

Automated Synthesis of Semantic Malware Signatures using MaxSAT



*Yu
Feng*



*Osbert
Bastani*



*Ruben
Martins*



*Isil
Dillig*



*Saswat
Anand*



NDSS'17, San Diego

Newly Found Malware can steal bank details on Android phones



by **Ali Raza**
9 months ago



<https://www.hackread.com/malware-can-steal-bank-details-android-phones/>

Hundreds Of Operations Canceled After Malware Hacks Hospitals Systems

Thursday, November 03, 2016 Mohit Kumar

94 Like 3.3K Share 1187 Tweet 529 Share 279 share 2068



<http://thehackernews.com/2016/11/hospital-cyber-attack-virus.html>

Android Malware Used to Hack and Steal a Tesla Car

By [Catalin Cimpanu](#)

November 25, 2016 06:05 AM 2



<http://www.bleepingcomputer.com/news/security/android-malware-used-to-hack-and-steal-a-tesla-car/>

Statistics

<https://www.symantec.com/content/dam/symantec/docs/reports/istr-21-2016-en.pdf>

<http://www.mcafee.com/us/resources/reports/rp-mobile-threat-report-2016.pdf>

Statistics

37M

Total count of malware
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Hundreds of signatures

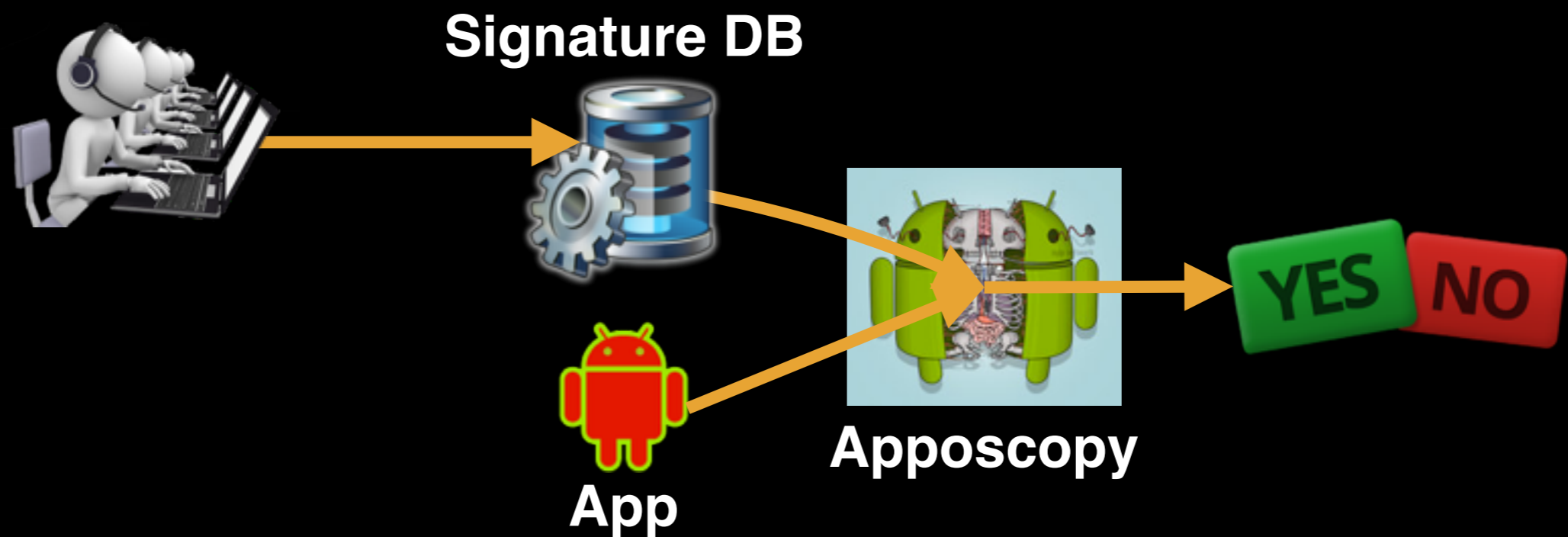


Millions of samples

<https://www.symantec.com/content/dam/symantec/docs/reports/istr-21-2016-en.pdf>

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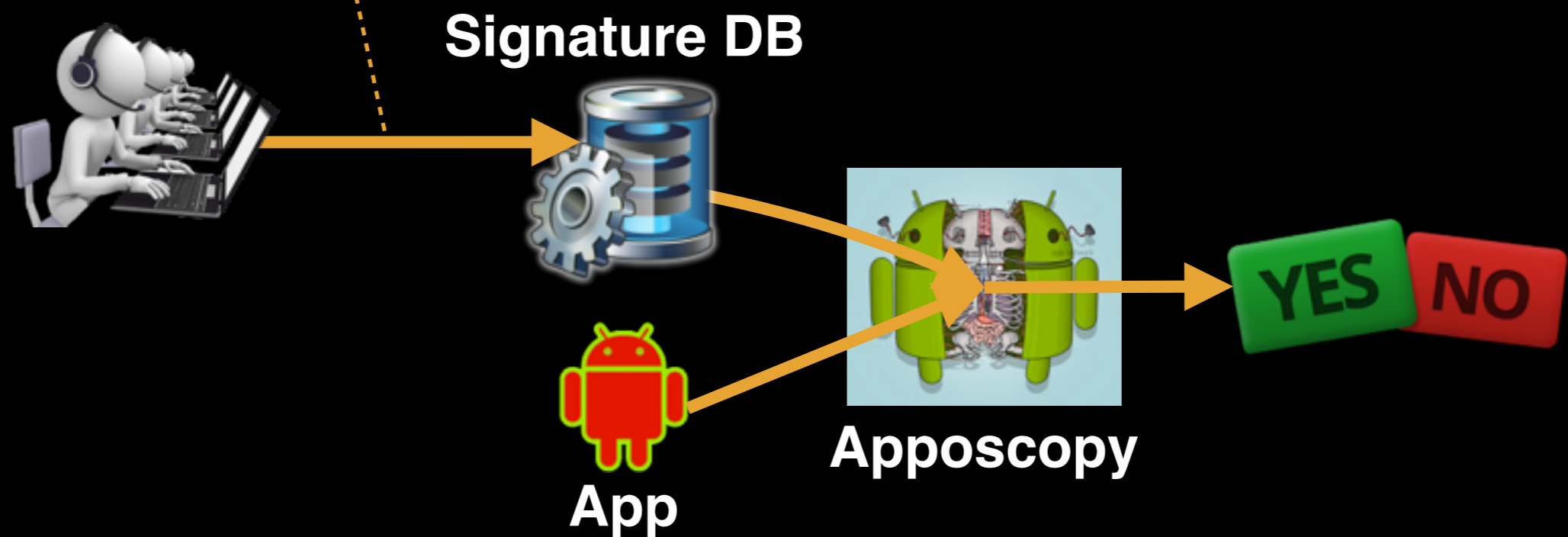
Apposcopy Overview



