Android Malware Classification

How to deal with extremely sparse features?

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Problem formulation

Android Malware

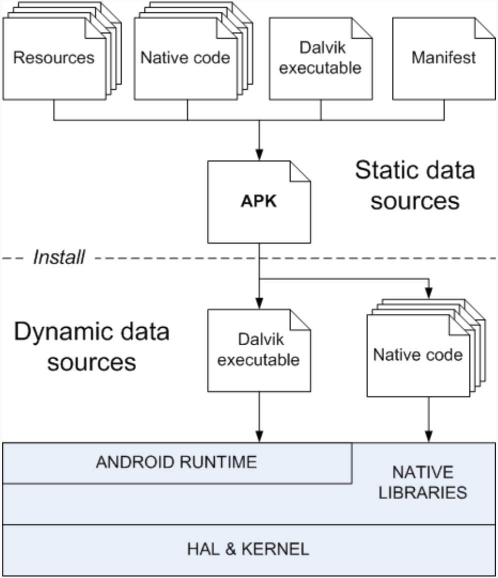
- More than 99% of all malware designed for mobile devices targets Android devices
- Extensive usage of mobile banking and internet browsing
- Harmful content via email attachments

Android application as an object for classification

Android app as an object for classification

- APK installation package distribution
- Application is described by a set of files, only 3 of which are fixed
- As a result files have only a small set of same kind of application descriptors

Dynamic and static approach in Android Malware Classification



Application JSON scheme

```
{
 "items": [{
  "name": "EICARAntiVirusTestFile.com",
  "hash": "3395856ce81f2b7382dee72602f798b642f14140",
  "path": "assets",
  "size": 68,
  "type": "file"
 },
 ...
 {
  "manifest": {
   "entries": [{
    "type": "activity",
    "name": ".EICARAntiVirusTestMainActivity",
    "filters": [{
     "actions": ["android.intent.action.MAIN"],
     "category": ["android.intent.category.LAUNCHER"]
    }]
   }],
   ...
  },
  "name": "AndroidManifest.xml",
  ...
  "type": "file"
 },
 ...
 {
  "name": "CERT.RSA",
  ...
  "type": "file"
 }],
 "name": "EICAR_Anti_virus_Test_1.0.apk",
 "hash": "3a5a91b58bb38454dedd90c2fc498a29a4def82c",
 "path": "",
 "size": 17922,
 "type": "file"
}
```

Extracted features

Feature type	Nmal=1K	Nclean=1K	Nmal=10K	Nclean=10K
Manifest strings (MSTR)	73,292	113,106	742,335	1,093,489
Permissions (PERM)	13,590	11,457	137,776	111,548
Dex strings (DEXS)	4,362,573	9,960,902	44,155,410	99,268,349
Hashes (HASH)	133,683	431,243	1,370,128	4,490,554

Table 1: The size of raw extracted features from different groups. With growth of dataset, the feature space reaches millions of features for DEXS and HASH features.

Feature selection

Log-odds feature selection

The chance of the feature i to contribute to a malicious file is defined as follows:

$$\theta_i = \frac{mal + k}{ben + k} \cdot \frac{B}{M}, \tag{1}$$

where B and M are the number of benign and malicious files respectively.

If we want to select the features being present only in the malicious class, we can achieve the following approximation, when k is small:

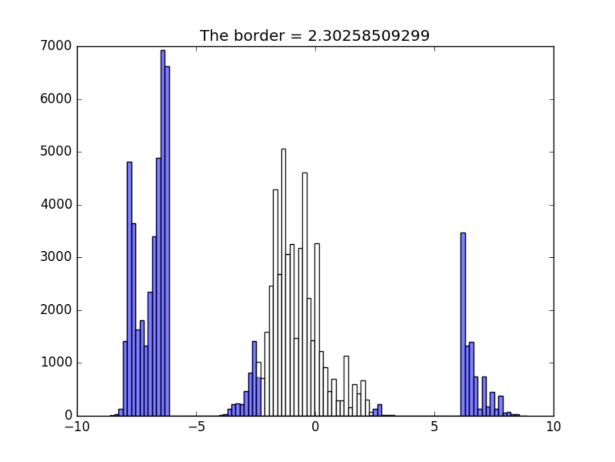
$$\log(\theta_i) = \log(mal + k) - \log(ben + k) \approx \log(mal) - \log(k) \tag{2}$$

