# MaMaDroid: Detecting Android Malware by Building Markov Chains of Behavioral Models

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# Motivation: Android & Malware

- **Android market share is growing**
  - In 2016, 85% of smartphone sales
- **At the same pace the interest by cybercriminals is growing**
  - Bypassing two-factor authentication
  - Stealing sensitive information, etc.

# Motivations: Current Defenses

- **Can't use complex on-device operations**
  - Limited battery and memory resources
- **Google's centralized analysis**
  - Previous work shown a few incidents
  - Users buy apps from third party markets
- **Lots of research in the field! However**
  - Permission-based models prone to false positive
  - Relying on API calls frequently used by malware needs constant, costly retraining

# Motivations: Our Idea

**Intuition: malware uses calls for different actions and in different order than benign apps**

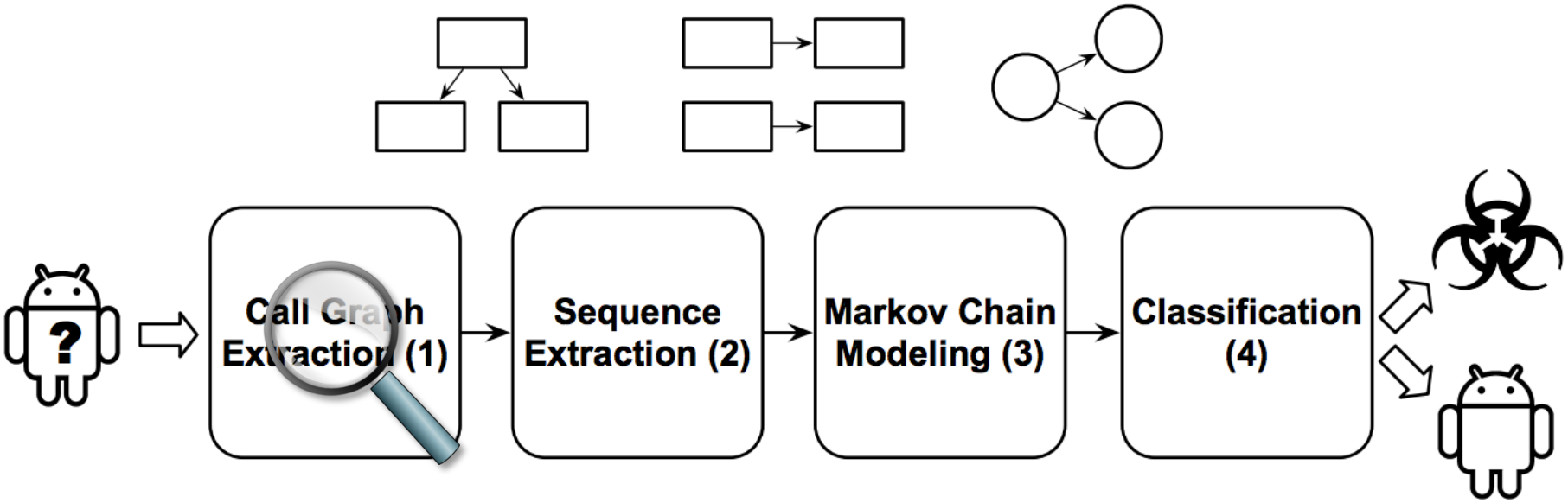
- E.g. android.media.MediaRecorder used by any app with permission to record audio
- Only using it after calls to getRunningTasks(), which allows to record conversations, may suggest maliciousness

**Rely on the sequence of abstracted calls**

1. Sequence captures the behavioral model
2. Abstraction provides resilience to API changes

# MaMaDroid

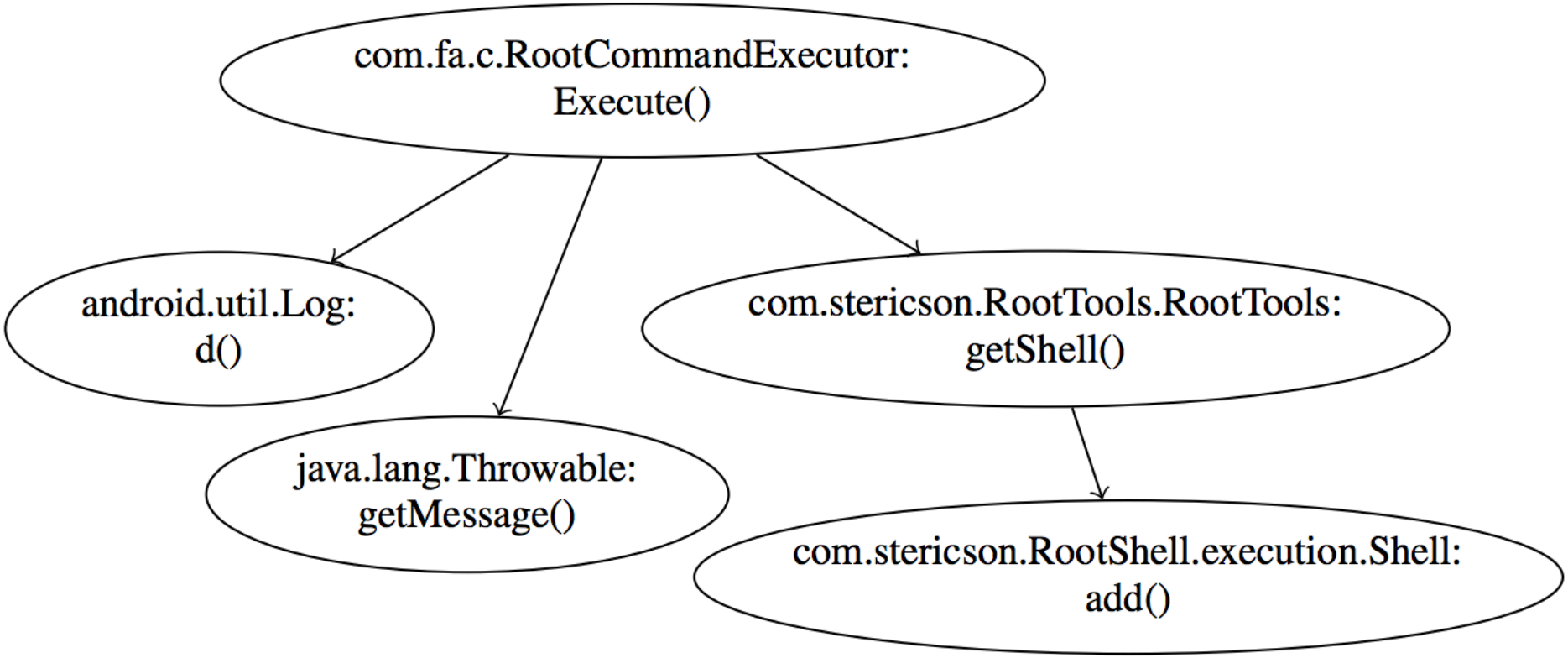
# Overview


Call Graph Extraction (1)
Sequence Extraction (2)
Markov Chain Modeling (3)
Classification (4)