Feng, et al. FSE'14

Apposcopy Overview

A high-level language for describing semantic properties of malware

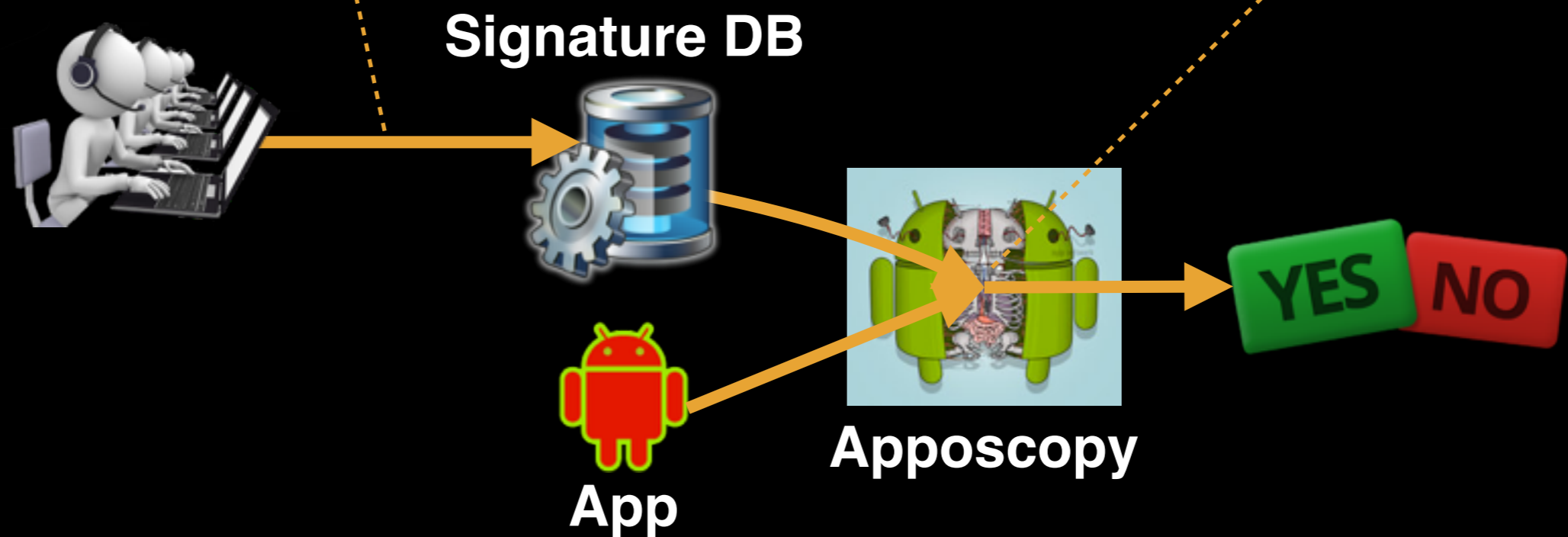


Feng, et al. FSE'14

Apposcopy Overview

A high-level language for describing semantic properties of malware

A novel static analysis for deciding if an app matches the signature of a family



Feng, et al. FSE'14

Caveats

Caveats



Writing signatures
is tedious

Caveats

Monkey Test & Time Service

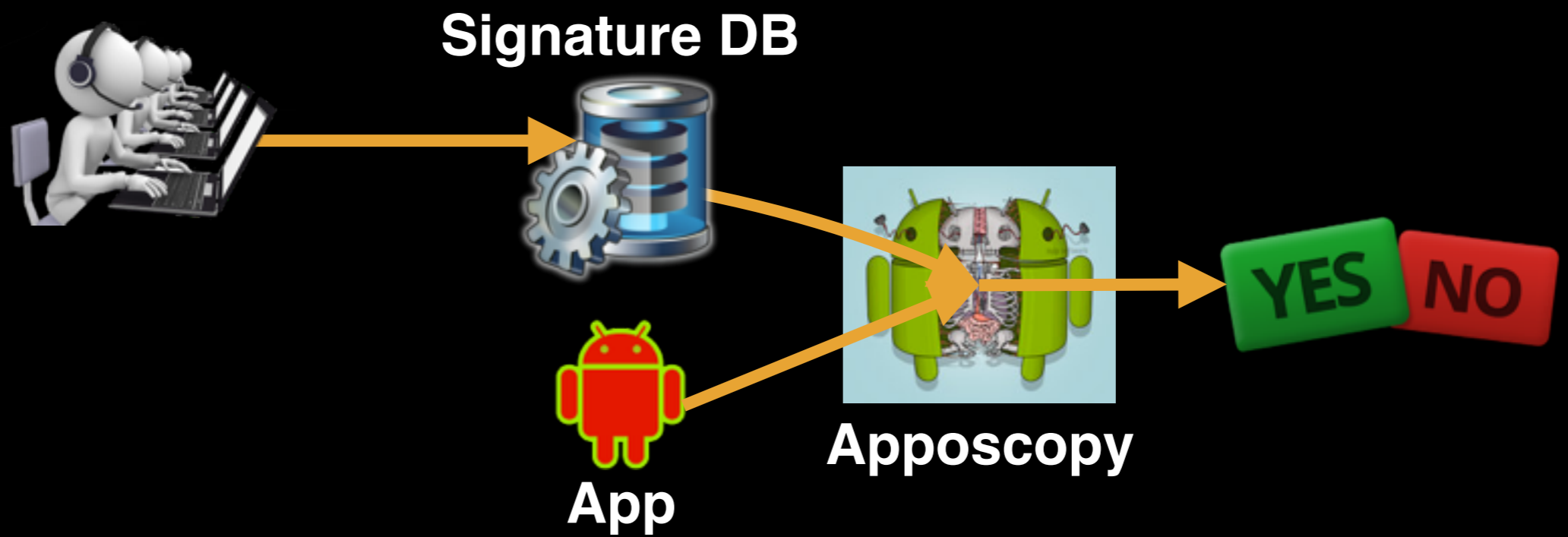


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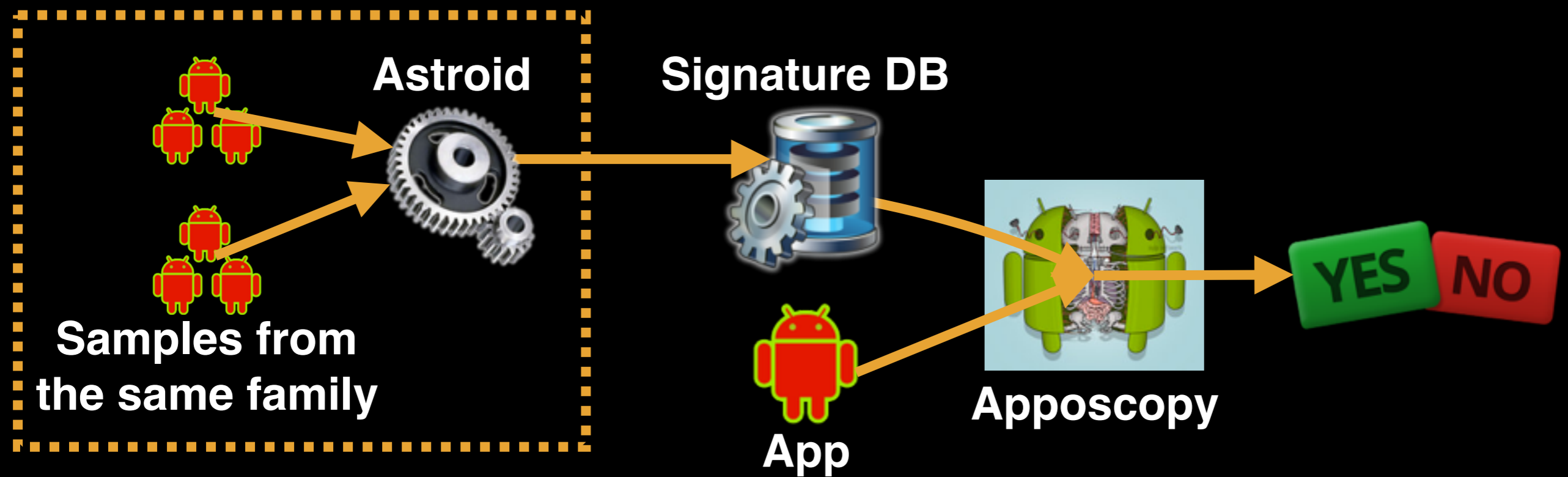
Vulnerable to
semantic obfuscation

Goal



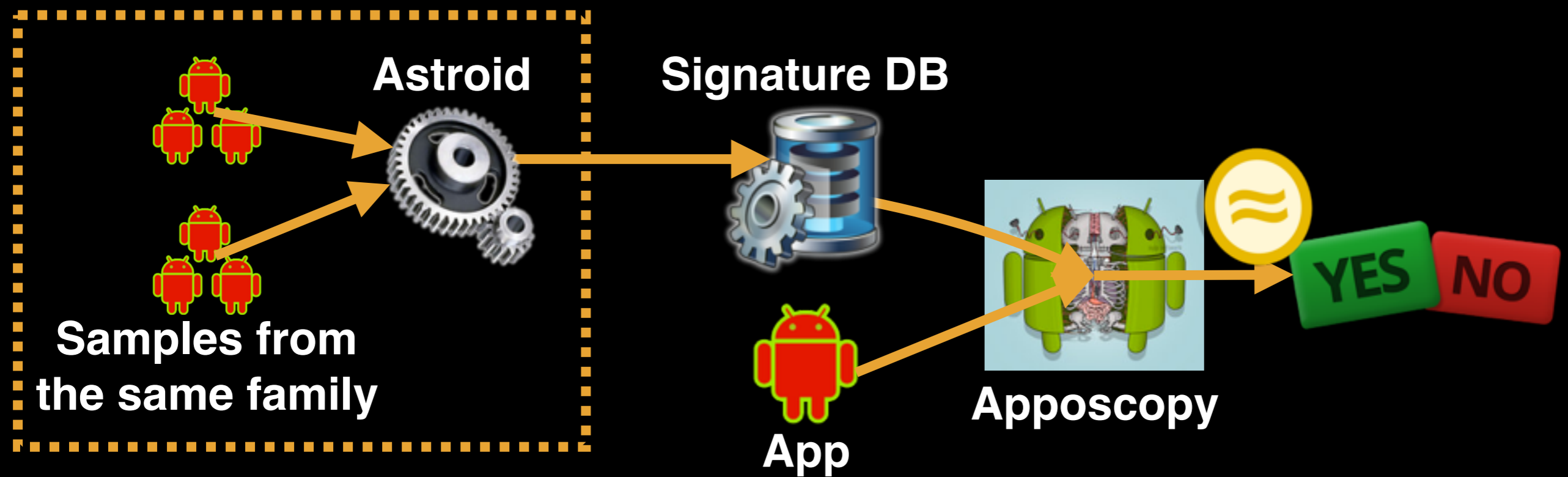
Goal

- Infer a signature from few samples of a malware family



Goal

- Infer a signature from few samples of a malware family
- Approximate matching algorithm that is resistant to semantic obfuscation



Our Signature in a Nutshell

*Inter-Component
Call Graph*

*Feng, et al. FSE'14
Feng, et al. OOPSLA'15*

Our Signature in a Nutshell



Activity1

*Inter-Component
Call Graph*



ANDROID

Android

Feng, et al. FSE'14
Feng, et al. OOPSLA'15

Our Signature in a Nutshell



Activity1



Activity2

*Inter-Component
Call Graph*



ANDROID

Android

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Our Signature in a Nutshell



Feng, et al. FSE'14
Feng, et al. OOPSLA'15

Our Signature in a Nutshell



Solid line: control property
Dashed line: data property

Feng, et al. FSE'14
Feng, et al. OOPSLA'15

Our Signature in a Nutshell



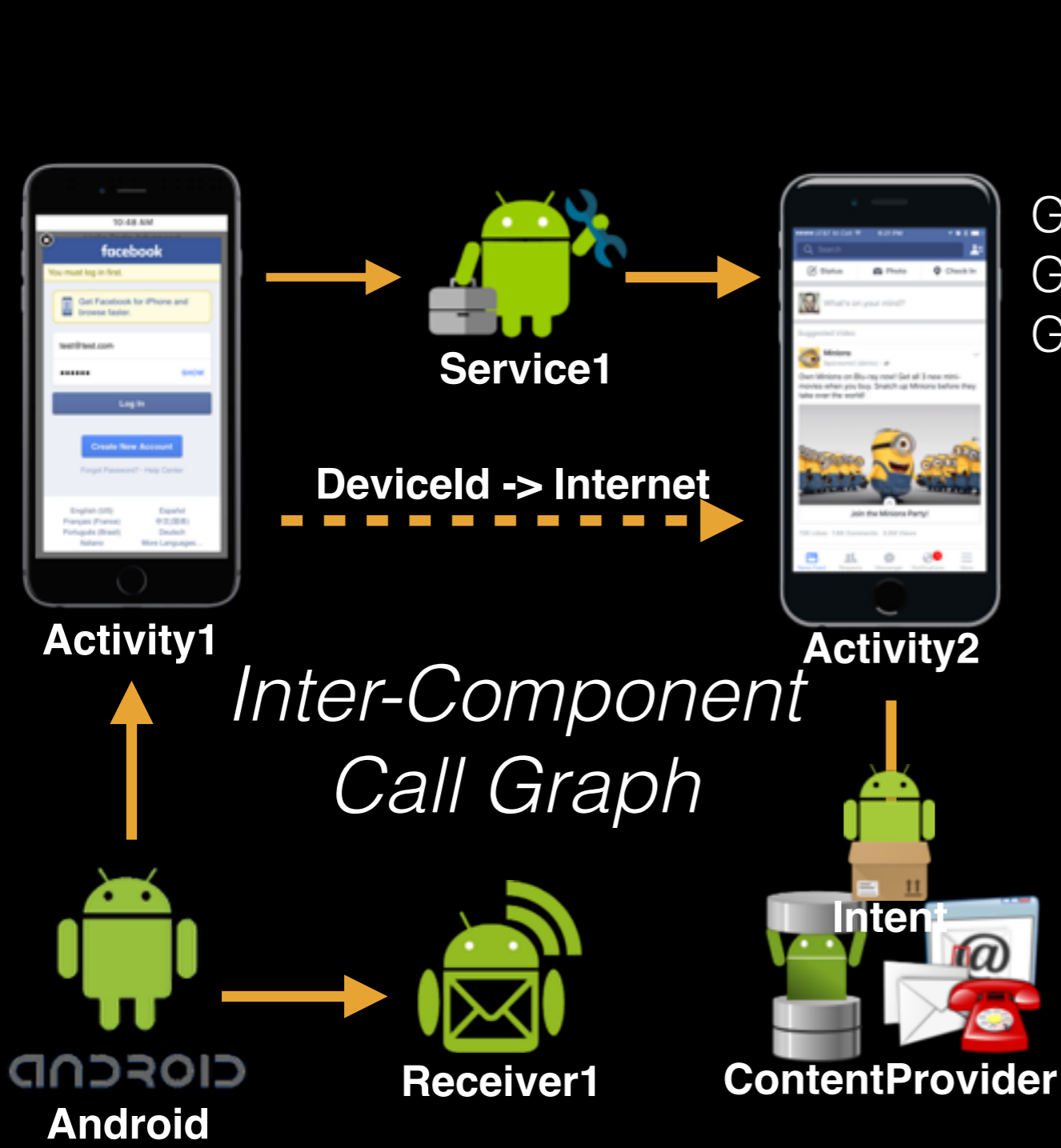
GDEvent(SMS_RECEIEVED).
 GDEvent(NEW_OUTGOING_CALL).
 GoldDream :- **receiver(r)**,
 icc(SYSTEM, r, e, _), GDEvent(e),
 service(s), **icc*(r, s)**,
 flow(s, Deviceld, s, Internet),
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GoldDream Signature