Log-odds feature selection

- Hence the feature occurs one or more times in malicious file when $\log(\theta_i) \geq \log(1) - \log(k) \geq -\log(k)$.
- Accordingly to have the feature only being present in benign files the following inequality should hold: $\log(\theta_i) \leq \log(k)$.
- Both inequalities hold when feature occurs in either of the classes and $|\log(\theta_i)| \geq -\log(k)$.
- To allow the feature occur in both classes a constant c can be used: $|\log(\theta_i)| \geq -\log(ck)$.

Log-odds feature selection

- The distribution of $\log(\theta_i)$ values
- Only features with $|\log(\theta_i)| > -\log(0.1) \approx 2.30$ are selected



From *Efficient Detection of Zero-day Android Malware Using*

Choosing Laplace smoothing parameter

K	FPR	TPR
1	0.08	43.16
0.1	0.08	62.78
0.01	0.18	75.0
0.001	0.32	80.04
0.0001	0.42	83.14

Table 2: The effect of parameter k on the classification performance in the test set with Naive Bayes Classifier using BOW model.

Dimensionality reduction

Random Projections

For a given matrix $A \in \mathbb{R}^{N \times D}$ a random projection [1] defines a transformation to a lower dimensional space by multiplying by a randomly generated matrix $R \in \mathbb{R}^{D \times K}$, namely:

$$B = A \cdot R\,. \tag{3}$$

Initialization of random matrix can be expressed as follows, s « $\sqrt{D}$:

$$R = \sqrt{s} \begin{cases} 1 & \text{with probability } \frac{1}{2s} \\ 0 & \text{with probability } 1 - \frac{1}{s} \\ -1 & \text{with probability } \frac{1}{2s} \end{cases}. \tag{4}$$

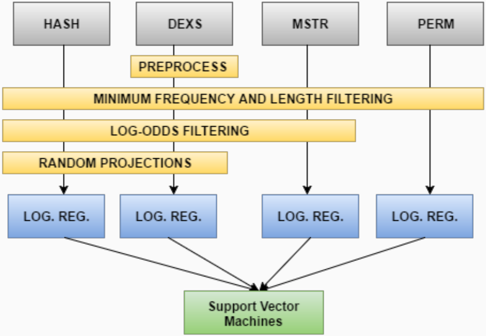
Validation of random projection matrix

K	ROC AUC
2,000	0.9913 ± 0.00052
4,000	0.9935 ± 0.00032
10,000	0.9944 ± 0.00027

Table 3: The effect of random projection initialization on DEX strings on the AUC. In other words, one does not need to try different RP initializations and find the best one; with sufficiently enough chosen features, the classification performance varies much less.

Proposed method and evaluation

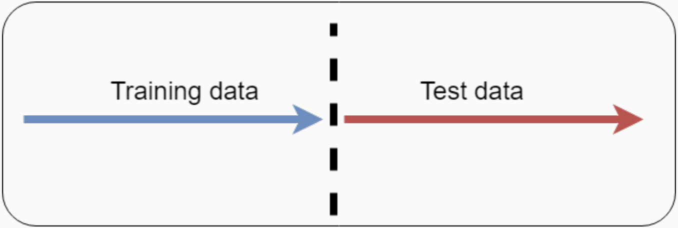
Feature ensemble



From *Android Malware Detection: Building Useful Representations by Sayfullina et al. [3]*

On evaluation

- Fixed datasets and unreliable estimates
- Importance of having chronologically separated training and test sets
- Aim at low false positive rate
- Continuous model retraining



From *Pragmatic Android Malware Classification" by Palumbo et al. [2]*

Experimental results

Method	Feat.	AUC	TP	FP
Proposed	DEXS, MSTR PERM, HASH	**0.9991**	**88.24**%	**0.04**%
NB	DEXS, MSTR PERM, HASH	0.9726	67.72%	0.04%
Proposed	DEXS, MSTR PERM	0.9986	86.92%	0.04%
NB	DEXS, MSTR PERM	0.9726	67.28%	0.04%

Table 4: The comparison between the performances of the proposed approach against the Naive Bayes implementation, split by different sets of features.

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