# Call Graph Extraction

- **Based on static analysis**
  - Given an apk, extract call graphs
- **Tools**
  - Soot (Java optimization and analysis framework)
  - FlowDroid

# Call Graph


com.fa.c.RootCommandExecutor:
Execute()
android.util.Log:
d()
java.lang.Throwable:
getMessage()
com.stericson.RootTools.RootTools:
getShell()
com.stericson.RootShell.execution.Shell:
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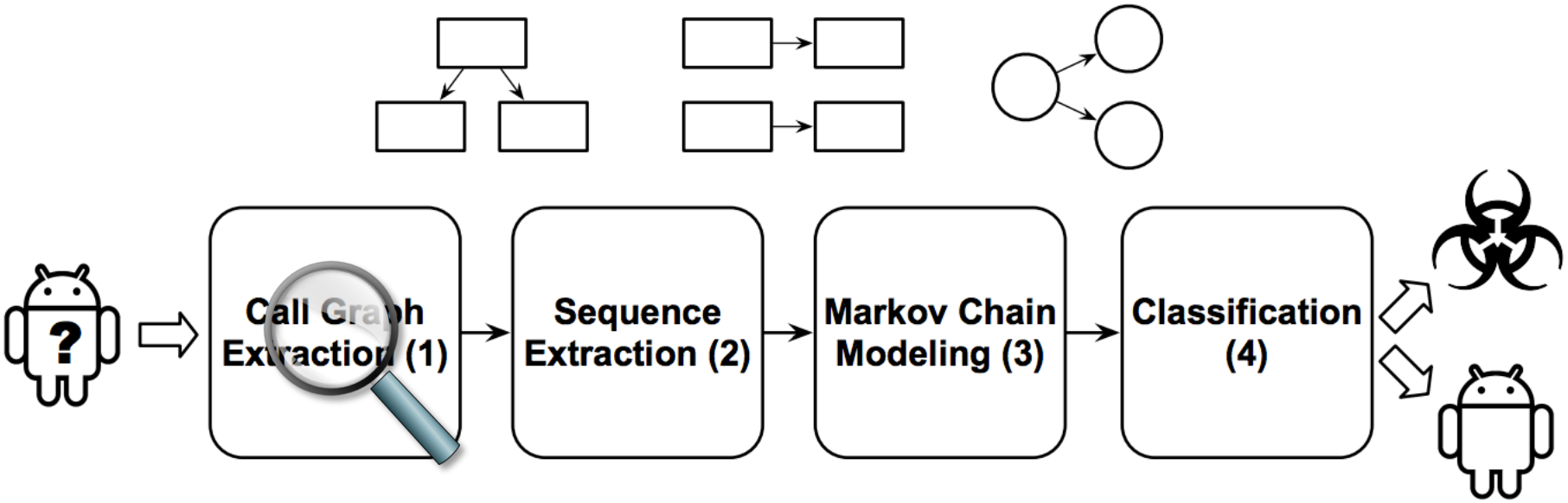
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# Sequence Extraction

- **Soot gives the call graph from which we extract the sequence of functions that are potentially called by the program, but…**

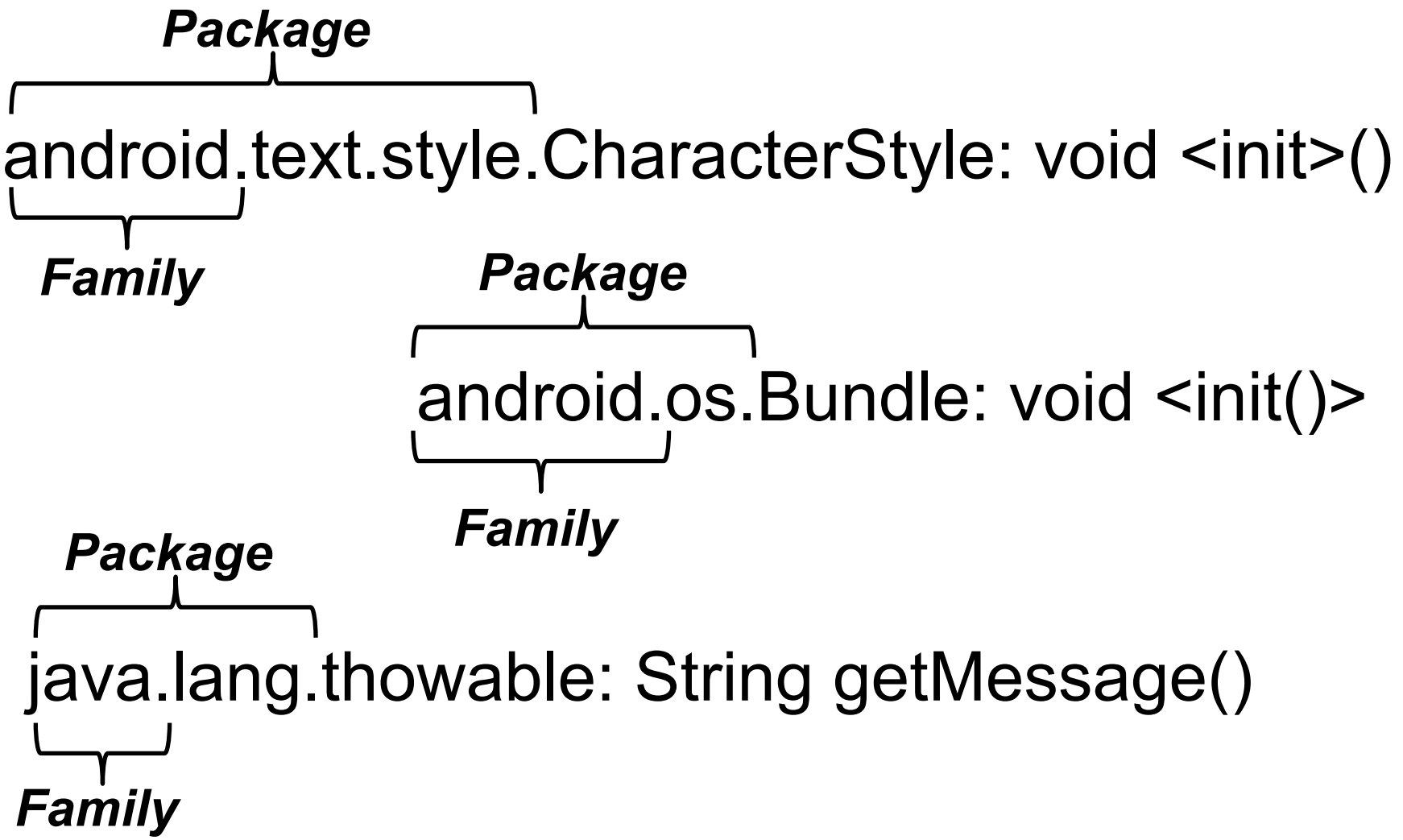
- **When running example multiple times…**
  - Execute() may be followed by different calls, e.g., getShell() only in try or getShell() + getMessage() in catch