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Dashed line: data property

Feng, et al. FSE'14
 Feng, et al. OOPSLA'15

Our Signature in a Nutshell



Component Predicate

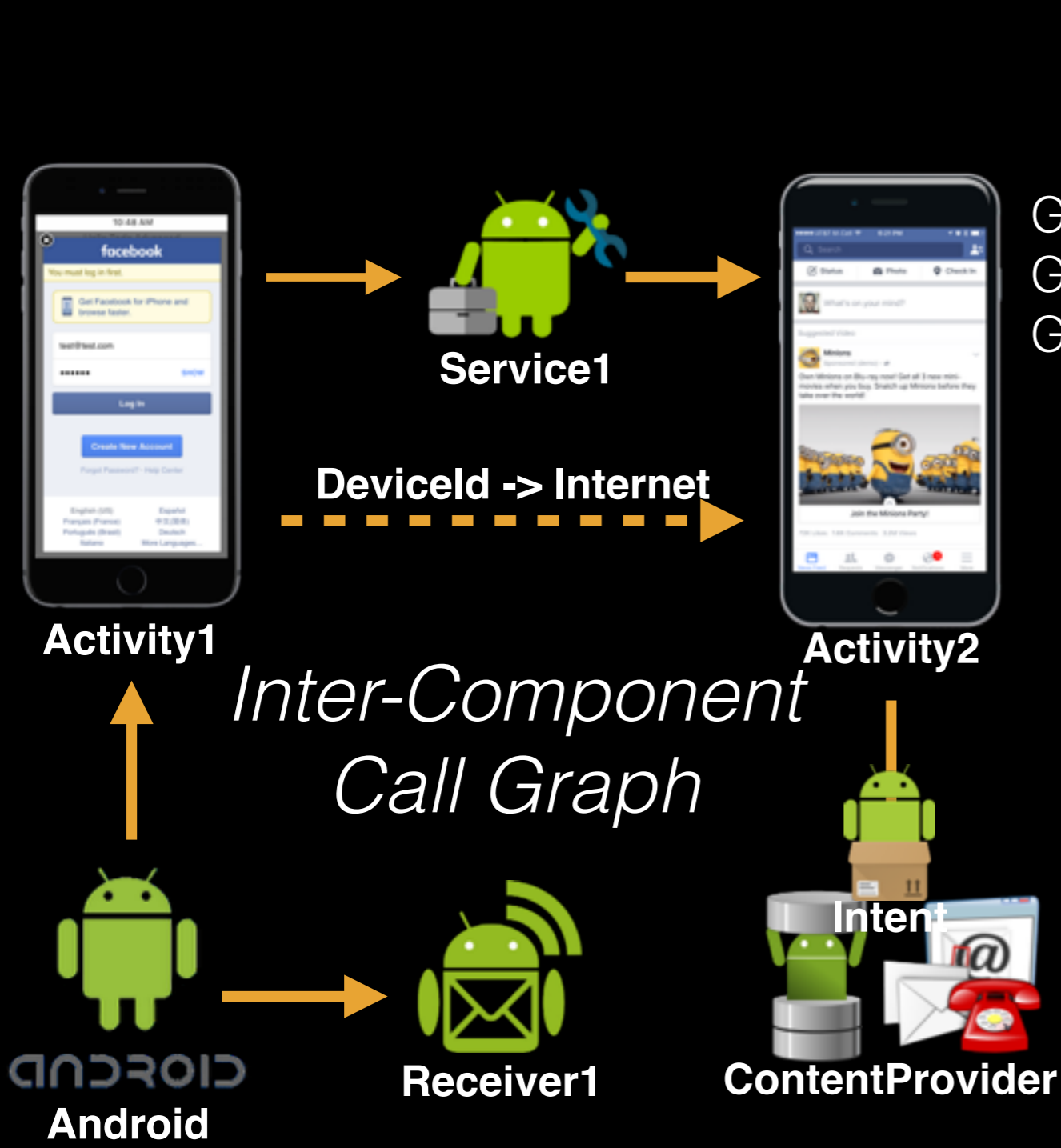
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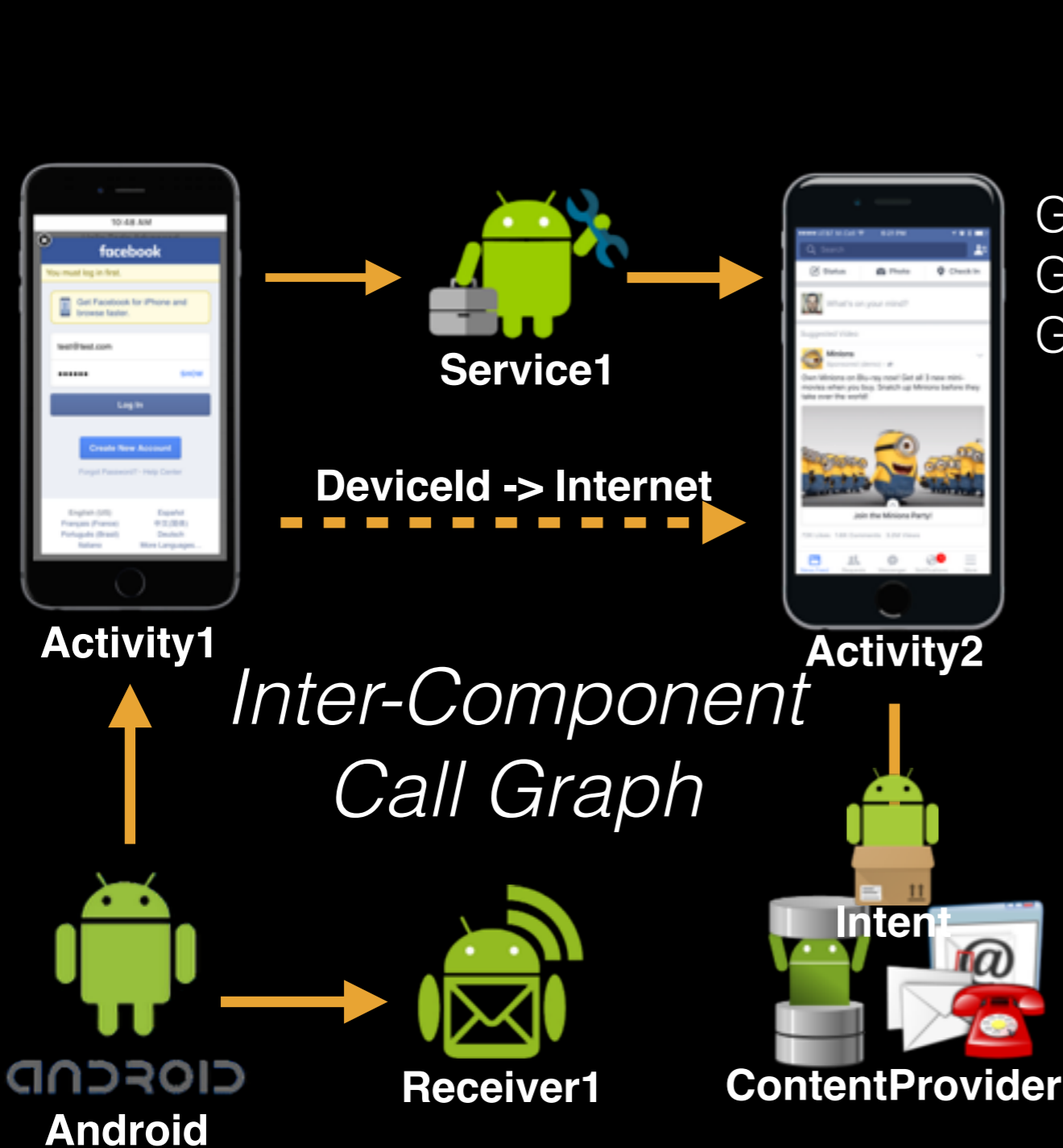
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Our Signature in a Nutshell



Component Predicate

Control Predicate

Flow Predicate

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GoldDream Signature

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Signature Inference

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Given n malware samples from family F , compute its signature S

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Any signature that matches n samples

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Empty signature could also be a solution!

Insight

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Given n malware samples from family F , compute its signature S

- Our candidate S should be

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 - Maximally suspicious to minimize false positives

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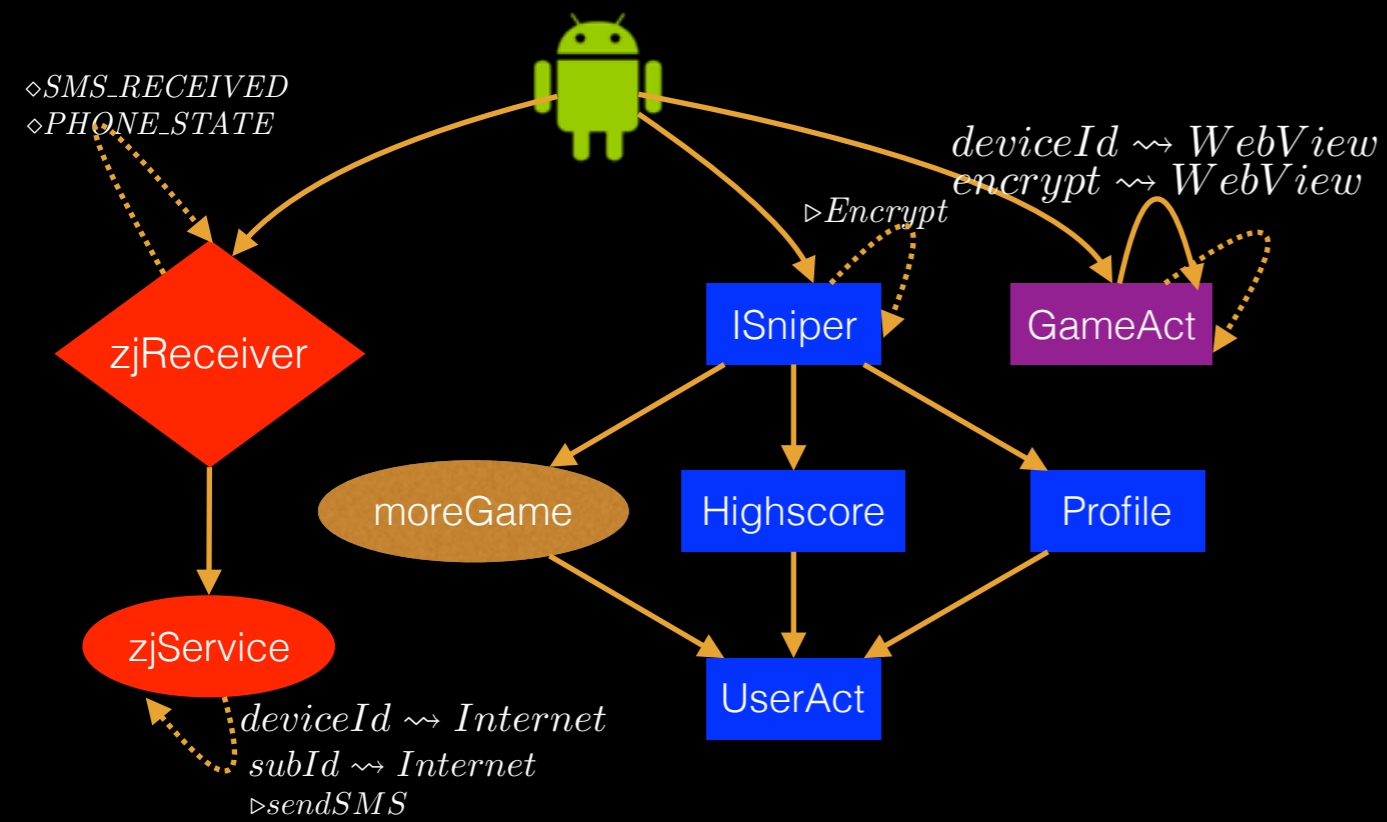
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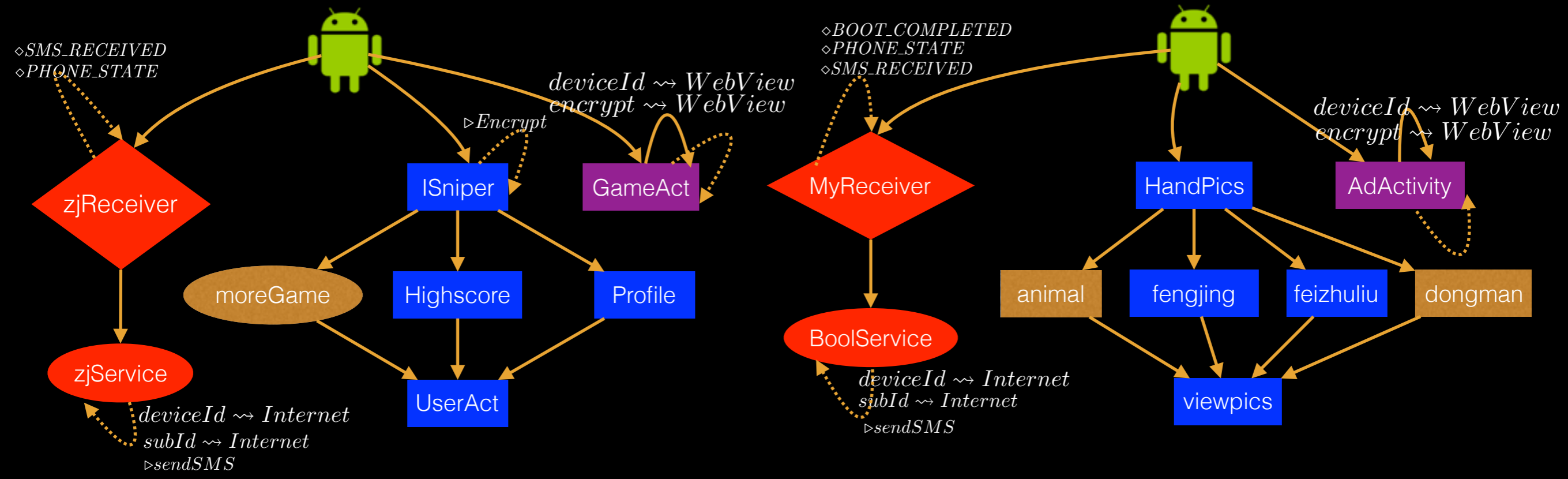
Infer signatures by finding a Maximally Suspicious Common Subgraph of n malware samples

