Android Malware Classification

How to deal with extremely sparse features?

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1. Problem formulation

2. Android application as an object for classification

3. Feature selection

4. Dimensionality reduction

5. Proposed method and evaluation
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

Static data sources

Dynamic data sources

Install

APK

Android Runtime

Native Libraries

HAL & Kernel
Application JSON scheme

```json
{
  "items": [
    {
      "name": "EICARAntiVirusTestFile.com",
      "hash": "3335856ce81f2b7382dde72602f798b642f14140",
      "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": "3a5a91b50bb38454dedd90c2fc498a29a4def82c",
"path": ".",
"size": 17922,
"type": "file"
}```
### 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:

$$\theta_i = \frac{mal + k}{ben + k} \cdot \frac{B}{M},$$  \hspace{1cm} (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:

$$\log(\theta_i) = \log(mal + k) - \log(ben + k) \approx \log(mal) - \log(k) \quad (2)$$
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
Choosing Laplace smoothing parameter

<table>
<thead>
<tr>
<th>K</th>
<th>FPR</th>
<th>TPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.08</td>
<td>43.16</td>
</tr>
<tr>
<td>0.1</td>
<td>0.08</td>
<td>62.78</td>
</tr>
<tr>
<td>0.01</td>
<td>0.18</td>
<td>75.0</td>
</tr>
<tr>
<td>0.001</td>
<td>0.32</td>
<td>80.04</td>
</tr>
<tr>
<td>0.0001</td>
<td>0.42</td>
<td>83.14</td>
</tr>
</tbody>
</table>

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

$$B = A \cdot R .$$

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

$$R = \sqrt{s} \begin{cases} 
1 & \text{with probability } \frac{1}{2s} \\
0 & \text{with probability } 1 - \frac{1}{s} \\
-1 & \text{with probability } \frac{1}{2s}
\end{cases} .$$
Validation of random projection matrix

<table>
<thead>
<tr>
<th>K</th>
<th>ROC AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>2,000</td>
<td>0.9913 ± 0.00052</td>
</tr>
<tr>
<td>4,000</td>
<td>0.9935 ± 0.00032</td>
</tr>
<tr>
<td>10,000</td>
<td>0.9944 ± 0.00027</td>
</tr>
</tbody>
</table>

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]
Table 4: The comparison between the performances of the proposed approach against the Naive Bayes implementation, split by different sets of features.
D. Achlioptas. 
**Database-friendly random projections: Johnson-lindenstrauss with binary coins.**  

**A pragmatic android malware detection procedure.**  

L. Sayfullina, E. Eirola, D. Komashinsky, P. Palumbo, and J. Karhunen.  
**Android malware detection: Building useful representations.**  

**Efficient detection of zero-day android malware using normalized bernoulli naive bayes.**