

# On Impact of Semantically Similar Apps in Android Malware Datasets

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Roopak Surendran  
Kerala, India

**Abstract**—Malware authors reuse the same program segments found in other applications for performing the similar kind of malicious activities such as information stealing, sending SMS and so on. Hence, there may exist several semantically similar malware samples in a family/dataset. Many researchers unaware about these semantically similar apps and use their features in their ML models for evaluation. Hence, the performance measures might be seriously affected by these similar kinds of apps. In this paper, we study the impact of semantically similar applications in the performance measures of ML based Android malware detectors. For this, we propose a novel opcode subsequence based malware clustering algorithm to identify the semantically similar malware and goodware apps. For studying the impact of semantically similar apps in the performance measures, we tested the performance of distinct ML models based on API call and permission features of malware and goodware application with/without semantically similar apps. In our experimentation with Drebin dataset, we found that, after removing the exact duplicate apps from the dataset ( $\epsilon = 0$ ) the malware detection rate (TPR) of API call based ML models is dropped from 0.95 to 0.91 and permission based model is dropped from 0.94 to 0.90. In order to overcome this issue, we advise the research community to use our clustering algorithm to get rid of semantically similar apps before evaluating their malware detection mechanism.

**Index Terms**—Code reuse, Android malware, Opcodes

## I. INTRODUCTION

It is known that, malware apps frequently reuse the program segments of previously detected malware apps [1]. Also, they can add some junk codes or remove redundant codes to change the signatures. However, these malicious apps tend to preserve the malicious program segments intended for some specific functionalities such as information stealing, sending SMS and so on. Hence, it is clear that there may exist common malicious program segments shared by the Android malware families.

Android is an open source operating system which provides specific APIs (Application Programming Interface) to perform sensitive operations such as sending SMS, making phone call and so on [2]. For example, `sendTextMessage()` API call can be used for sending SMS to others. Initially, a malware author constructs a malicious program segment which is intended to perform a particular kind of malicious activity. This is done by invoking some specific API calls in a particular manner.

For convenience, evolving malware apps tend to reuse these existing malicious program segments to perform the same kind of behavior. Furthermore, there exists several other existing frameworks such as kwetza for injecting the existing malicious program segments into benign applications.

Most of the existing works use machine learning algorithms for malware classification [3]. These approaches randomly select malware and goodware samples from the dataset for training and testing the classifiers. Some of the malware or goodware apps are semantically similar and may contain similar features. These semantically similar apps can result in overrated performance of the machine learning classifier especially in holdout evaluation. So, the reported accuracies in their paper may be biased. However, the performance of the models are not highly affected in k-fold cross validation based evaluation. In this paper, we make a study about this problem and propose a clustering algorithm to filter out the semantically similar apps from malware and goodware datasets.

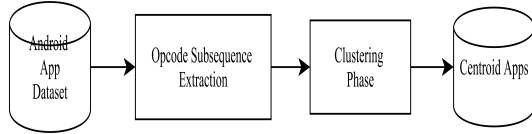
In recent years, many research papers have been published in the area of Android malware detection. These works are classified into static, dynamic and hybrid analysis. In static analysis, the source code level features such as API calls, permissions etc. are used for malware detection. However, in the cases of dynamic analysis, the runtime features such as system calls, network packets etc. are used. In hybrid analysis, both static and dynamic features are used. Most of the existing works use Drebin dataset for evaluating their mechanism. Drebin is a public malware dataset which contains 5560 malware apps from 179 malware families [4]. Because of this popularity of Drebin dataset, we have selected this Drebin dataset for studying the impact of semantically similar apps in ML models. The usage of applications with similar program segments in experimental evaluations can give biased results. So it is necessary to identify applications to similar programs segments. For this, we propose a novel malware clustering algorithm based on opcode subsequences to filter out semantically similar apps. The researchers can use the filtered datasets for their experimental purpose for eliminating the bias in their results.

In this work, we study the impact of semantically similar apps in machine learning models for malware detection. A clustering algorithm is proposed to filter out similar applications

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from both goodware and malware dataset. Then, we tested the performance of ML models in various features of malware and goodware samples with and without the semantically similar apps. We found that the performance of ML models very slightly dropped after the semantically similar apps from the dataset when k-fold cross validation technique is used. Hence, it is advised to use k-fold cross validation for evaluating the models or filter out the semantically similar apps from malware and goodware dataset for fair evaluation.