Example

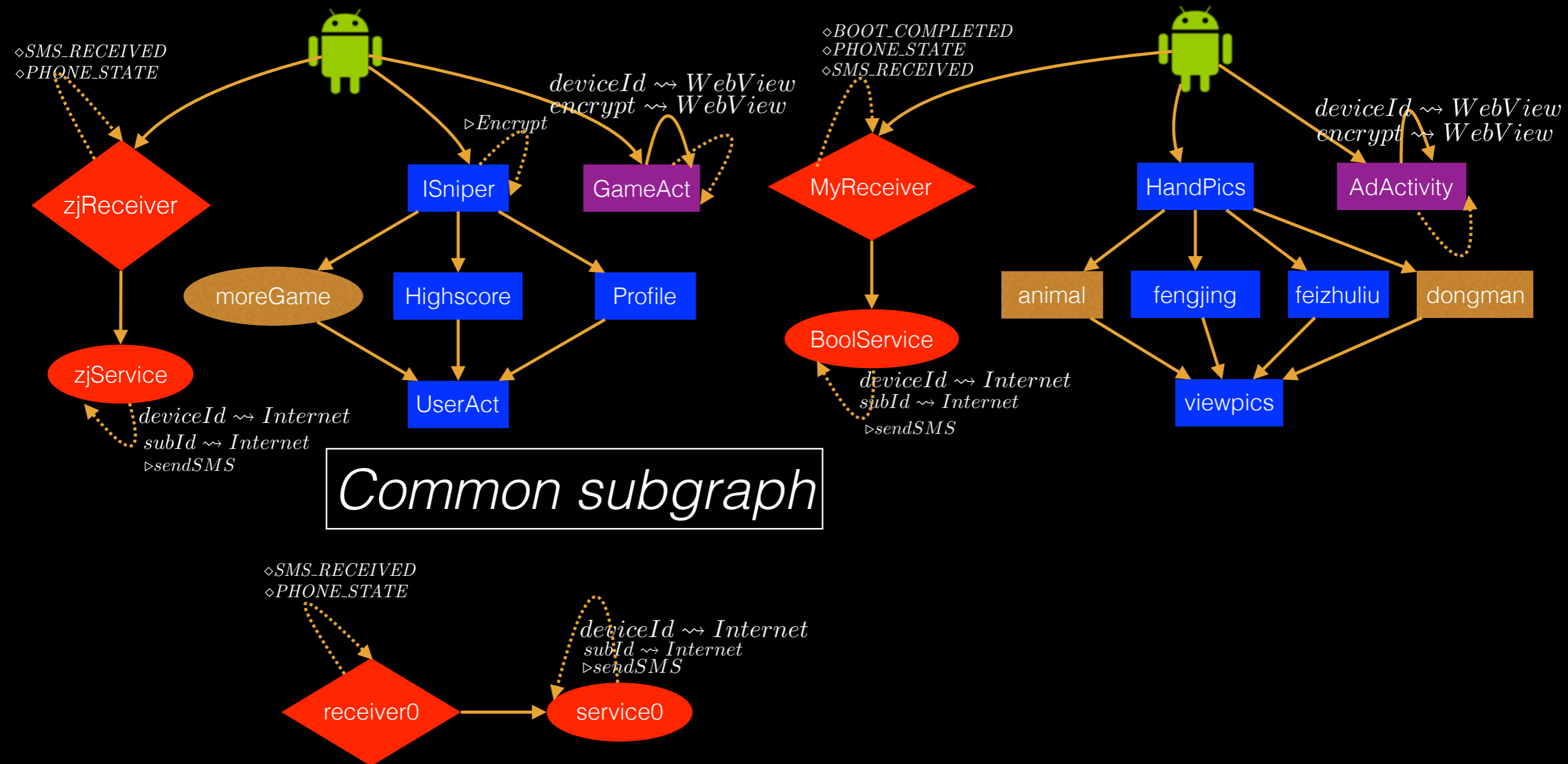
Example



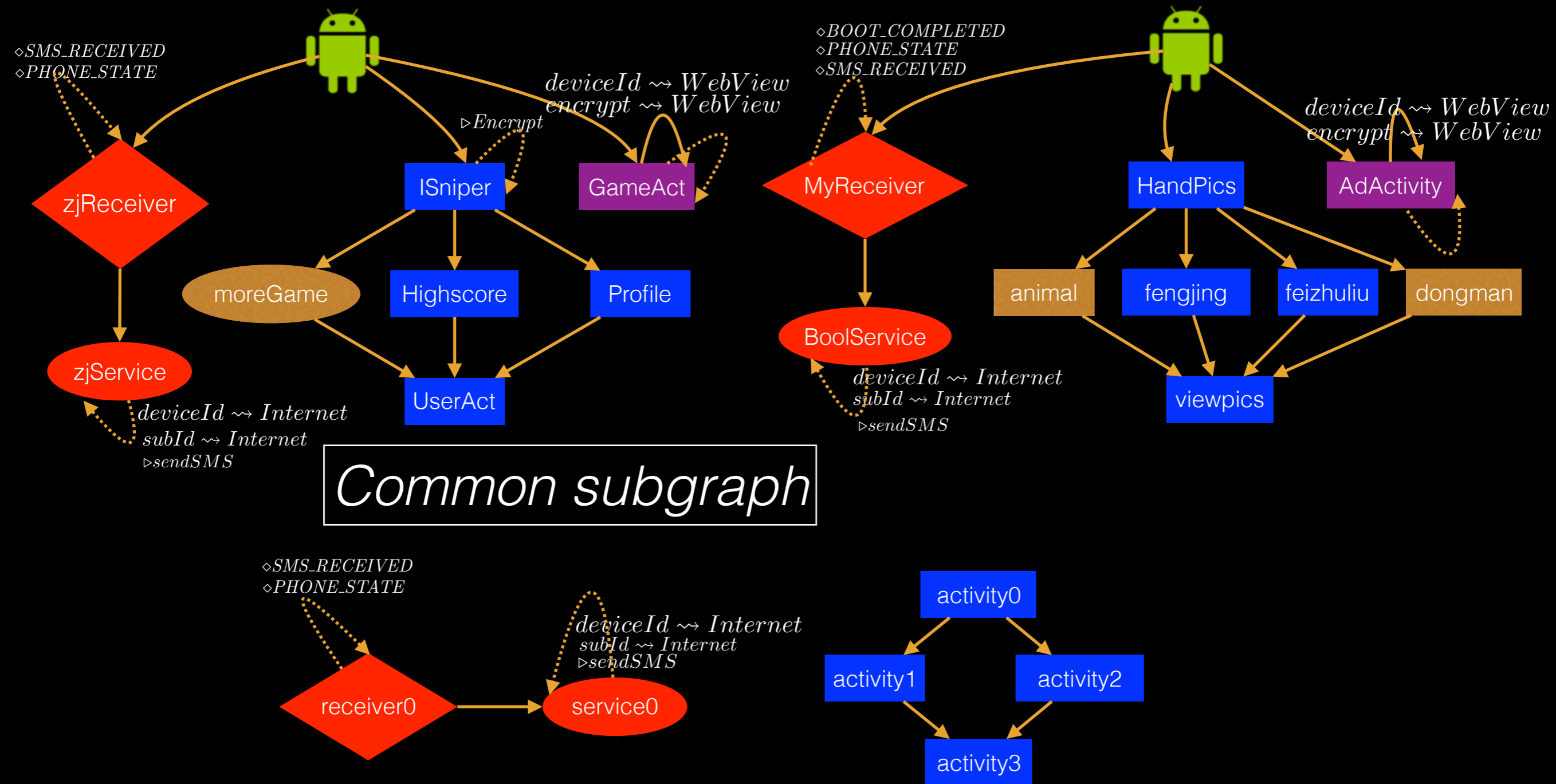
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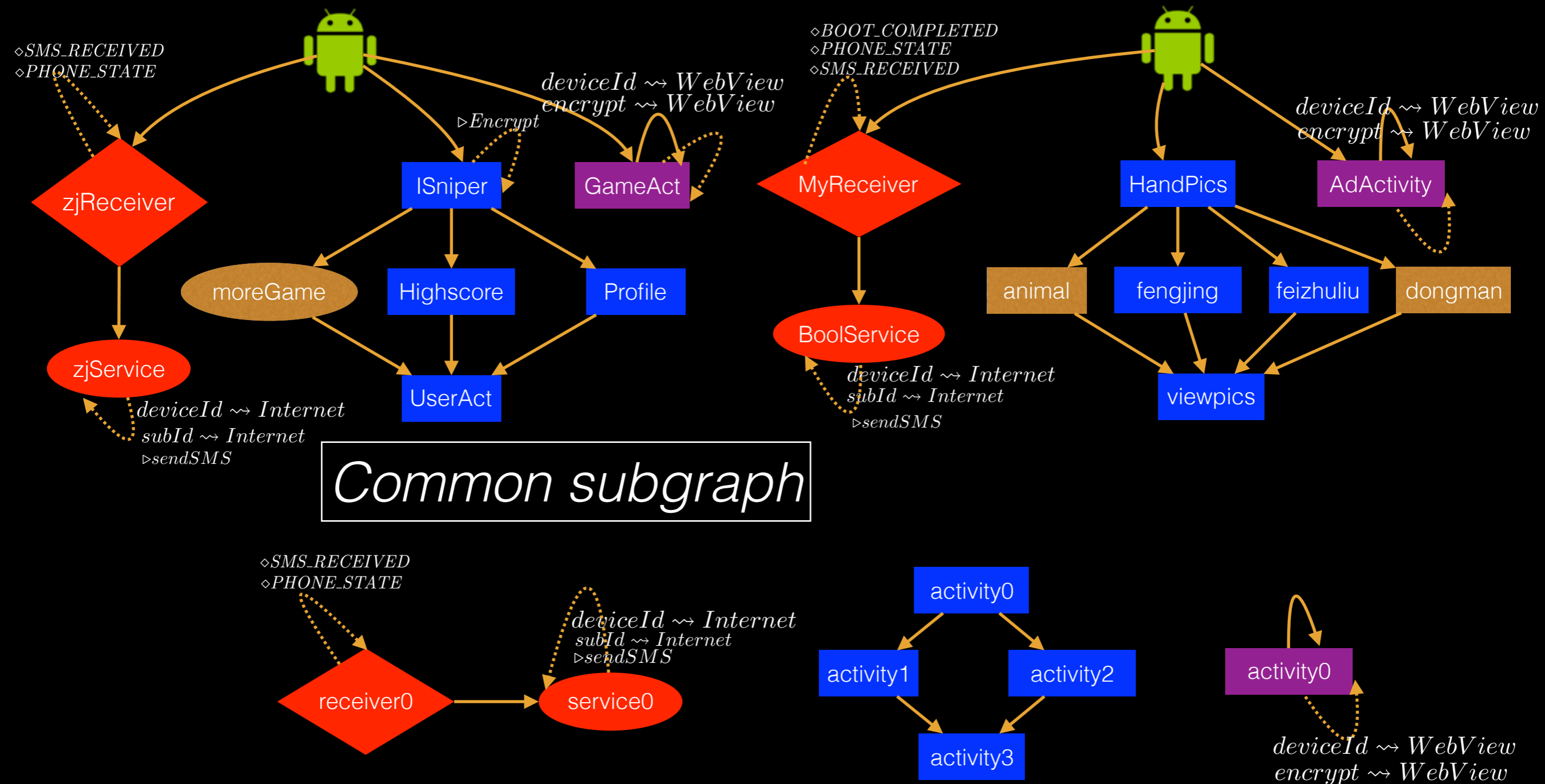
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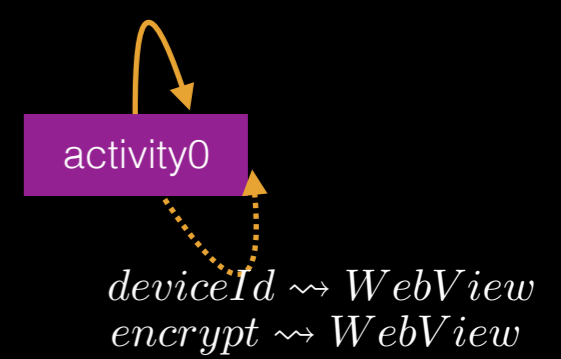
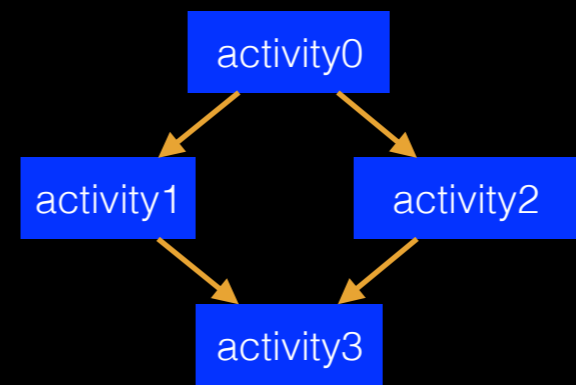
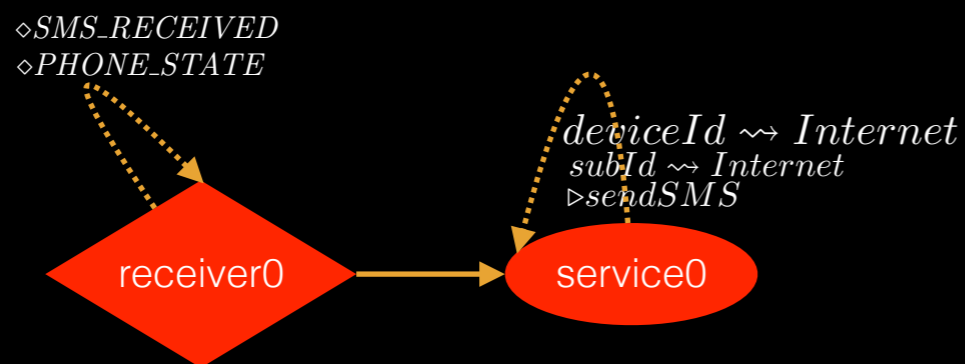