# Sequence Extraction

- **We proceed as follows:**
  1. Identify set of entry nodes
  2. Enumerate paths
  3. Output set of all paths as the sequences of API calls

- **But we said we were using abstracted calls!**

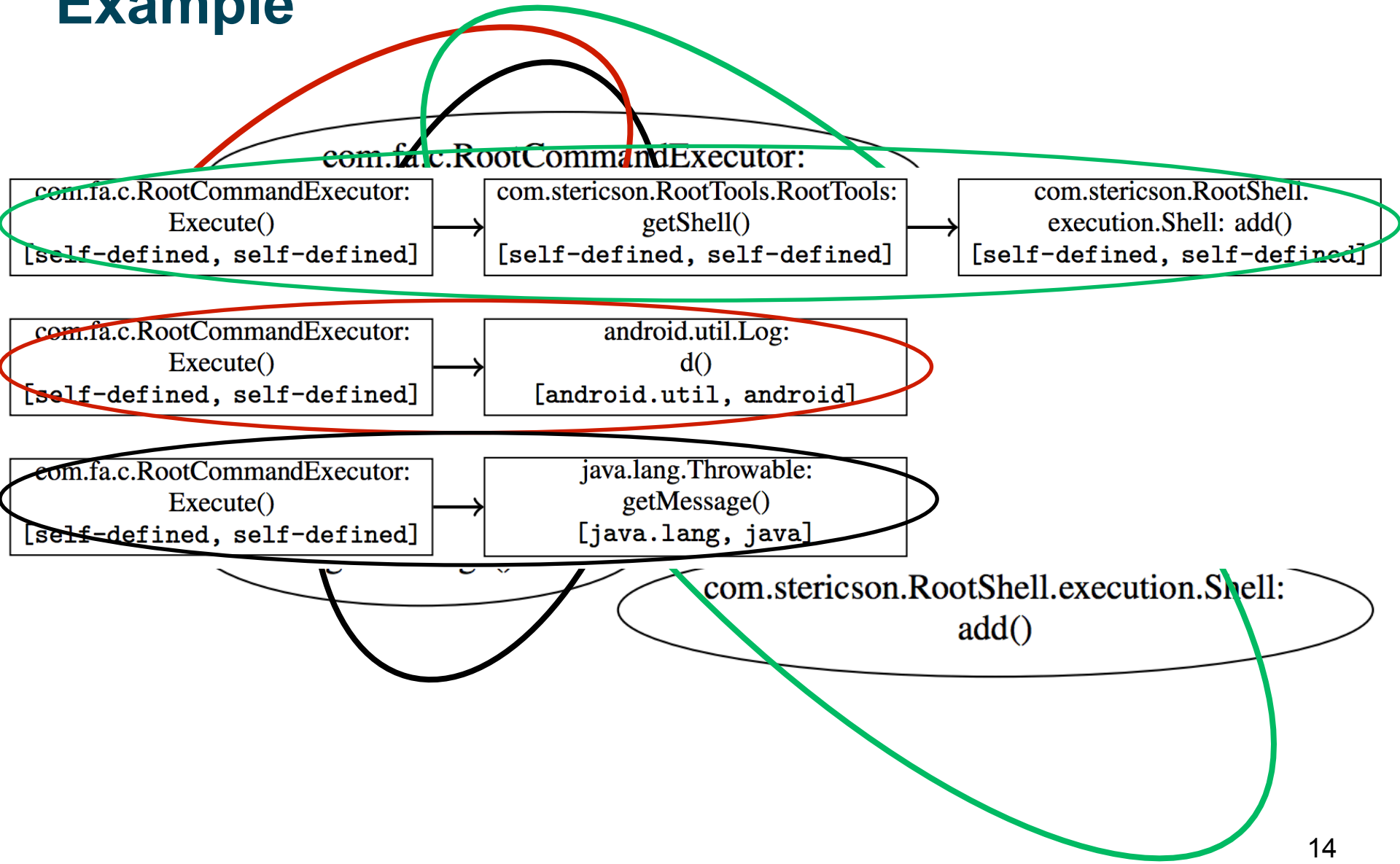
# Abstraction



# Abstraction

- **Packages**
  - Using the list of 243 packages (as of API level 24) + 95 from the Google API
  - Packages defined by developers → “self-defined”
  - If we can’t tell what its class implements → “obfuscated”
- **Families**
  - 9 families: android, google, java, javax, xml, apache, junit, json, dom
  - Plus self-defined and obfuscated