Fig. 1. Clustering of Android Apps in the Dataset



The rest of the paper organized as follows. In Section 2, we discuss about the literature review. In Section 3, we discuss about the procedure of extracting opcode subsequences of an application. Our malware clustering algorithm is discussed in Section 4. In Section 5, we discuss about the performance of ML models in Drebin dataset with and without the semantically similar apps. In Section 6, we discuss about the limitations and future directions for our work.

## II. LITERATURE REVIEW

In this section, we discuss about the existing research works on code reuse and Android malware detection.

### A. Detection of Code Reuse

Many researchers discussed about the impact of code reuse in Android applications. By using the existing program segment dedicated for a particular functionality, an application developer can significantly save his time and effort. Moreover, it is very helpful to reduce errors or bugs in the application. However, now a days, this feature is increasingly misused by the hackers. They generate several versions of a particular kind of malware app by injecting its payload (malicious code segments) into other legitimate apps. Because of the dissimilarity in hash values, anti-malware solutions are easily evaded by these repackaged malware apps. In this section, we discuss about the main works related to the code reuse detection in malware apps.

In GroupDroid [5], static control flow graphs were used for clustering 4211 Android malware apps into different groups. In Droidsim [1], component based-control flow graphs were used for identifying similarities among malware apps and found the code reuse in a dataset of 706 malware applications. Hanna et al. [6] proposed a framework called JuxtApp for detecting code reuse among Android applications. In JuxtApp, the feature matrix of applications were constructed for measuring the similarities. JuxtApp identified the malicious code reuse in 463 vulnerable apps and 34 malware apps. In DNADroid [7], program dependency graphs were used for measuring the similarities among the applications and found code cloning in at least 141 apps in their dataset.

In the area of Android malware detection, many researchers considered the features of cloned apps (semantically similar) in their ML model. In this work, we study the impact of these semantically apps in ML models. For this, we propose a simple and lightweight algorithm to detect semantically similar applications in a malware dataset. Here, we used opcode subsequences as features for measuring the similarities. It is because the program segments (program statements in a function or methods) of an application can be conveniently represented with opcode subsequences. Hence, similarity/dissimilarity values can be easily computed from by comparing different sets of opcode subsequences.

### B. Review on Malware Detection Mechanisms

In existing works, machine learning algorithms are used for malware analysis because of the ability to predict malicious behavior in unseen data points [8]. Most of the popular works use Drebin dataset for evaluation. Drebin is the public malware dataset which contains 5560 malware apps from 179 malware families [4]. Also, Drebin dataset contains malicious applications from MalGenome dataset. Hence, we have selected Drebin dataset for studying the impact of semantically similar apps in ML models. The existing Android malware detection mechanisms use either static features such as API calls, permissions etc. or dynamic features such as system calls, network packets etc. (or the combination of both) for malware analysis. The popular static and dynamic malware analysis mechanisms in Drebin/MalGenome dataset are discussed below.

In static analysis, the features associated with the source code of an application is used for malware detection. In [9], the authors used probabilistic machine learning classifiers trained with API call based features for malware detection. In [10], the app permissions are used as input features of a machine learning classifier for malware detection. In [11], the data flows are extracted from an application for finding malicious behavior. In [12], the intent based features are used in a machine learning classifier for malware detection. In [13], n-gram frequencies of opcode level features are used in a machine learning classifier for malware detection.

In dynamic analysis, an application is executed in an emulator or in a real device and collect the features such as system calls, network packets using the third party utilities. In [14], the runtime API calls are used for malware detection. In [15], authors used system metric level features such as CPU, memory usages for malware detection. In [16], the authors used system calls as features of supervised binary classifiers for malware detection. In [17], the authors used network packets as features for malware detection.

In all of the above mechanisms, the authors used entire samples in their dataset (Drebin/MalGenome) for the experimental purpose. It is known that a malware author reuses existing malicious codes to generate new variants. Hence, these malware dataset may contain several semantically similar apps. In this paper, we study the impact of semantically similar apps in machine learning models for malware detection. We propose a clustering algorithm to filter out the semantically similar

apps from datasets. After removing the semantically similar apps, we tested the performance of ML models in datasets with and without semantically similar apps. From our experimental evaluations, we conclude that the presence of semantically similar apps result in the overrated performance of ML models in malware detection.

### III. OPCODE BASED CLUSTERING ALGORITHM

In this section, we investigate the impact of semantically similar apps in Android malware datasets. Our mechanism has three phases. In the first phase, we extract opcode subsequences from a set of malware and goodware applications. In the next phase, we filter out the semantically similar applications from the opcode subsequence dataset using our novel clustering algorithm. In the final phase, we evaluate the performance of ML models in dataset with and without semantically similar apps. On the basis of this performance evaluation, we will make conclusions. The clustering procedure is given in Figure 1.