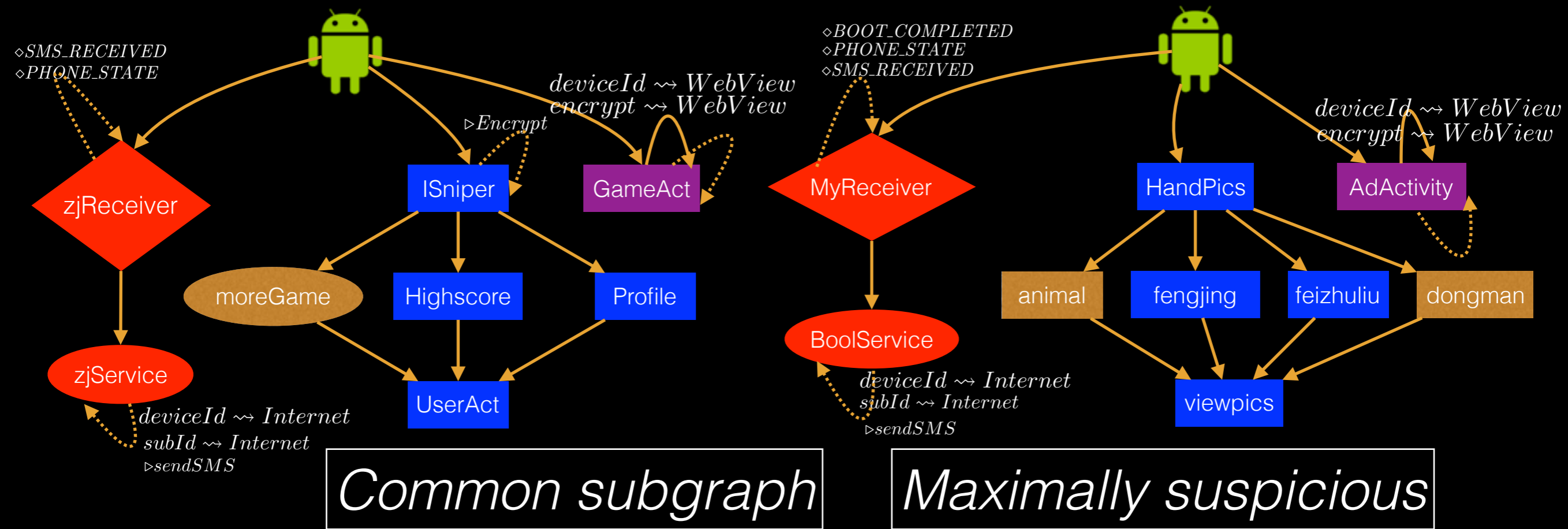
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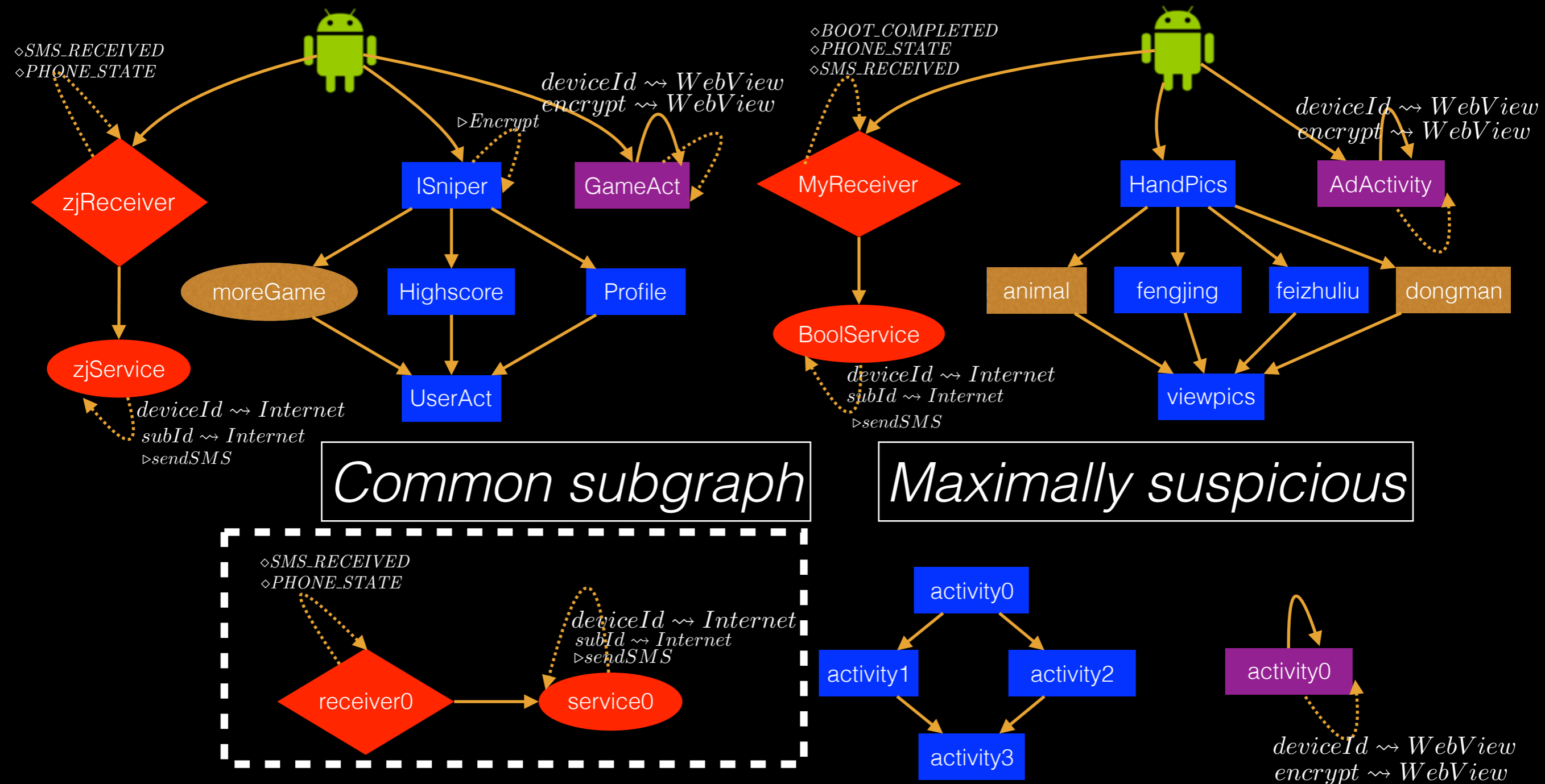
Example



Example



Example



How to infer the signature



*Infer signatures by finding a
Maximally Suspicious Common
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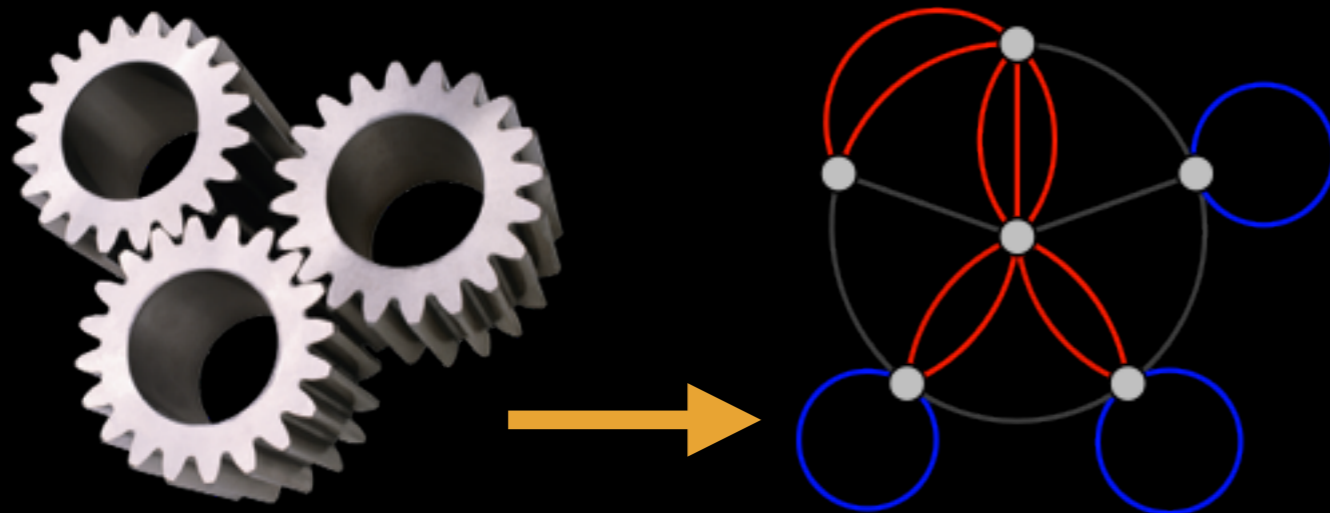