# Example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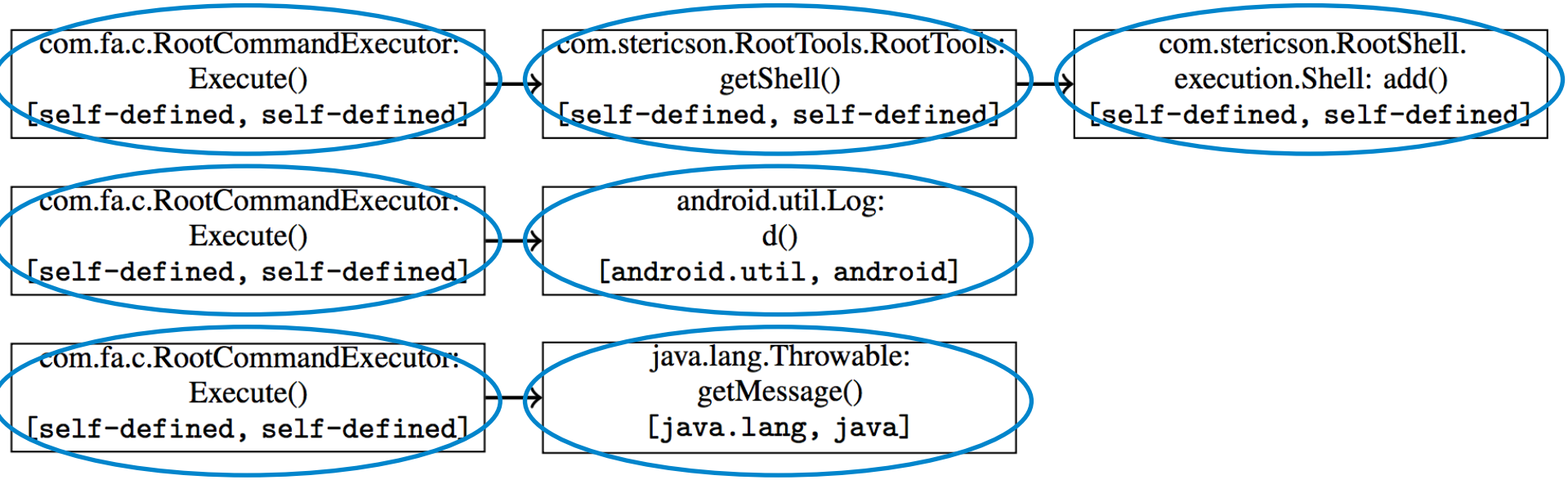
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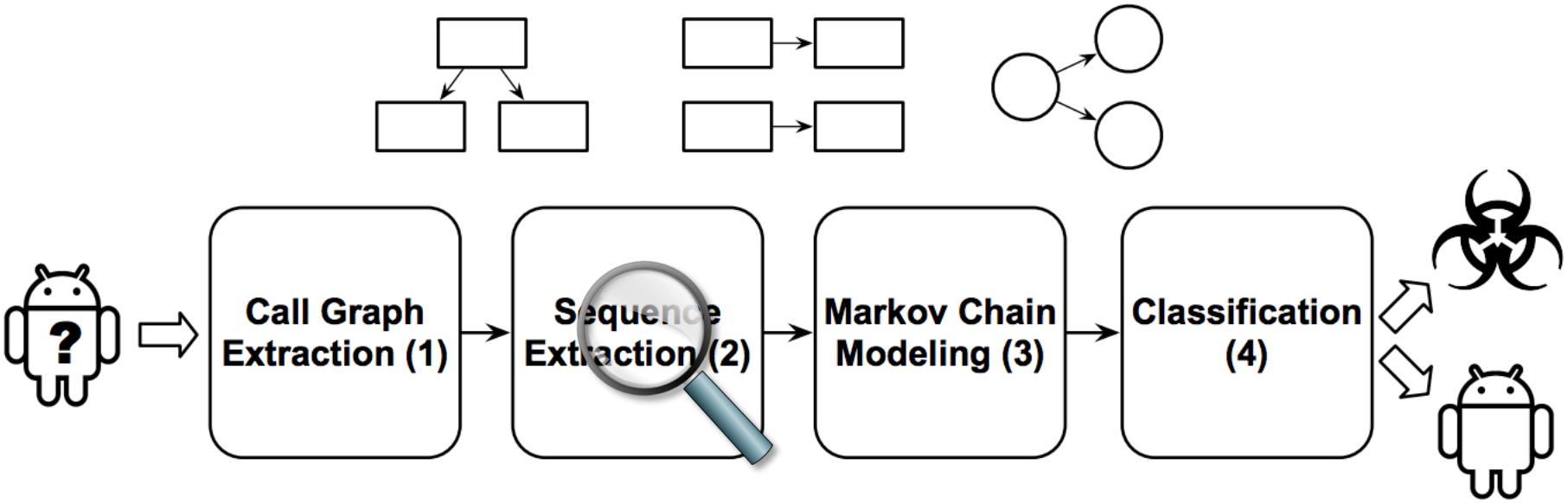
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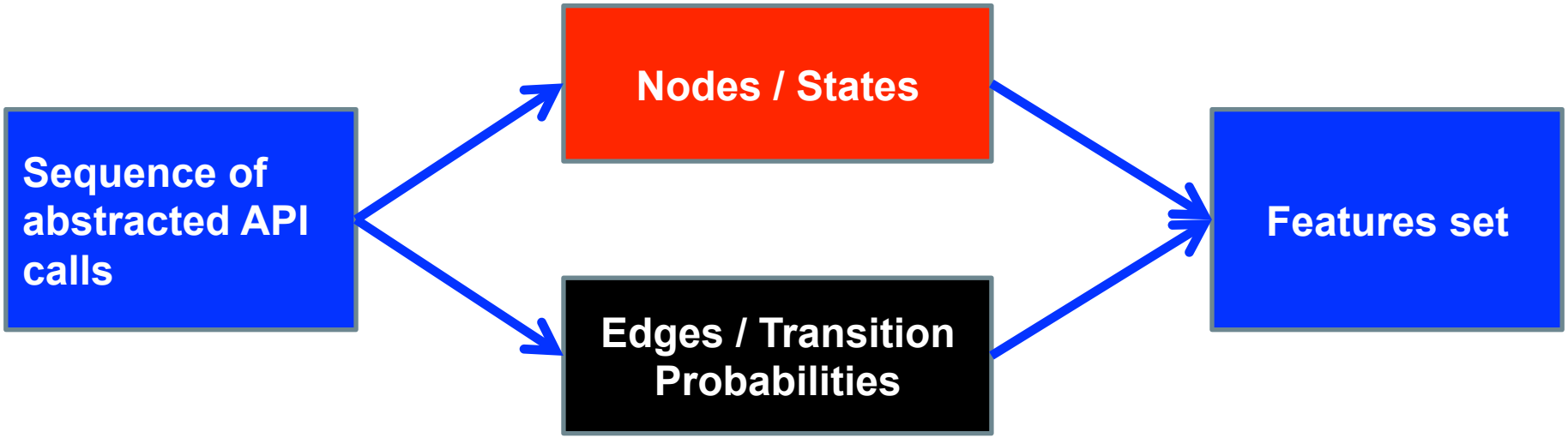
# Markov Chain

