan – 31. PetaDroid rebuilds new CNN ensemble for each three-month samples by retraining on  $X_{build(t)} = X_{build(t-1)} \cap X_{extend}$ .

Update Epoch	Before Update (F1 %)		After Update (F1 %)	
	General	Confidence	General	Confidence
2013-01-31	/	/	/	/
2013-04-30	96.02	98.43	99.01	99.71
2013-07-31	94.52	96.12	97.95	99.56
2013-10-31	94.42	97.37	97.03	99.56
2014-01-31	83.45	92.74	95.45	99.37
2014-04-30	90.48	96.21	94.15	99.43
2014-07-31	86.98	95.79	91.53	99.11
2014-10-31	92.32	98.47	93.11	99.00
2015-01-31	91.57	97.72	90.91	99.18
2015-04-30	91.31	98.55	92.72	99.09
2015-07-31	88.16	97.46	88.90	98.99
2015-10-31	73.82	87.45	83.44	97.57
2016-01-31	78.59	90.92	85.11	96.26
2016-04-30	84.78	95.44	86.38	98.33
2016-07-31	71.39	88.08	80.27	93.54
2016-10-31	78.31	85.79	79.68	90.75

TABLE XVII: Autonomous Adaptation on a Market-Scale Dataset

In Table XVII, we report the general and confidence performance before and after updating PetaDroid CNN ensemble on an extended build dataset. The automatic adaption feature achieves very good results. The general and confidence-based performance in terms of f1-score vary between 71.39–96.02% and 85.79 – 98.55%, respectively. These performance results increase considerably (90.75 – 99.71% f1-score) after revising the previous detection decisions using an updated CNN ensemble with a new  $X_{extend}$  on each epoch.

## VIII. RELATED WORK

The Android malware analysis techniques can be classified to *static analysis*, *dynamic analysis*, or *hybrid analysis*. The static analysis methods [8], [47], [7], [26] use static features that are extracted from the app, such as: requested permissions and APIs to detect malicious app. The dynamic analysis methods [10], [20], [22] aim to identify behavioral signature or behavioral anomaly of the running app. These methods are more resistant to obfuscation. The dynamic methods offer limited scalability as they incur additional cost in terms of processing and memory. The hybrid analysis [30], [21], combine between both analyses to improve detection accuracy, which costs additional computational cost. Assuming that malicious apps of the same family share similar features, some methods [27], [23], [25], measure the similarity between the features of two samples (similar malicious code). The deep learning techniques are more suitable than conventional machine learning techniques for Android malware detection [49]. Research works on deep learning for Android malware detection are recently getting more attention [24], [52]. These deep learning models are more venerable to common machine

learning adversarial attacks as described in [12]. In contrast, PetaDroid employs the ensemble technique to mitigate such adversarial attacks [44] and to enhance the overall performance. In DroidEvolver [48], the authors use online machine learning techniques to enhance the time resiliency of the Android malware detection system. In contrast, PetaDroid employs batch training techniques instead of online training, which means that in each epoch  $t$  PetaDroid builds new models using the extended dataset at once. We argue that batch learning could generalize better since the training system has a complete view of the app dataset. It is less vulnerable to biases that could be introduced by the order of the apps in online training.

PetaDroid provides Android malware detection and family clustering using advanced natural language processing and machine learning techniques. PetaDroid is resilient to common obfuscation techniques due to code randomization during the training. PetaDroid introduces a novel automatic adaption technique inspired from [29] that leverages the result confidence to build a new CNN ensemble on confidence detection samples. Our automatic adaptation technique aims to overcome the issue of new Android APIs over time, while other methods could be less resilient and might require updates with a manually crafted dataset. The empirical comparison with state-of-the-art solutions, MaMaDroid [37] and MalDozer [24], shows that PetaDroid outperforms MaMaDroid and MalDozer under the various evaluation settings in the malware detection effectiveness and efficiency.

## IX. LIMITATION

Although the high obfuscation resiliency of PetaDroid showed in Section V-D, PetaDroid is not immune to complex obfuscation techniques. Also, PetaDroid most likely will not be able to detect Android malware that downloads the payload during runtime. PetaDroid focuses on the fingerprinting process on DEX bytecode. Therefore, Android malware, which employs C/C++ native code, is less likely to be detected because we do not consider native code in our fingerprinting process. Covering native code is a possible future enhancement for PetaDroid. We consider including selective dynamic analysis for low confidence detection as future work. The latter will empower PetaDroid against sophisticated obfuscation techniques. PetaDroid system needs more validation on real world deployments to check the performance as proposed in previous investigations [38], [19]. Also, we need to check the correctness of the dataset split to prevent bias results as a result of *spatial bias* and *temporal bias* [38]. In section VI-C and IX, we partially addressed this issues by (1) evaluating the system on temporal splits from AndroZoo dataset and (2) employing collected samples dataset (VirusShare) in addition to multiple references datasets.

## X. CONCLUSION

In this paper, we presented PetaDroid, an Android malware detection and family clustering framework for large scale deployments. PetaDroid employs supervised machine learning, an ensemble of CNN models on top of *Inst2Vec* features, to fingerprint Android malicious apps accurately. DBScan clustering on top of *InstNGram2Vec* and deep auto-encoders features, to cluster highly similar malicious apps into

their most likely malware family groups. In PetaDroid, we introduced fragment-based detection, in which we randomize the macro-action of Dalvik assembly instructions while keeping the inner order of methods' sequences. We introduced the automatic adaption technique that leverages confidence-based decision making to build a new CNN ensemble on confidence detection samples. The adaptation technique automatically enhances PetaDroid time resiliency. We conducted a thorough evaluation of different reference datasets and various settings. We evaluate PetaDroid on a market scale Android dataset, 10 Million samples and over 100TB of data. PetaDroid achieved high detection (98-99% f1-score) and family clustering (96% cluster homogeneity) performance. Our comparative study between PetaDroid, MaMaDroid [37] and MalDozer shows that PetaDroid outperforms state-of-the-art solutions on various evaluation settings.

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