Signature
Inference

How to infer the signature



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Signature
Inference

MSCS

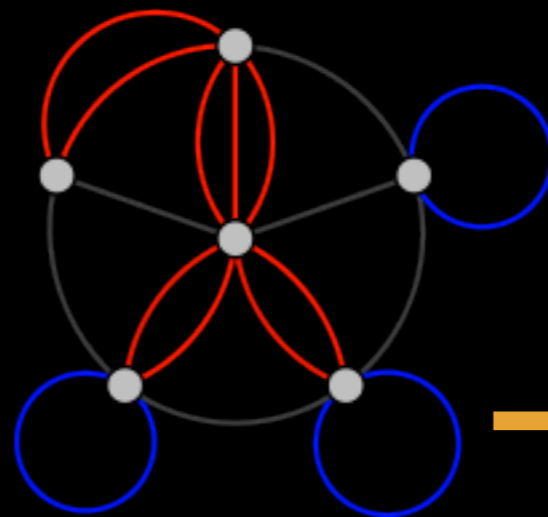
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Signature
Inference



MSCS



MaxSat

MaxSat in a nutshell

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MaxSat: Given a UNSAT boolean formula in CNF, determine the maximum number of satisfied clauses

$$(x_0 \vee x_1) \wedge (\neg x_0 \vee x_1) \wedge (x_0 \vee \neg x_1) \wedge (\neg x_0 \vee \neg x_1)$$

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Find an assignment s.t. the total weight of satisfied clauses is maximized

$$\{x_0 \mapsto 0, x_1 \mapsto 0\}$$

Synthesis using MaxSat

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- Hard Clause: common subgraph (control-flow property)

Synthesis using MaxSat

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- Soft Clause: maximally suspiciousness (data-flow property)

Synthesis using MaxSat

- Hard Clause: common subgraph (control-flow property)
- Soft Clause: maximally suspiciousness (data-flow property)
- Weight for each clause
 - Inverse frequency from benign samples
 - Higher weight to features that are commonly found in malware

$$\mathcal{O} = \sum_{v, v' \in V} x_0(v, v') + \sum_{v, v' \in V} \sum_{d \in \mathcal{D}} w_{(v, v', d)} y_0(v, v', d).$$

Hard *Soft*

Example, cont.

$$\mathcal{O} = \sum_{v,v' \in V} x_0(v,v') \underset{\text{Hard}}{+} \sum_{v,v' \in V} \sum_{d \in \mathcal{D}} w_{(v,v',d)} y_0(v,v',d) \underset{\text{Soft}}{.}$$

Example, cont.

Control properties

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Control properties

Data properties

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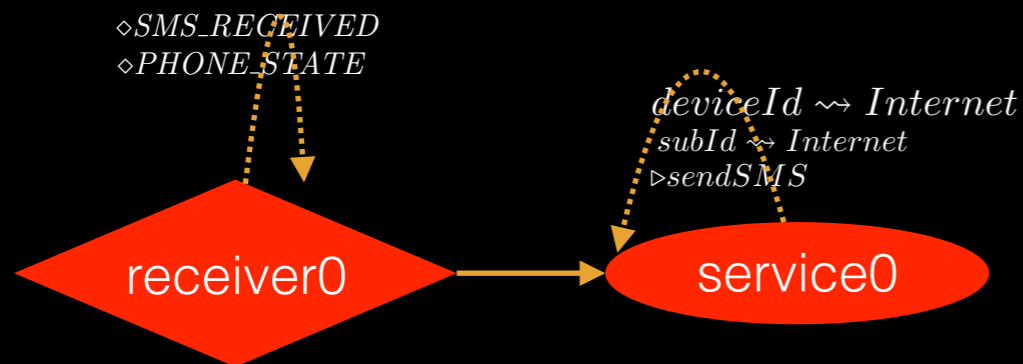
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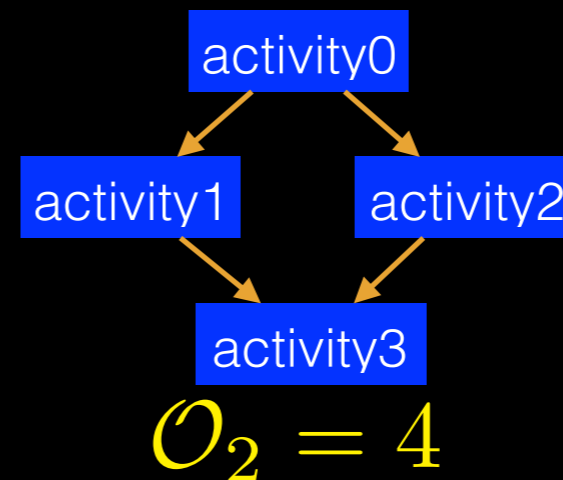
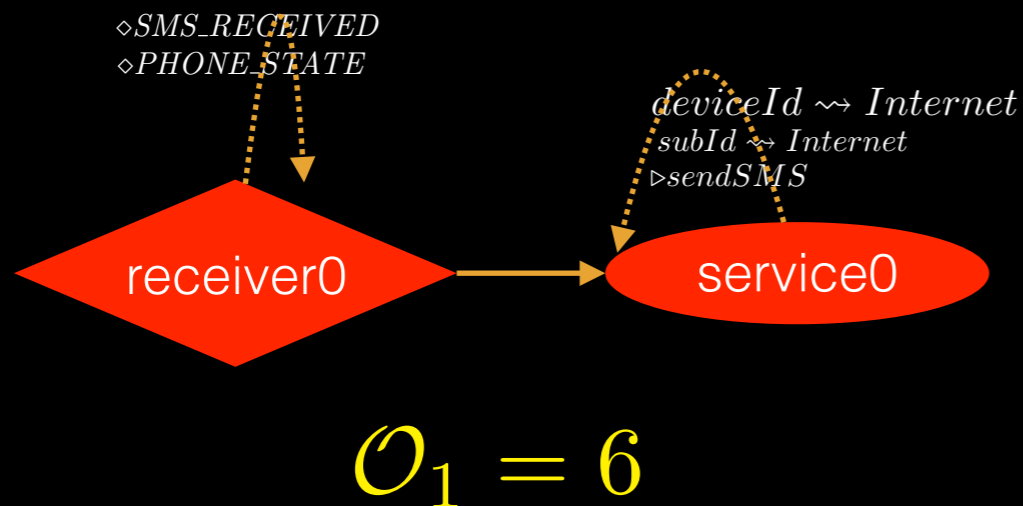
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Example, cont.

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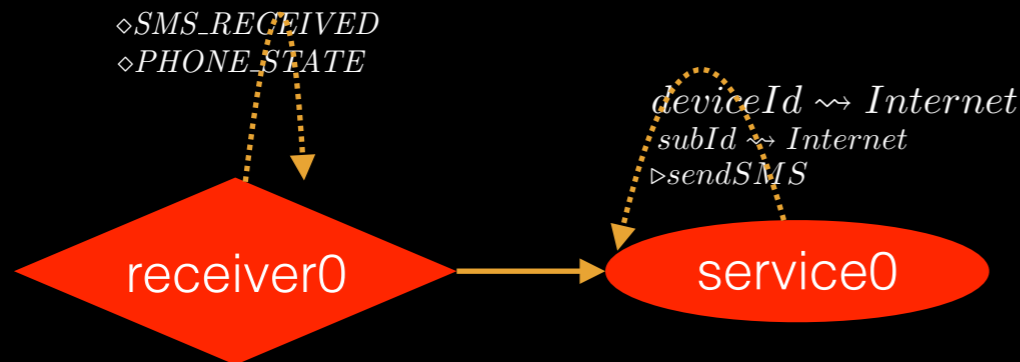


Example, cont.

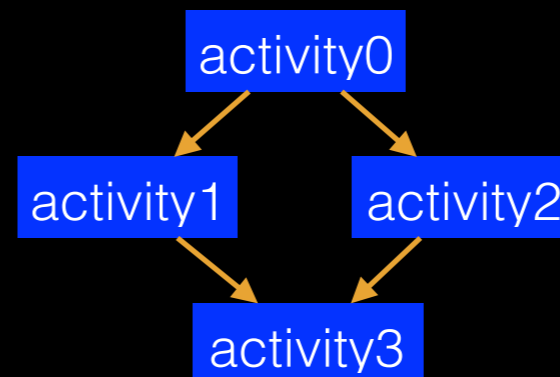
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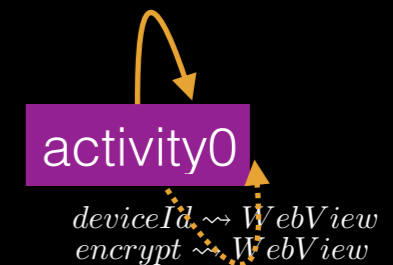
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$$\mathcal{O}_1 = 6$$



$$\mathcal{O}_2 = 4$$



$$\mathcal{O}_3 = 3$$

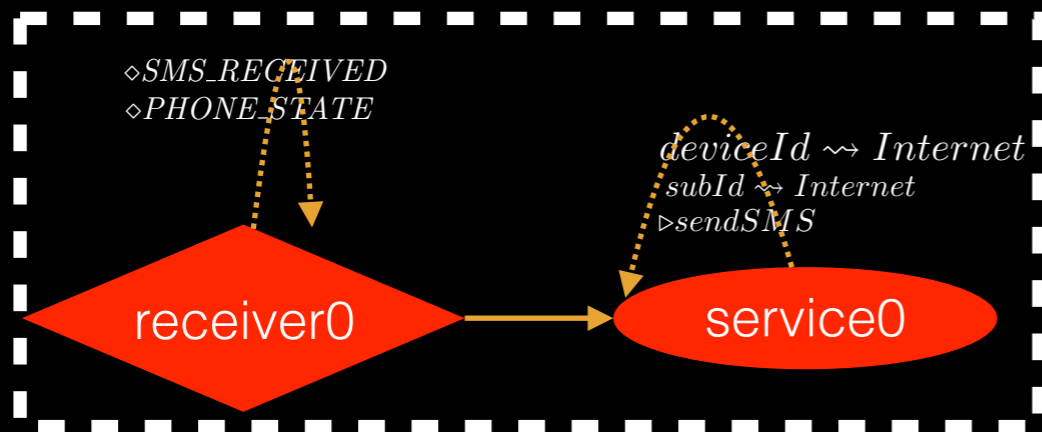
Example, cont.

Control properties

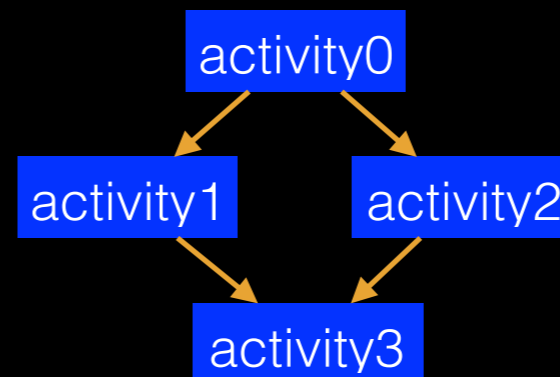
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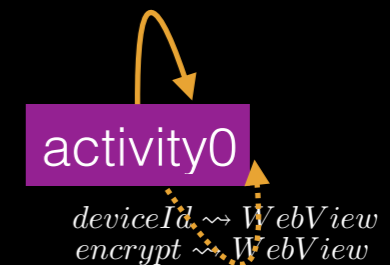
Hard
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Approximate matching

Now that we have the signature...