- Memoryless models
  - Probability of transition from a state to another only depends on the current state
- Represented as a set of nodes
  - Each corresponding to a different state, and a set of edges labeled with the probability of transition.
- Sum of all probabilities associated to all edges from any node is exactly 1

# Building the Markov Chains



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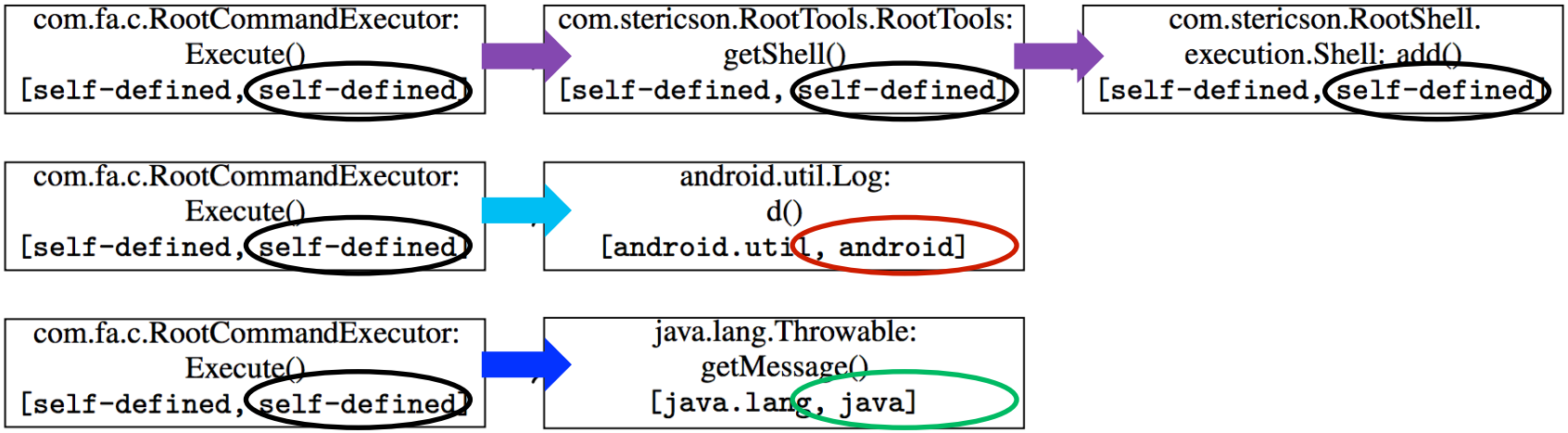
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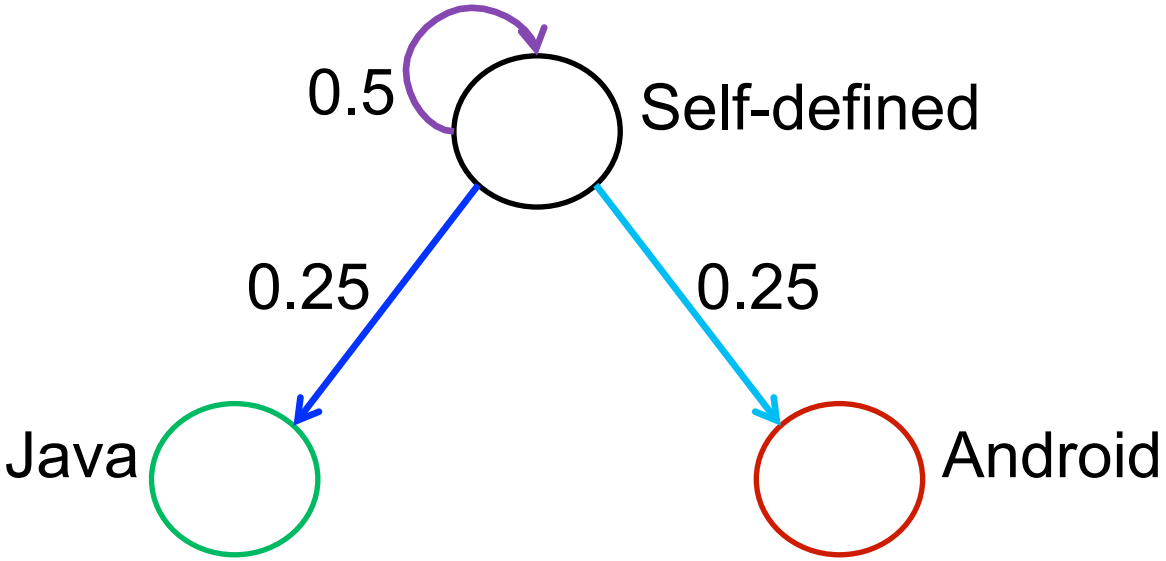
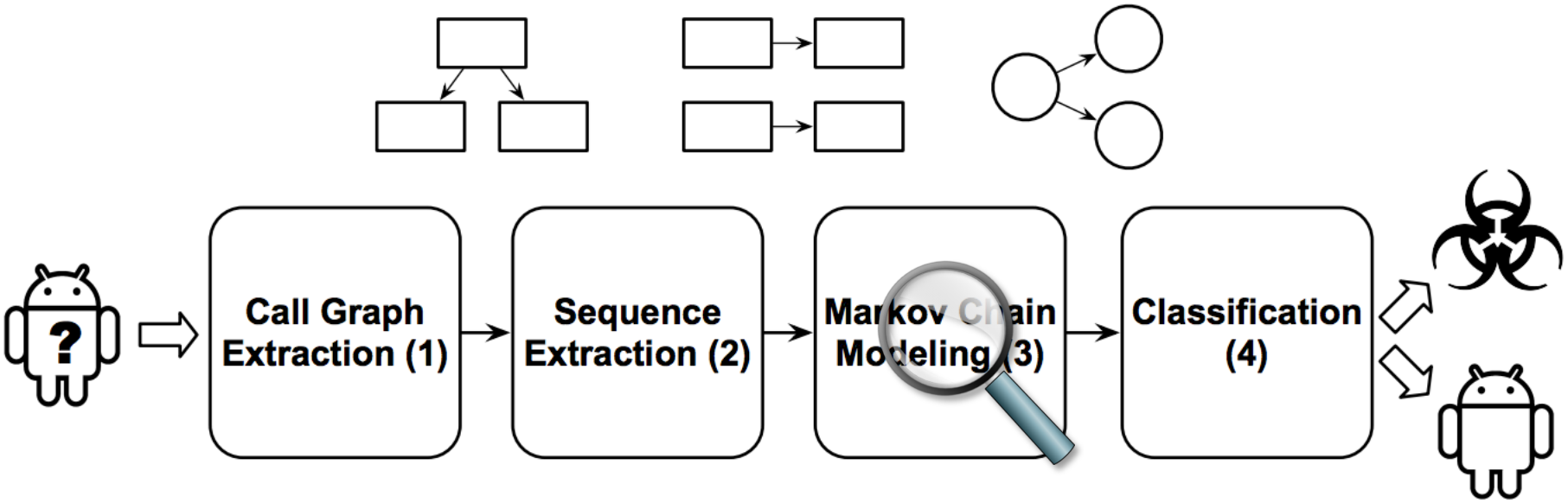