#### A. Extraction of Opcodes Subsequences from an Android Application

In this section, we discuss about the procedure of extracting opcode subsequences from Android applications. Opcodes (Operation Codes) are used to specify the kind of operations need to be performed by the device hardware. It is a part of machine language program. The details about the opcodes in Android operating system are given in Table I.

In Android operating system, ART (Android Runtime) or Dalvik Virtual Machine (DVM) is responsible for handling the opcodes in the form of dex (dalvik executable format) file format [18] [19]. Android programs are written in java or kotlin language and then compiled to a ‘dex’ (dalvik executable format) file [19].

In an Android application, the program segments are written in the form of various functions or methods. Hence, there exist opcode subsequences corresponding to each program segment in that application. We extract the set of opcode subsequences from an application and use this opcode subsequence set for representing it.

Reverse engineering tools such as apktool can be used to extract opcode sequences from the ‘dex’ file [20]. Apktool extracts the opcode subsequences from it. Here, we considered opcode subsequences as the sequence of opcodes in a method segment. A sample opcode subsequence of an application is given in Figure 2. The procedure of extracting opcode subsequences is given in Figure 3.

#### B. Clustering Opcode Subsequences

In this section, we propose a novel algorithm for clustering the malware apps in a dataset. Here, we cluster the malware apps in the malware dataset by using our algorithm. Here, we use Ochiai coefficient (Euclidean distance) [21]–[23] for measuring the similarities between two applications. Cosine similarity works well even if the opcode subsequences of apps differs in size. Assume that  $A$  and  $B$  are the two sets of opcode

subsequences of applications  $P$  and  $Q$ . The Ochiai coefficient  $S$  is calculated as:

$$S = 1 - \frac{|A \cap B|}{\sqrt{|A| \times |B|}}, \quad (1)$$

where  $|A \cap B|$  is the number of opcode subsequences that are found in both  $A$  and  $B$ ,  $|A|$  is the number of opcode subsequences in  $A$  and  $|B|$  is the number of opcode subsequences in  $B$ . ////////////////

The proposed malware clustering algorithm is based on DBSCAN algorithm [24] [25]. The algorithm accepts a malware family dataset  $X = \{X_1, X_2, X_3, \dots, X_n\}$  as input and gives the cluster centers  $C = \{C_1, C_2, \dots\}$  as output. Let  $\epsilon$  be the distance value ranging from 0 to 1. The steps in our algorithm are given below.

- 1) Initialize  $j = 1$ .
- 2) Select a random malware app  $X_i$  from  $X$  and mark  $X_i$  as visited.
- 3) Find out the neighbours of  $X_i$  using  $\epsilon$  (All malware apps which are within the  $\epsilon$  distance value are considered as neighbours).
- 4) Form a cluster having centroid  $C_j = X_i$  and update  $j = j + 1$ .
  - a) Remove all the clustered apps from  $X$
- 5) Go to step 1 and repeat the process until all apps in  $X$  are visited

### IV. ILLUSTRATION OF OUR CLUSTERING ALGORITHM IN DREBIN DATASET

In this section, we discuss about the performance of our clustering algorithm in dataset [4] because of its wide acceptance and popularity in research works. Drebin dataset consists of 5560 malware applications selected from 179 malware families over a period ranging from 2010 to 2012.

Our clustering algorithm is developed and tested in an Ubuntu PC having 32 GB of memory. We reused an existing python program [26] to extract opcode subsequences of the applications in our malware family dataset. In that python code, apktool [27] is used to decompile an application and extract smali code from it. From the smali code, opcode subsequences are extracted and saved in a file. Then, we cluster all these files using our algorithm to identify the semantically similar applications.

We execute our clustering algorithm in different values of  $\epsilon$ . With the value  $\epsilon = 0$ , we can remove all duplicate applications in the dataset. Also, the obtained clusters are more reliable. The number of clusters get reduced by increasing the value of  $\epsilon$ . Hence, by increasing the value of  $\epsilon$ , we can identify the highly dissimilar apps in the dataset. The number of clusters in different  $\epsilon$  values are given in Figure 4. Here, we found that almost 50% of apps in drebin dataset are the exact copies of others. These duplicate apps might affect the actual performance of the machine learning based malware detection mechanisms. In the next section, we investigate this with the help of API calls and permissions based classifiers.