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Utilize existing signature inference algorithm to decide if a sample A belongs to a family F :

Approximate matching

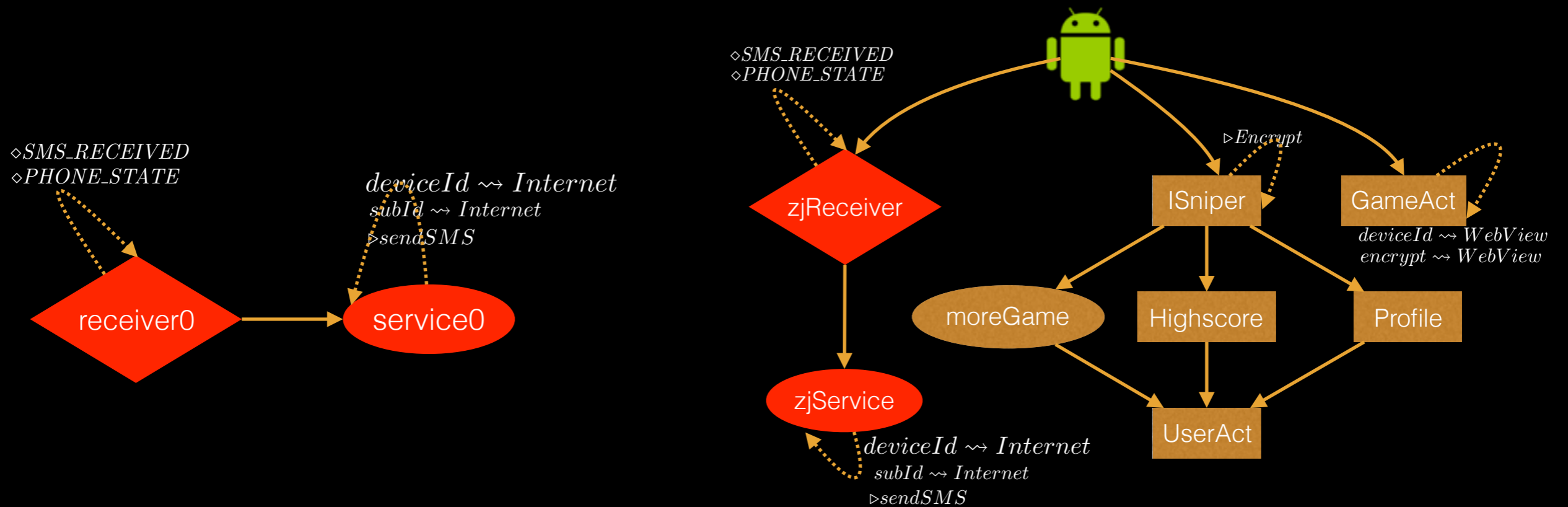
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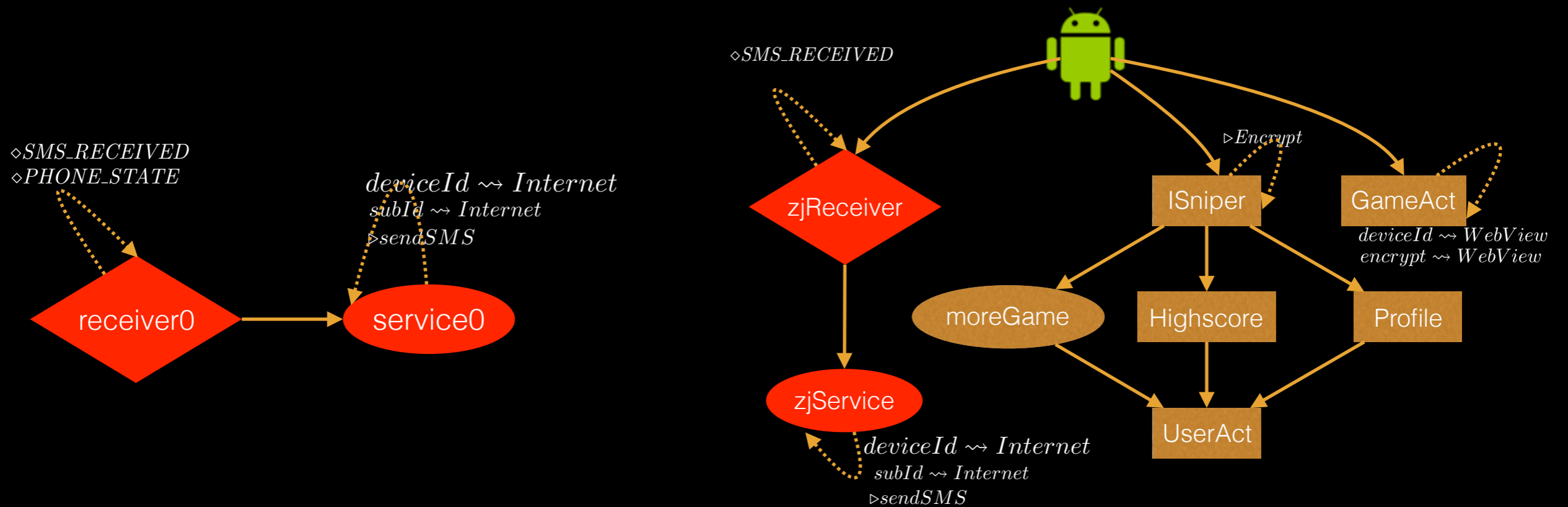
$$\delta(\mathcal{A}, \mathcal{F}) = \frac{f(\text{INFERSIGNATURE}(\mathcal{A}, \mathcal{S}_{\mathcal{F}}))}{f(\mathcal{S}_{\mathcal{F}})}$$

$f(S)$: *Weighted sum of the number of nodes and edges in S*

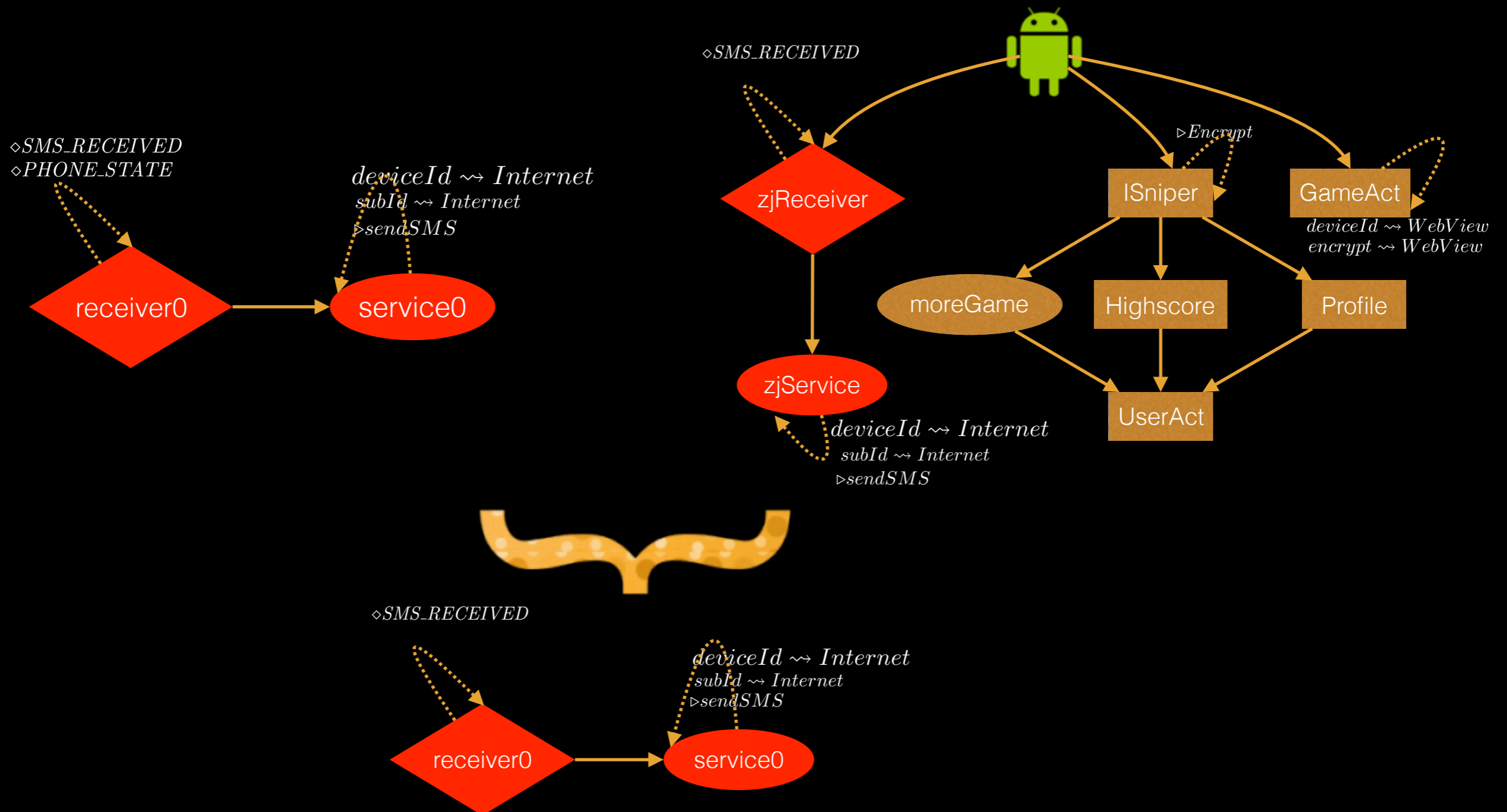
Example, cont.



Example, cont.



Example, cont.



Example, cont.

Example, cont.



Example, cont.



Resistant to semantic obfuscation!

Evaluation

Evaluation

- RQ1: How do the signatures synthesized by Astroid compare with manual version?

