DroidScribe

Classifying Android Malware Based on Runtime Behavior

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Mobile Security Technologies (MoST)

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Background

Automated Analysis

- Obtain rich **static** view of an app
- Obtain rich **dynamic** view of an app

Type of Problems

- Malware Detection
  - Crucial for final users
- **Family Identification**
  - Crucial for analysis of threats and mitigation planning

Smart Phones		Desktop	
Static	Dynamic	Static	Dynamic
1			

- In the mobile realm
  - 1 Dendroid : CFG

API: Application Programming Interface, API-F: Information Flow between APIs, INT: Intents, CG: Call Graph, PER: Requested Permissions, CFG: Control Flow Graph, PKG: Package information of API, SYS: System Calls

Smart Phones		Desktop	
Static	**Dynamic**	**Static**	**Dynamic**
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  - 4 DroidSIFT : API-F

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State of the Art
On Family Identification

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Smart Phones		Desktop	
Static	Dynamic	Static	Dynamic
			

- In the mobile realm
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  - (2) DroidLegacy : API
  - (3) DroidMiner : CG, API
  - (4) DroidSIFT : API-F
  - (5) RevealDroid : PER, API, API-F, INT, PKG
- In the desktop realm
  - **SYS** have been successfully used

`API`: Application Programming Interface, `API-F`: Information Flow between APIs, `INT`: Intents, `CG`: Call Graph, `PER`: Requested Permissions, `CFG`: Control Flow Graph, `PKG`: Package information of API, `SYS`: System Calls

State of the Art
On Family Identification

Smart Phones		Desktop	
Static	**Dynamic**	**Static**	**Dynamic**
			

Android System Call Profile

- Android services are invoked through `ioctl`
- `ioctl`s are dispatched to the *Binder* kernel driver, which implements Android's main **IPC** and **ICC**
- Distinguishing Binder calls is essential for the malware classif.

Our Contribution

Smart Phones		Desktop	
Static	Dynamic	Static	Dynamic
☹	☺	☹	☹

Goal To evaluate the use of dynamic analysis for family identification under **challenging conditions**

Challenges

- Similar/sparse behaviors

Our contributions

- **RQ1**: What is the best level abstraction?
- **RQ2**: Can we deal with sparse behaviors?

Dynamic Analysis Component

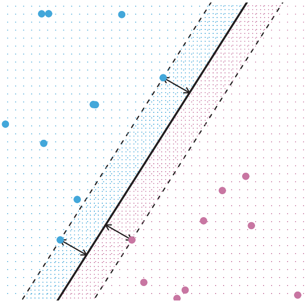
CopperDroid[1]

- Runs apps in a sandbox, records system calls and their arguments, and reconstructs high-level behavior
- Reconstructs contents of all transactions going through the Binder mechanism for inter-process communication

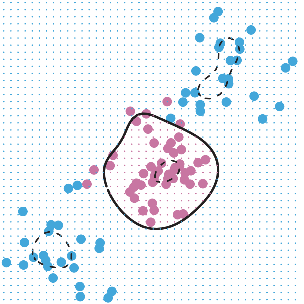
[1] Tam, K., Khan, S.J., Fattori, A. and Cavallaro, L. "CopperDroid: Automatic Reconstruction of Android Malware Behaviors." NDSS. 2015.

Machine Learning Component

- Use existing malware classified into families as training data
- Use Support Vector Machines as the classification algorithm



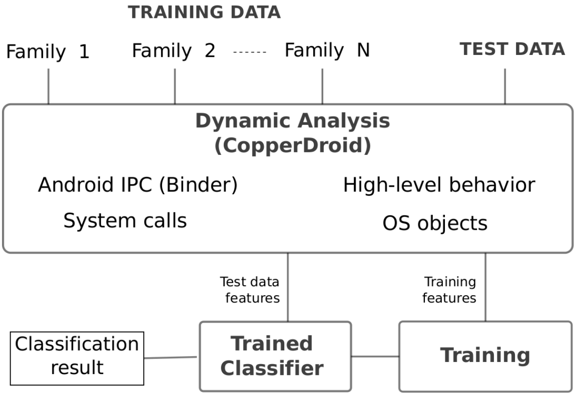
Linear function



Radial-basis function

Source: An Introduction to Statistical Learning–G. James et al.