Fig. 2. Method Based Opcode Sub sequence of an Application

```

.method public StartMyService()V
    .locals 2

    .prologue
    .line 22
    :try_start_0
    new-instance v0, Landroid/content/Intent;

    const-class v1, Lcom/example/allinone/MainService;

    invoke-direct {v0, p0, v1}, Landroid/content/Intent;-><init>(Landroid/content/Context;Ljava/lang/Class;)V

    .line 23
    .local v0, "i":Landroid/content/Intent;
    invoke-virtual {p0, v0}, Lcom/example/allinone/MainActivity;->startService(Landroid/content/Intent;)Landroid/content/ComponentName;
    :try_end_0
    .catch Ljava/lang/Exception; {:try_start_0 .. :try_end_0} :catch_0

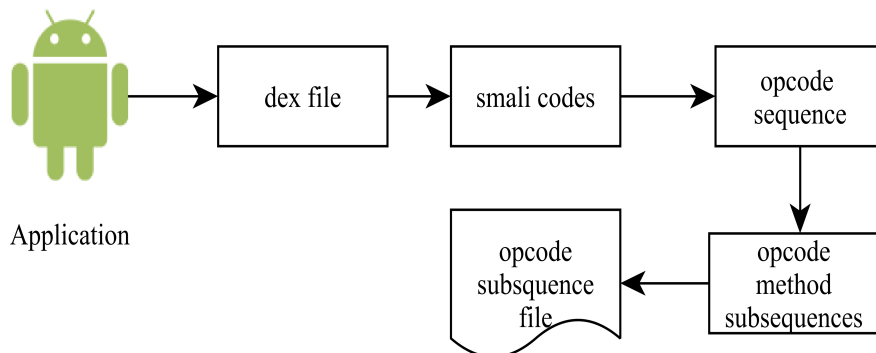
    .line 27
    .end local v0 # "i":Landroid/content/Intent;
    :goto_0
    return-void

    .line 24
    :catch_0
    move-exception v1

    goto :goto_0
.end method

```

Fig. 3. Process of Extracting Opcode Sub sequences of an Application



## V. EVALUATION OF DREBIN MALWARE SAMPLES WITH AND WITHOUT SEMANTICALLY SIMILAR APPS

In this section, we make a study about the impact of semantically similar application in machine learning based malware detection mechanisms. For analyzing false positives, we collected 5500 goodwill samples from Androozoo dataset [28]. In order to avoid the bias in the API levels, we selected the goodwill samples ranging from 2010 to 2012 (same period/API level as that of drebin dataset). The overall evaluation dataset consisting of malware and goodwill samples. From this dataset, we filtered out the semantically similar goodwill and malware apps and constructed datasets with semantically dissimilar samples. The statistics of apps in the datasets are given in Table II. All the datasets are evaluated in machine learning

algorithms trained with different kinds of features. The used features are given as follows:

- 1) API calls;
- 2) Permissions.

### A. Permission Analysis

In this section, we re-implement permission based malware detection mechanism in our datasets (with and without semantically similar apps) for analyzing the impact of semantically similar in dataset. Here, we used the key permission based features mentioned in our previous work [29]. The list of permission based features are given in Table III. We extract the permission based features of malware and goodwill apps in the dataset and a Comma Separated Value (CSV) file is constructed. This CSV file is supplied to Weka framework [30]