0.5
Self-defined
0.25
0.25
Java
Android

# Feature Extraction

- **For each app:**
  - Feature vector = probabilities of transition from one state to another in the Markov chain
  - With families, 11 possible states → 121 possible transitions in each chain
  - With packages, 340 states → 115,600 transitions

# Overview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# Classification

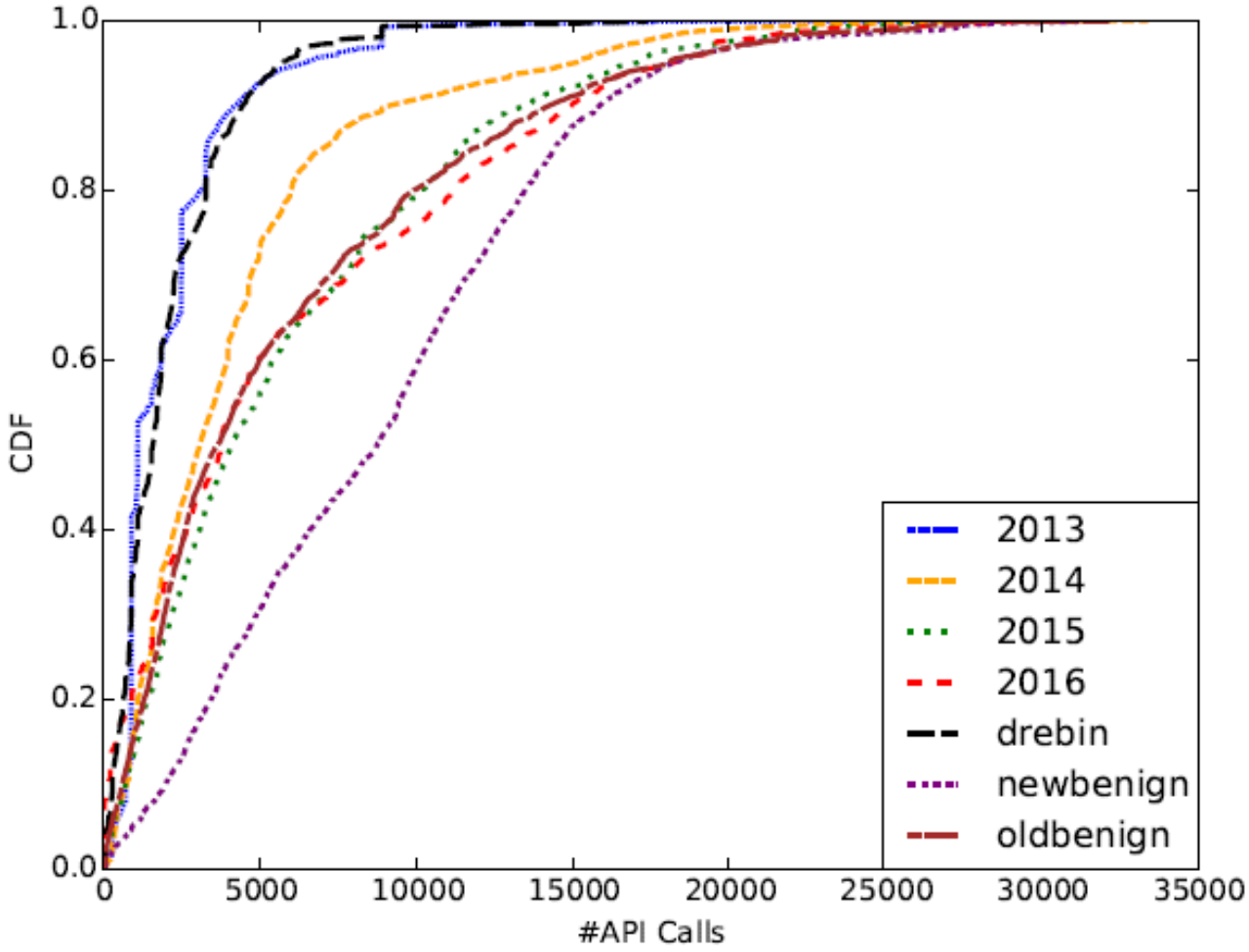
- **Build a classifier using the extracted features**
  - Each app labeled as benign or malware
- **We tested our idea using:**
  - Random Forests
  - 1-NN, 3-NN
  - SVM
- **SVM was less efficient than the other systems**

# Dataset

# Datasets

| Category | Name | Date Range | # Samples | # Samples (API Calls) | # Samples (Call Graph) |
|---|---|---|---|---|---|
| Benign | OldBenign | Apr 13 – Nov 13 | 5,879 | 5,837 | 5,572 |
| | NewBenign | Mar 16 – Mar 16 | 2,568 | 2,565 | 2,465 |
| | | **Total Benign** | **8,447** | **8,402** | **8,037** |
| Malicious | Drebin | Oct 10 – Aug 12 | 5,560 | 5,546 | 5,538 |
| | 2013 | Jan 13 – Jun 13 | 6,228 | 6,146 | 6,123 |
| | 2014 | Jun 13 – Mar 14 | 15,417 | 14,866 | 14,827 |
| | 2015 | Jan 15 – Jun 15 | 5,314 | 5,161 | 4,725 |
| | 2016 | Jan 16 – May 16 | 2,974 | 2,802 | 2,657 |
| | | **Total Malicious** | **35,493** | **34,521** | **33,870** |