Overview of the Classification Framework

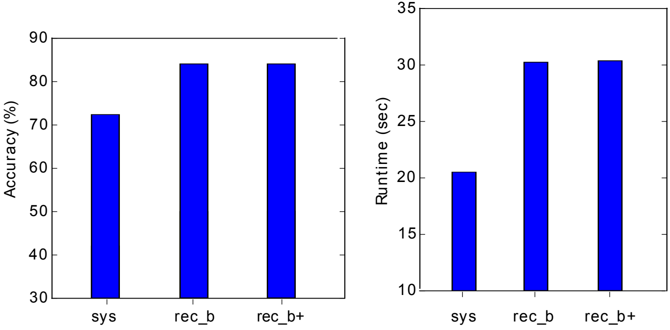


System-calls vs. abstract behaviors

RQ1

What is the best level abstraction?

- Experiments on the Drebin dataset (5,246 malware samples).
- Reconstructing Binder calls adds 141 meaningful features.
- High level behaviors added 3 explanatory features.



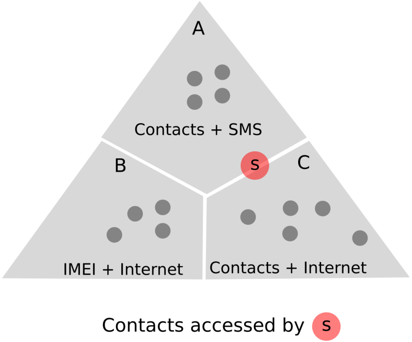
(a) Accuracy (b) Runtime

Set-Based Prediction

- Dynamic analysis is limited by code coverage
- Classifier has only partial information about its behaviors
- Identify when malware cannot be classified into a family
  - Based on a measure of the statistical confidence
- Helpful human analyst by identifying the top matching families

Classification from Observed Features

- When more than one choice of similar likelihood exists, ...
- ... traditional classification algorithms are prone to error



Conformal Predictor (CP)

- Is statistical learning algorithm tailored at classification
- Provides statistical evidences on the results

Credibility

Supports how good a sample fits into a class

Confidence

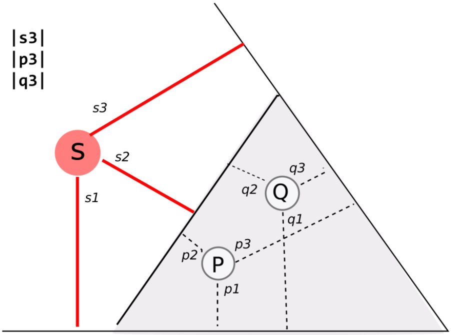
Indicates if there are other good choices

Robust Against Outliers

Aware of values from other members of the same class

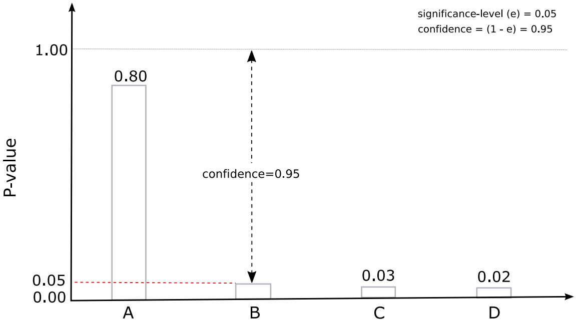
- P-value is the probability of truth for the hypothesis that a sample belongs to a class

```
ncm_S = |s1| + |s2| + |s3|
ncm_P = |p1| + |p2| + |p3|
ncm_Q = |q1| + |q2| + |q3|

ncm_S > ncm_P > ncm_Q

pval_S = 0/3
pval_P = 1/3
pval_Q = 2/3
```