TABLE I  
LIST OPCODES IN ANDROID OPERATING SYSTEM

Hex Value	Opcode	Hex Value	Opcode	Hex Value	Opcode	Hex Value	Opcode
00	nop	01	move	02	move/from 16	03	move/16
04	move-wide/from	05	move-wide/16	07	move-object	08	move-object/from16
09	move-object/16	0A	move-result	0B	move-result-wide	0C	move-result-object
0D	move-exception	0E	return-void	0F	return	10	return-wide
11	return-object	12	const/4	13	const/16	14	const
15	const	16	const-wide/16	17	const-wide/32	18	const-wide
19	const-wide/high 16	1A	const-string	1B	const-string-jumbo	1C	const-class
1D	monitor-enter	1E	monitor-exit	1F	check-cast	20	instance-of
21	array-length	22	new-instance	23	new-array	24	filled-new-array
25	filled-new-array-range	26	fill-array-data	27	throw	28	goto
29	goto/16	2A	goto/32	2B	packed-switch	2C	sparse-switch
2D	cmpl-float	2E	cmpg-float	2F	cmpl-double	30	cmpg-double
31	cmp-long	32	if-eq	33	if-ne	34	if-lt
35	if-ge	36	if-gt	37	if-le	38	if-eqz
39	if-nez	3A	if-ltz	3B	if-gez	3C	if-gtz
3D	if-lez	3E	unused_3E	3F	unused_3F	40	unused_40
41	unused_41	42	unused_42	43	unused_43	44	aget
45	aget-wide	46	aget-object	47	aget-boolean	48	aget-byte
49	aget-char	4A	aget-short	4B	aput	4C	aput-wide
4D	aput-object	4E	aput-boolean	4F	aput-byte	50	aput-char
51	aput-short	52	iget	53	iget-wide	54	iget-object
55	iget-boolean	56	iget-byte	57	iget-char	58	iget-short
59	iput	5A	iput-wide	5B	iput-object	5C	iput-boolean
5D	iput-byte	5E	iput-char	5F	iput-short	60	sget
61	sget-wide	62	sget-object	63	sget-boolean	64	sget-byte
65	sget-char	66	sget-short	67	sput	68	sput-wide
69	sput-object	6A	sput-boolean	6B	sput-byte	6C	sput-char
6D	sput-short	6E	invoke-virtual	6F	invoke-super	70	invoke-direct
71	invoke-static	72	invoke-interface	73	unused_73	74	invoke-virtual/range
75	invoke-super/range	76	invoke-direct/range	77	invoke-static/range	78	invoke-interface-range
79	unused_79	7A	unused_7A	7B	neg-int	7C	not-int
7D	neg-long	7E	not-long	7F	neg-float	80	neg-double
81	int-to-long	82	int-to-float	83	83 int-to-double	84	long-to-int
85	long-to-float	86	long-to-double	87	float-to-int	88	float-to-long
89	float-to-double	8A	double-to-int	8B	double-to-long	8C	double-to-float
8D	int-to-byte	8E	int-to-char	8F	int-to-short	90	add-int
91	sub-int	92	mul-int	93	div-int	94	rem-int
95	and-int	96	or-int	97	xor-int	98	shl-int
99	shr-int	9A	ushr-int	9B	add-long	9C	sub-long
9D	mul-long	9E	div-long	9F	rem-long	A0	and-long
A1	or-long	A2	xor-long	A3	shl-long	A4	shr-long
A5	ushr-long	A6	add-float	A7	sub-float	A8	mul-float
A9	div-float	AA	rem-float	AB	add-double	AC	sub-double
AD	mul-double	AE	div-double	AF	rem-double	B0	add-int/2addr
B1	sub-int/2addr	B2	mul-int/2addr	B3	div-int/2addr	B4	rem-int/2addr
B5	and-int/2addr	B6	or-int/2addr	B7	xor-int/2addr	B8	shl-int/2addr
B9	shr-int/2addr	BA	ushr-int/2addr	BB	add-long/2addr	BC	sub-long/2addr
BD	mul-long/2addr	BE	div-long/2addr	BF	rem-long/2addr	C0	and-long/2addr
C1	or-long/2addr	C2	xor-long/2addr	C3	shl-long/2addr	C4	shr-long/2addr
C5	ushr-long/2addr	C6	add-float/2addr	C7	sub-float/2addr	C8	mul-float/2addr
C9	div-float/2addr	CA	rem-float/2addr	CB	add-double/2addr	CC	sub-double/2addr
CD	mul-double/2addr	CE	div-double/2addr	CF	rem-double/2addr	D0	add-int/lit16
D1	add-int/lit16	D2	sub-int/lit16	D3	mul-int/lit16	D4	div-int/lit16
D5	and-int/lit16	D6	or-int/lit16	D7	xor-int/lit16	D8	add-int/lit8
D9	sub-int/lit8	DA	mul-int/lit8	DB	div-int/lit8	DC	rem-int/lit8
DD	and-int/lit8	DE	or-int/lit8	DF	xor-int/lit8	E0	shl-int/lit8
E1	shr-int/lit8	E2	ushr-int/lit8	E3	unused_E3	E4	unused_E4
E5	unused_E5	E6	unused_E6	E7	unused_E7	E8	unused_E8
E9	unused_E9	EA	unused_EA	EB	unused_EB	EC	unused_EC
ED	unused_ED	EE	execute-inline	EF	unused_EF	F0	invoke-direct-empty
F1	unused_F1	F2	iget-quick	F3	iget-wide-quick	F4	iget-object-quick
F5	iput-quick	F6	iput-wide-quick	F7	iput-object-quick	F8	invoke-virtual-quick
F9	invoke-virtual-quick/range	FA	invoke-super-quick	FB	invoke-super-quick/range	FC	unused_FC
FD	unused_FD	FE	unused_FE	FF	unused_FF		

and tested in machine learning classifiers by employing 10 fold cross validation technique. We obtained a high accuracy

in random forest classifier [31]. From Table IV, we can see that the performance of the classifiers dropped very slightly