# How many API calls?



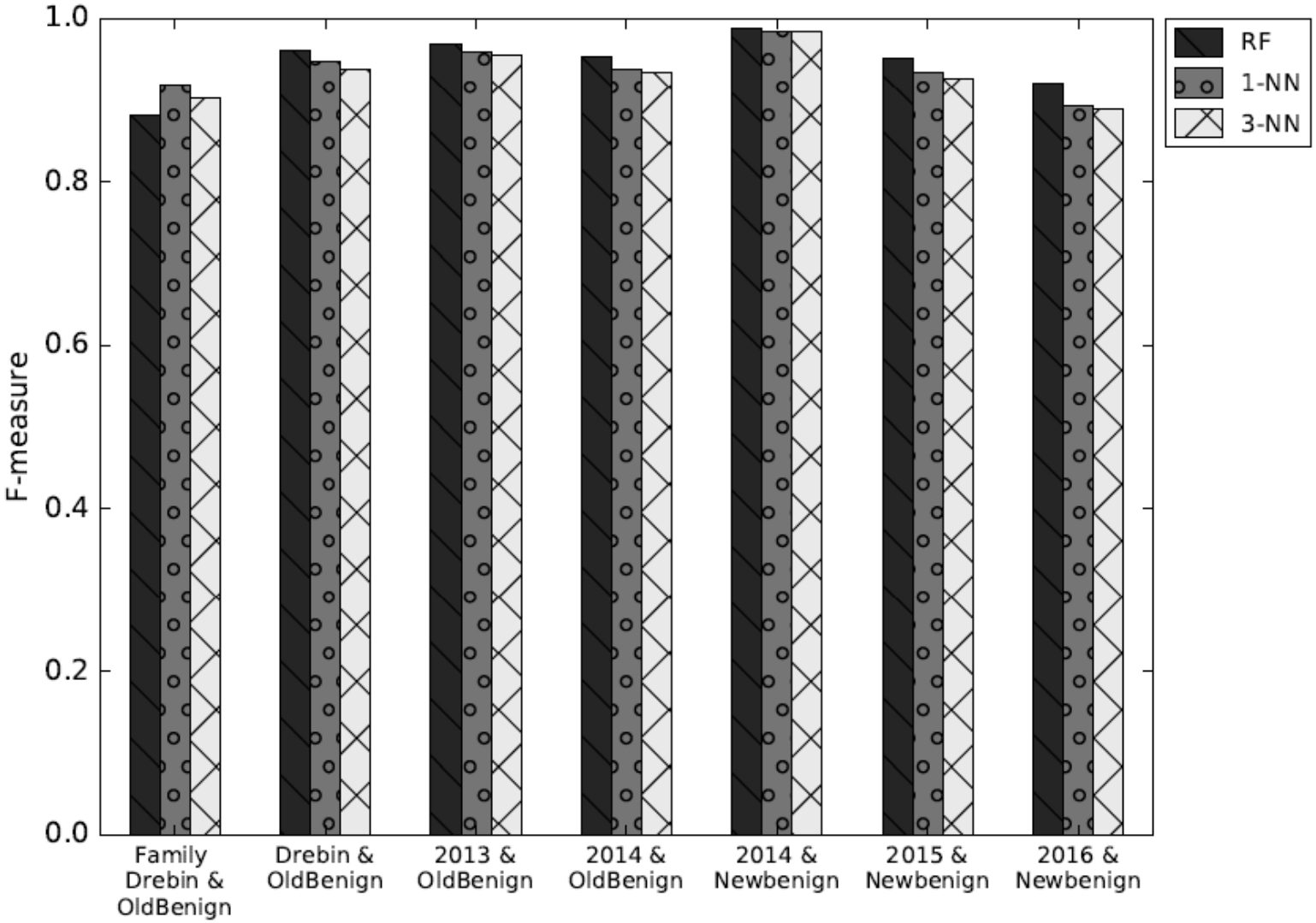
# Evaluation

# Evaluation

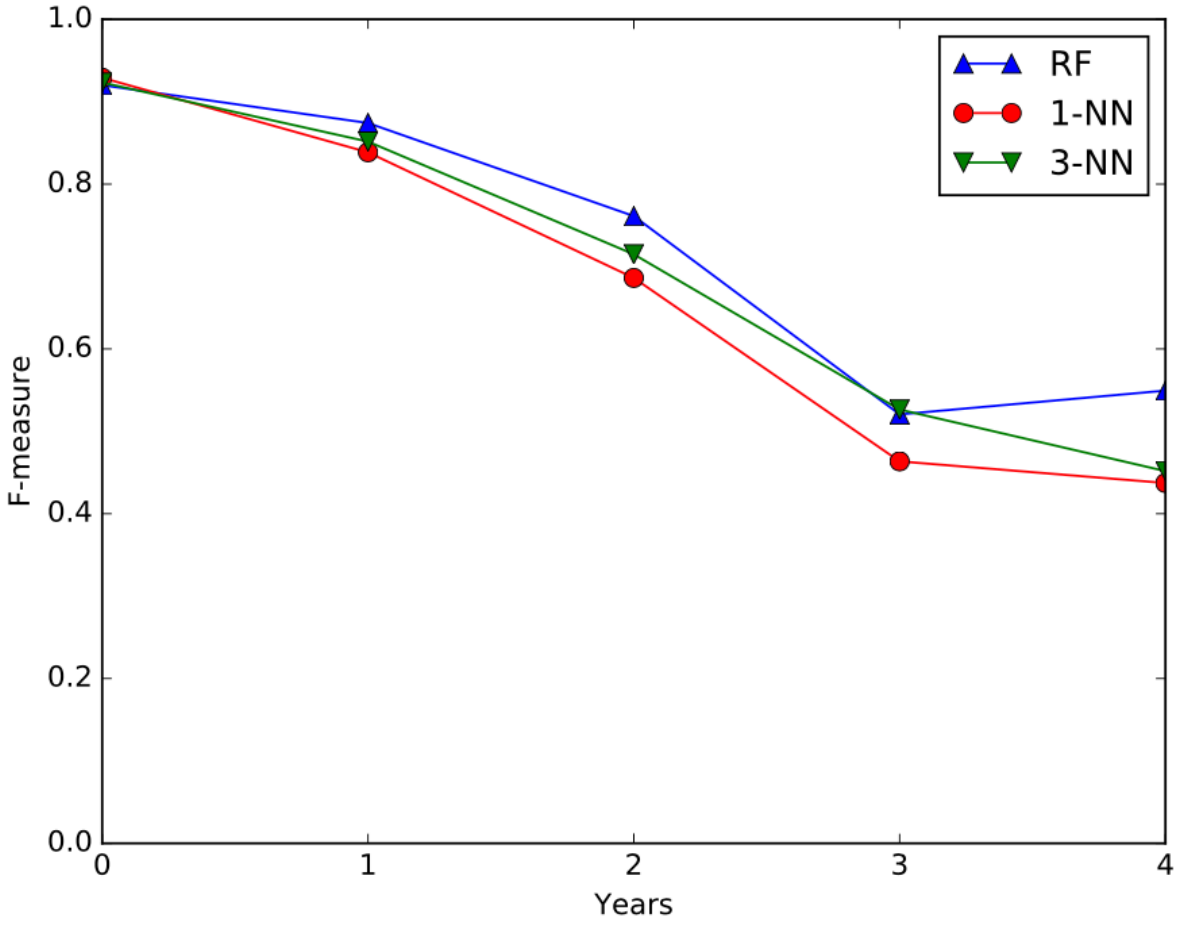
- Accuracy of classification on benign and malicious samples developed around the same time