In an ideal world

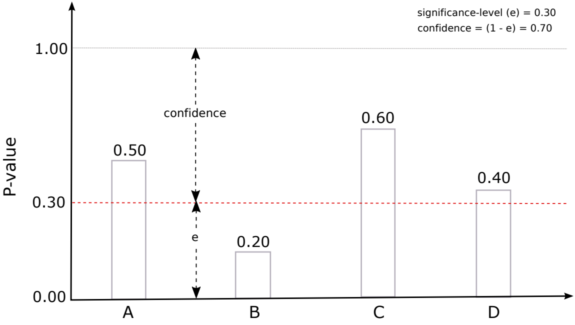
Given a new object s, conformal predictor picks the class with the highest p-value and return a singular prediction.



Prediction = A

Obtaining Prediction Sets

Given a new object s, we can set a significance-level e for p-values and obtain a prediction set Γ^e includes labels whose p-value is greater than e for the sample.



Prediction Set = {A, C, D}

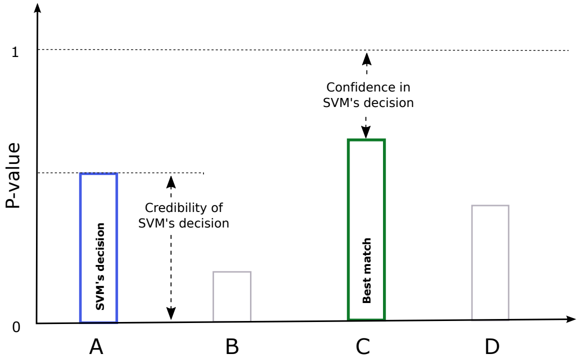
- CP is an expensive algorithm
  - For each sample, we need to derive a p-value for each class
  - Computation complexity of $O(nc)$ where n is number of samples and c is the number of classes

Conformation Evaluation

- Provide statistical evaluation of the quality of a ML algorithm
  - Quality threshold to understand when should be trusting SVM
  - Statistical evidences of the choices of SVM
  - Selectively invoke CP to alleviate runtime performance

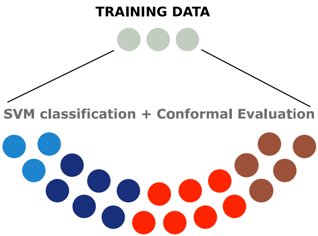
Step 1. Computing Confidence in Training Decisions

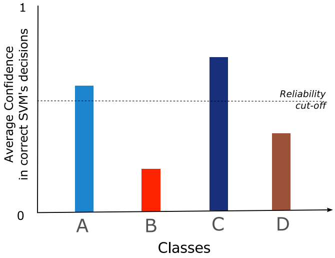
- During training, compute p-values for each sample for each class
- Compute the confidence in the decision for each sample



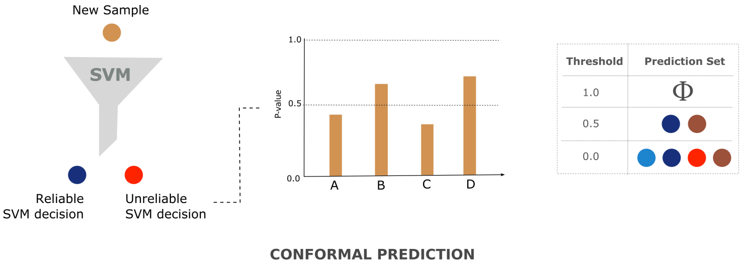
Step 2. Using Class-level Confidence Scores

- For each class, calculate the mean confidence for all decisions mapping to the class
- Use the median of the class-level confidence across all classes as a reliability threshold