TABLE II  
DISTRIBUTION OF SEMANTICALLY DISSIMILAR APPS

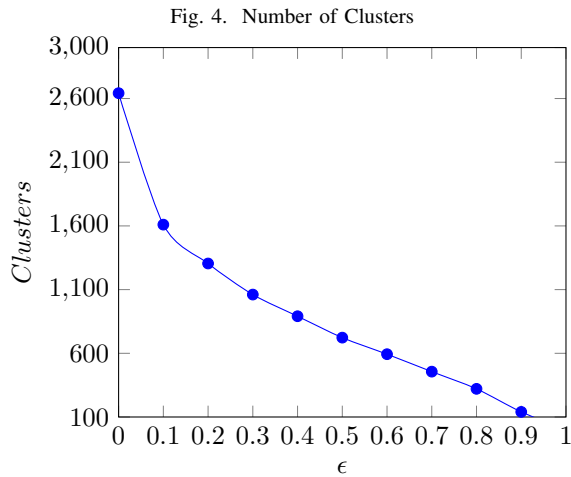
Dataset	$\epsilon$	Number of Malware Samples	Number of Goodware Samples
Dataset 1	0	2642	4655
Dataset 2	0.1	1650	3989
Dataset 3	0.2	1305	3610

TABLE III  
SELECTED PERMISSIONS FOR MALWARE DETECTION

SI.No	Permissions	SI.No	Permissions
1	READ_PHONE_STATE	2	WRITE_CONTACTS
3	CALL_PHONE	4	READ_CONTACTS
5	INTERNET	6	SEND_SMS
7	DISABLE_KEYGUARD	8	PROCESS_OUTGOING_CALLS
9	RECEIVE_BOOT_COMPLETED	10	READ_SMS
11	FACTORY_TEST	12	DEVICE_POWER
13	HARDWARE_TEST	14	CHANGE_WIFI_STATE
15	GET_ACCOUNTS	16	READ_HISTORY_BOOKMARKS
17	WRITE_APN_SETTINGS	18	MODIFY_PHONE_STATE
19	WRITE_HISTORY_BOOKMARKS	20	ACCESS_LOCATION
21	EXPAND_STATUS_BAR	22	WRITE_EXTERNAL_STORAGE
23	RECEIVE_SMS	24	WRITE_SMS
25	ACCESS_WIFI_STATE	26	MODIFY_AUDIO_SETTINGS
27	ACCESS_NETWORK_STATE	28	WRITE_SETTINGS
29	READ_EXTERNAL_STORAGE	30	ACCESS_MOCK_LOCATION
31	USE_CREDENTIALS	32	HARDWARE_TEST
33	VIBRATE	34	READ_LOGS
35	CHANGE_NETWORK_STATE	36	ACCESS_GPS
37	WAKE_LOCK	38	ACCESS_COARSE_UPDATES
39	ACCESS_LOCATION_EXTRA_COMMANDS	40	ACCESS_FINE_LOCATION
41	GET_TASKS	42	RESTART_PACKAGES
43	MOUNT_UNMOUNT_FILESYSTEMS	44	INSTALL_PACKAGES
45	KILL_BACKGROUND_PROCESS		

TABLE IV  
K-FOLD CROSS VALIDATION RESULTS IN PERMISSION CLASSIFIER

Dataset	TPR	FPR	Accuracy	Precision	FIScore
Overall Dataset	0.941	0.050	0.945	0.945	0.945
Dataset 1	0.900	0.051	0.931	0.931	0.931
Dataset 2	0.855	0.054	0.920	0.920	0.920
Dataset 3	0.826	0.051	0.917	0.917	0.917



in the datasets of semantically dissimilar apps. Random forest

algorithm works on the basis of information gain values [32]. Therefore, we have given the information gain values of permission based features in our Dataset is given in Table V. From Table V, we can see that the information gain values can be slightly affected by the semantically similar apps in the datasets.