- Robustness to the evolution of malware as well as of the Android framework (using older datasets for training and newer ones for testing and vice-versa)

# Same Year

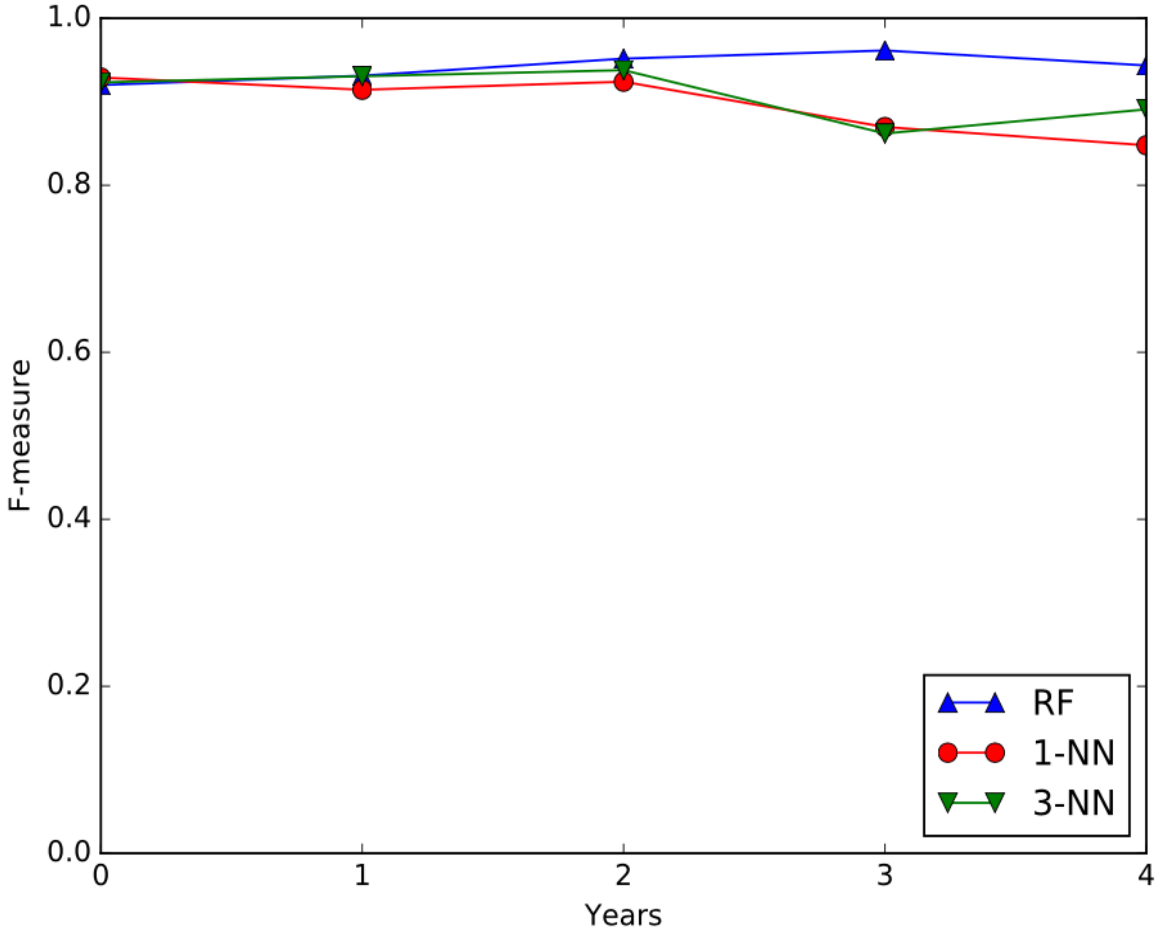

1.0
0.8
0.6
0.4
0.2
0.0
F-measure
RF
1-NN
3-NN
Family Drebin & OldBenign
Drebin & OldBenign
2013 & OldBenign
2014 & OldBenign
2014 & Newbenign
2015 & Newbenign
2016 & Newbenign

# Training on older samples




**Families abstraction**

# Training on newer samples




**Families abstraction**

# MaMaDroid Vs DroidAPIMiner

DroidAPIMiner is the previous work operating detection of malware samples from benign ones based on sequences of API calls.

| Tests | DroidAPIMiner | MaMaDroid |
|---|---|---|
| **Same Year** | 0.56 | 0.96 |
| **Older samples Training** | 0.42 | 0.68 |
| **Newer samples Training** | 0.50 | 0.96 |

# Discussion and Limitations

# Case Studies (2016/newbenign)

- **False Positives (164 samples)**
  - Most of them “dangerous permissions”
  - E.g., SMS permissions not clear why requested
- **False Negatives (114 samples)**
  - Actually not classified as malware by VirusTotal, might be legitimate
  - Most of them adware

# Evasion

- **Repackaging benign apps**
  - Difficult to embed malicious code while keeping similar Markov chain, viceversa is also hard
- **Imitating Markov chains**
  - Likely ineffective
- **Obfuscation/Mangling**
  - Still captured by the [obfuscated] abstraction
- **More in the paper**…

# Limitations

- Classification is memory hungry
- Soot is buggy, we lose ~4% of the samples
- Limits of static analysis only methods

# Future Work

- **Further investigate resilience to evasion**
  - Focus on repackaged malicious apps
  - Injection of API calls to mess with Markov chains
- **Enhancements**
  - Fine-grained abstractions (e.g., class)
  - Seed with dynamic analysis
- **Releasing**
  - MaMaDroid's python code
  - The list of used samples and their hashes
  - Parsed dataset

# Conclusions

• We created MaMaDroid, a system for android malware detection

• Static analysis only, based on Markov Chain modeling of sequences of API calls

• Up to 0.99 F-measure in tests, resilient to changes over time


*Enrico Mariconti*

Thanks for listening