Step 3. Invoking the Conformal Predictor

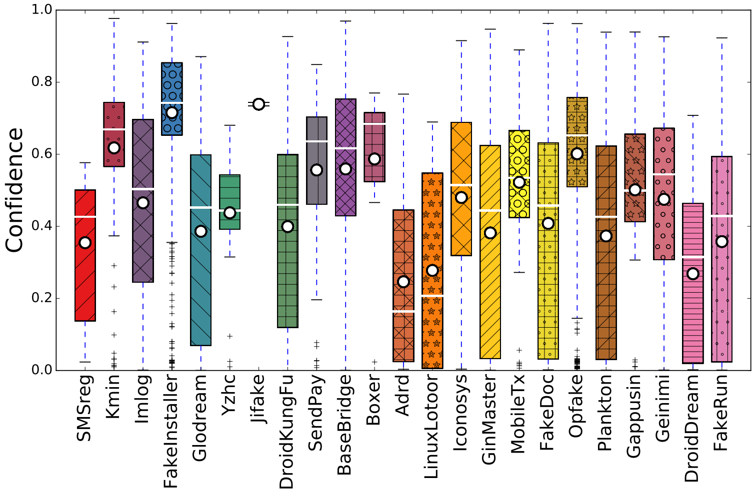


Threshold

The threshold for picking prediction sets is fully tunable

Confidence of correct SVM decisions

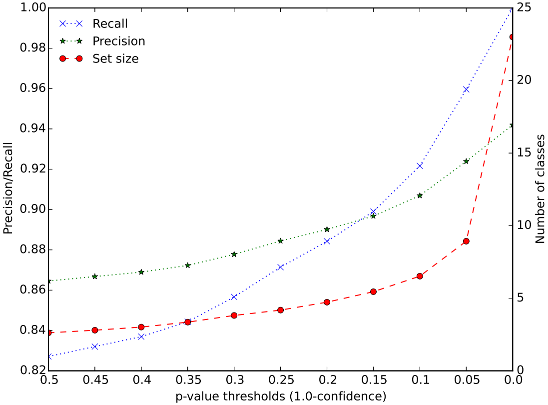
Invoke CP with a set of desired p-value cutoff size



Accuracy vs. Prediction Set Size

RQ2

Can we deal with sparse behaviors?



- Accuracy improves with the prediction set size

Conclusion

- Resolving Binder invocations improves classification accuracy
- Poor coverage leads to misclassification in dynamic analysis
- Predicting sets of top matches ameliorates this problem
- Statistical evaluation can be used to minimize computation
- DroidScribe can be integrated into dynamic analysis frameworks such as CopperDroid

DroidScribe

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Computing P-values

- *Nonconformity Measure* (NCM) is a **geometric measure** of how well a sample is far from a class.
  - For SVM, the NCM $\mathcal{N}_D^z$ of a sample z w.r.t. class D is sum distances from all hyperplanes bounding the class D.

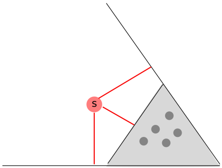
$$\mathcal{N}_D^z = \sum_i d(z, \mathcal{H}_i)$$

- *P-value* is a **statistical measure** of how well a sample fits in a class.
  - P-value $\mathcal{P}_D^z$ represents the proportion of samples in D that more different than z w.r.t. D.

$$\mathcal{P}_D^z = \frac{|\{j = 1, ..., n : \mathcal{N}_D^j \geq \mathcal{N}_D^z\}|}{n}$$

Probability of Membership

- Standard classification algorithms calculate probability of a sample belonging to a class
- For the case of SVM, this is based on Euclidean distance (Platt's scaling)



Using Probabilites

- Platt's scaling is based on logistic regression
- Logistic regression is sensitive to outliers which introduces inaccuracies
- Probabilities to sum up to one which introduces skewing