#### B. API Call Analysis

In this section, we re-implement API call based malware detection mechanism in our datasets for analyzing the impact of semantically similar in dataset. Here, we reused the key API call based features mentioned in our previous work [29]. The list of API call based features are given in Table VI. We extract the API call based features of malware and goodware apps in the dataset and a Comma Separated Value (CSV) file is constructed. This CSV file is supplied to Weka framework and tested in machine learning classifiers by employing 10 fold cross validation technique. We obtained a high accuracy in random forest classifier. From Table VII, we can see that

TABLE V  
CHANGES IN INFORMATION GAIN VALUES OF PERMISSIONS IN THE DATASETS

Permissions	Overall Dataset	Dataset1	Dataset2	Dataset3
READ_PHONE_STATE	0.379	0.334	0.283	0.264
SEND_SMS	0.257	0.112	0.121	0.126
RECEIVE_BOOT_COMPLETED	0.189	0.193	0.143	0.122
READ_SMS	0.175	0.127	0.115	0.109
RECEIVE_SMS	0.160	0.068	0.088	0.096
ACCESS_WIFI_STATE	0.138	0.209	0.169	0.142
WRITE_EXTERNAL_STORAGE	0.120	0.114	0.108	0.101
WRITE_SMS	0.096	0.083	0.074	0.070
WAKE_LOCK	0.081	0.073	0.057	0.049
INTERNET	0.079	0.060	0.052	0.053

the performance of the classifiers dropped very slightly in the datasets of semantically dissimilar apps. Random forest algorithm works on the basis of information gain values. Therefore, we have given the information gain values of API Call based features in our Dataset is given in Table VIII. From Table VIII, we can see that the information gain values can be slightly affected by the semantically similar apps in the datasets.

#### VI. TESTING THE PERFORMANCE IN BALANCED DATASETS

In this section, we evaluate the performance of API call and permission based classifiers in balanced datasets. From Table II, we can see that the number of unique apps in goodwill dataset is higher than that of malware dataset. That is, the distribution of apps in the classifier is not unique and class imbalance problem may occur in evaluation. Hence, it is required to evaluate the performances in balanced datasets before confirming our findings. From the goodwill datasets (dataset 1, dataset 2 and dataset 3), we removed some random goodwill apps for balancing the dataset. After balancing the datasets, we evaluated the performances in API call and permission based classifiers. The performance of API call and permission based classifiers in both balanced and unbalanced datasets are given in Fig 8. From Fig 8, we can see that the performance of the classifier is dropped after balancing the dataset.

#### VII. OVERRATED PERFORMANCE IN HOLDOUT EVALUATION

In this section, we illustrate the performance bias due to the semantically similar apps in test dataset. In ML based Android malware detection, a malware researcher randomly divides the dataset samples to train and test set for evaluation. Most of this time, he unaware about the duplicate copies in the dataset. The rate of duplicate samples in the test dataset may significantly affect the performance of the model. So, it is very difficult to generalize the model in accurately detecting the diverse malware apps. Here, we illustrate this phenomenon in API call based classifier.

We trained our API call and permission based classifier with the features diverse malware and goodwill samples and tested with more duplicate malware and goodwill samples. Further, the test dataset is constructed with more semantically similar apps of more malware samples those have more malicious

features and more semantically similar apps of more goodwill samples those have very few malicious features. Here, we followed thumb rule (80:20) for train-test split. Also, we shuffled the train and test set samples until obtaining the accuracy of 1. The performance metrics are given in Table IX. From the Table IX, it is clear that it is possible for a researcher to report his desired performance by shuffling the datasets in holdout evaluation. So, it has been advised to use our clustering algorithm to remove semantically similar apps from the dataset before holdout evaluation.

#### VIII. DISCUSSION AND CONCLUSIONS

In this work, we proposed a clustering mechanism to assess the impact of semantically similar apps in Android malware dataset. We found that, the presence of semantically similar apps especially duplicate apps those influence the performance of ML models in hold out evaluation. So, it has been advised to filter out all semantically similar apps before performing the holdout evaluation.

Our clustering algorithm have some limitations which affects the clustering process. In opcode injection attack, it is possible for an adversary to inject irrelevant opcodes in between the opcode subsequences of an application [33]. In such cases, the application has not become the part of any cluster. In future, we will explore some other additional features such as API calls and permission sequences for efficient clustering these apps.

In our experiments, the decompilation errors has occurred in some applications. Due to this decompilation errors, we cannot cluster these apps. In future, we will investigate the reason behind this decompilation errors and design some new tools to decompile these apps.

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TABLE VI  
SELECTED API CALLS FOR MALWARE DETECTION

Sl.No	API Calls	Sl.No	API Calls
1	getNetworkType	18	getDisplayMessageBody
2	getNetworkOperator	19	getPackageInfo
3	loadClass	20	getLastKnownLocation
4	getMessage	21	getAppPackageName
5	getMethod	22	getCookies
6	getClassLoader	23	isProviderEnabled
7	GetLongitude	24	getSimOperatorName
8	GetLatitude	25	getDeviceId
9	createFromPdu	26	getCertStatus
10	getInputStream	27	getSimSerialNumber
11	getOutputStream	28	getLine1Number
12	getWifiState	29	killProcess
13	abortBroadCast	30	exec
14	RequestFocus	31	getAppPackageName
15	getSubscriberId	32	setSerialNumber
16	getDisplayOriginatingAddress	33	getSessions
17	sendTextMessage	34	getCredential

TABLE VII  
K-FOLD CROSS VALIDATION RESULTS IN API CALL CLASSIFIER

Dataset	TPR	FPR	Accuracy	Precision	FIScore
Overall Dataset	0.954	0.046	0.957	0.957	0.957
Dataset 1	0.91	0.037	0.944	0.944	0.944
Dataset 2	0.856	0.044	0.929	0.929	0.928
Dataset 3	0.831	0.044	0.925	0.925	0.924

TABLE VIII  
CHANGES IN INFORMATION GAIN VALUES OF API CALLS IN THE DATASETS

API Call	Overall Dataset	Dataset1	Dataset2	Dataset3
getDeviceId	0.205	0.301	0.249	0.229
sendTextMessage	0.175	0.110	0.106	0.108
getLine1Number	0.164	0.224	0.194	0.180
getNetworkOperator	0.157	0.128	0.087	0.069
getSubscriberId	0.154	0.199	0.228	0.237
createFromPdu	0.082	0.157	0.062	0.065
abortBroadcast	0.081	0.047	0.055	0.059
getSimOperatorName	0.068	0.093	0.055	0.045
getSimSerialNumber	0.065	0.114	0.128	0.122
getCellLocation	0.049	0.076	0.064	0.059

TABLE IX  
HOLDOUT EVALUATION RESULTS IN API CALL AND PERMISSION CLASSIFIER

Classifier	TPR	FPR	Accuracy	Precision	FIScore
API Call Classifier	1	0	1	1	1
Permission Classifier	1	0	1	1	1

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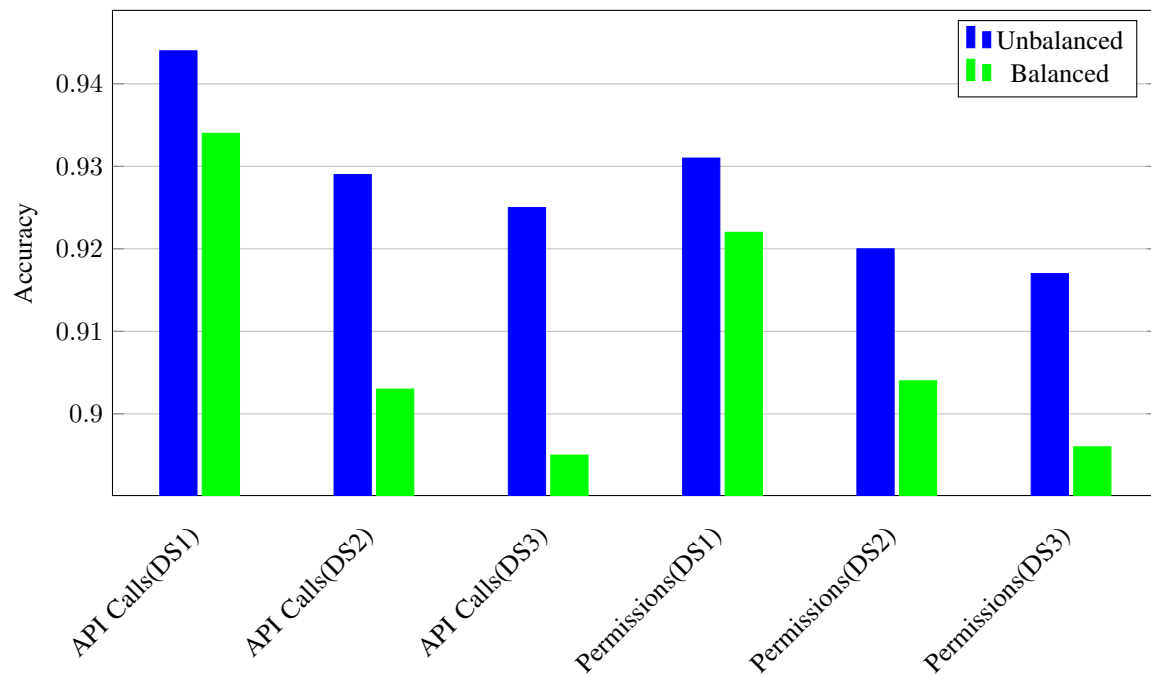


Fig. 5. Accuracy of Balanced Datasets without Semantically Similar Apps

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