Evaluation

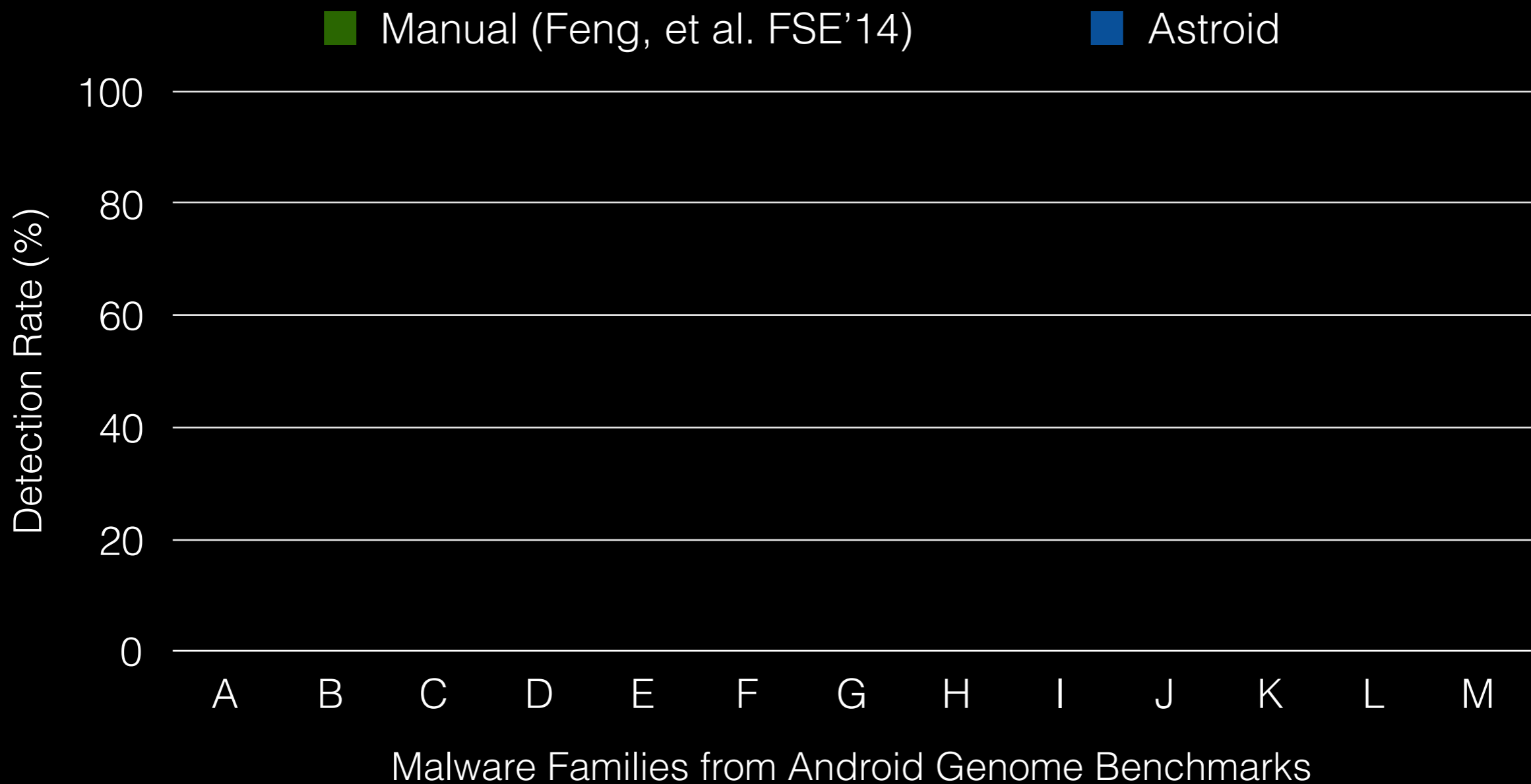
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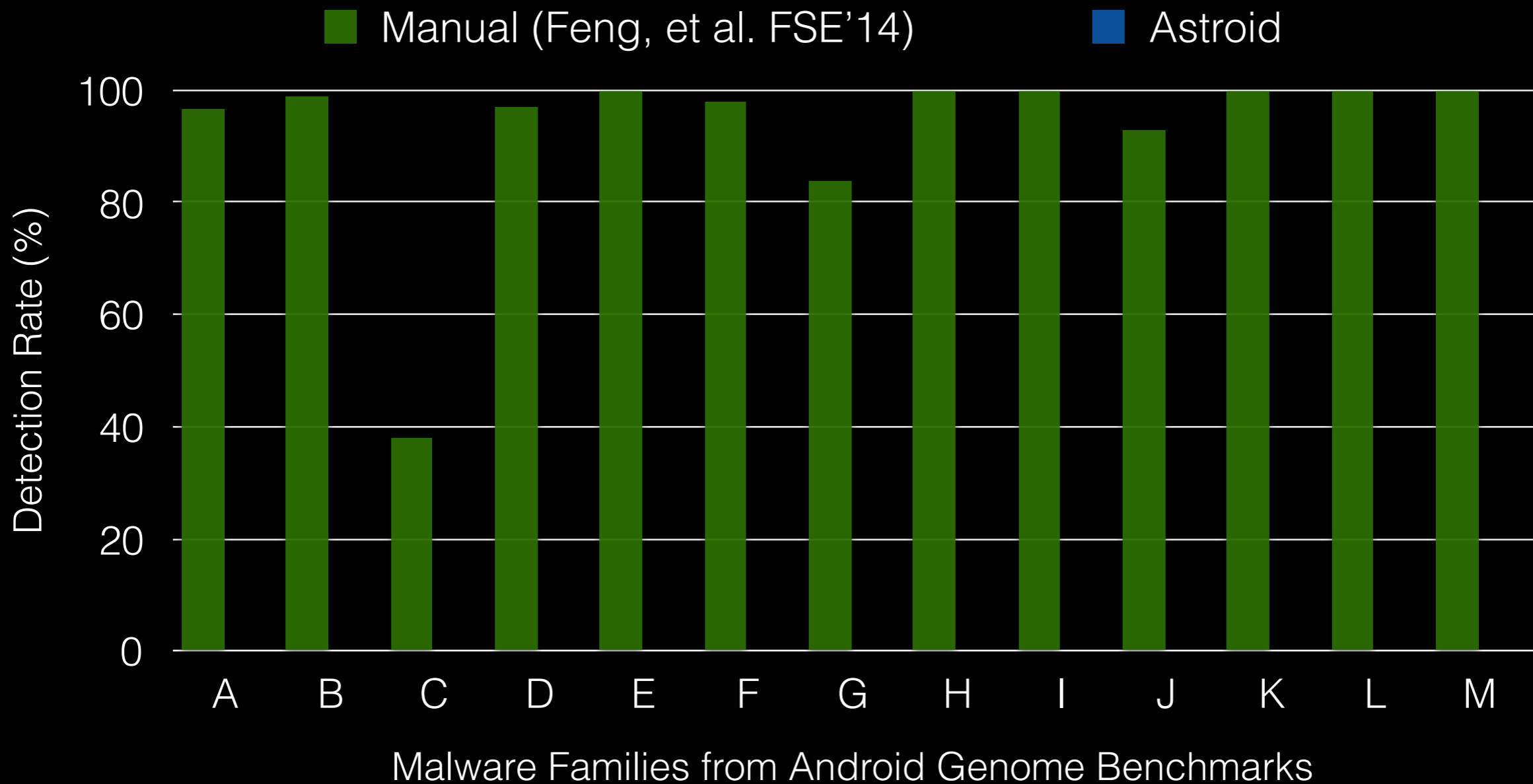
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Manual v.s. Automated

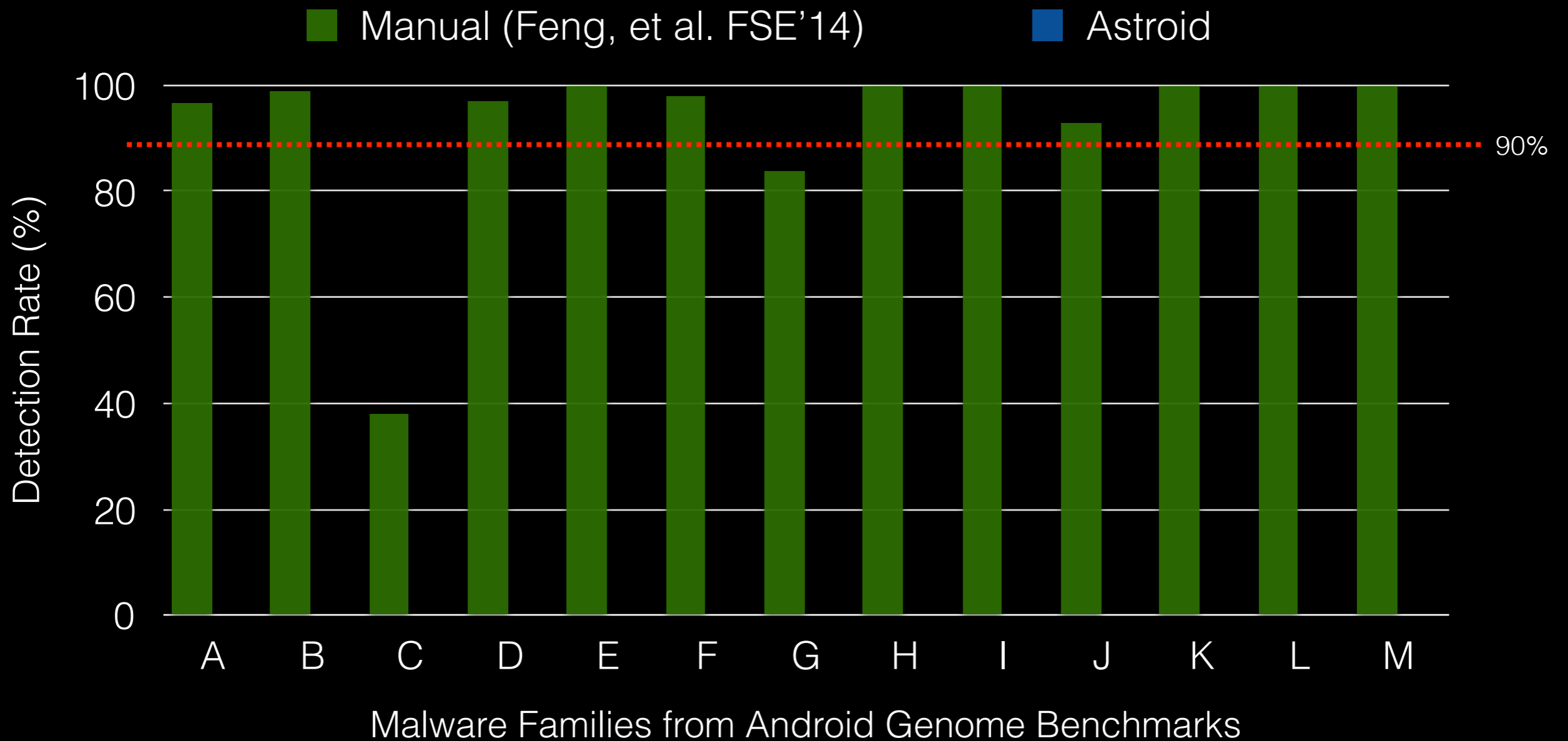
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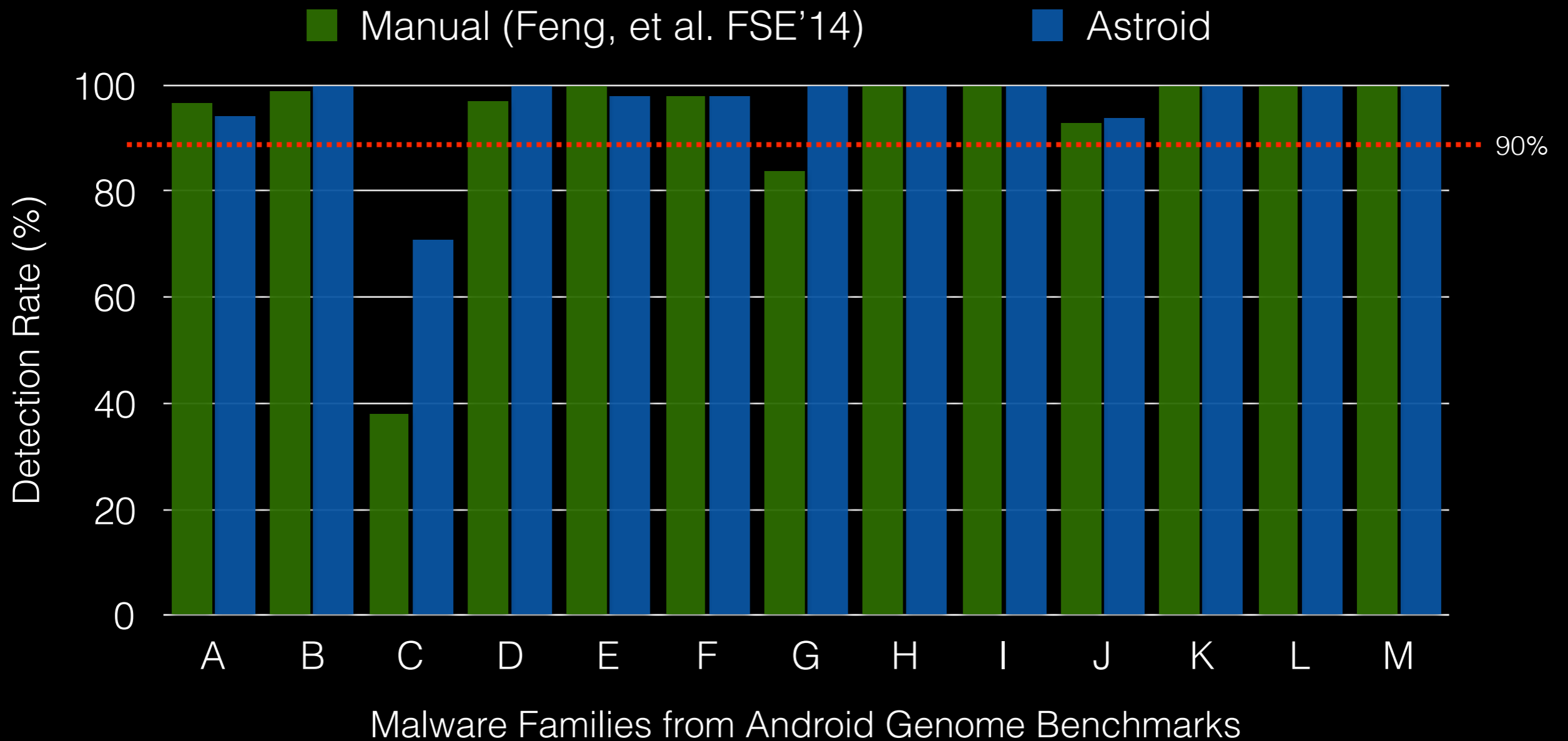
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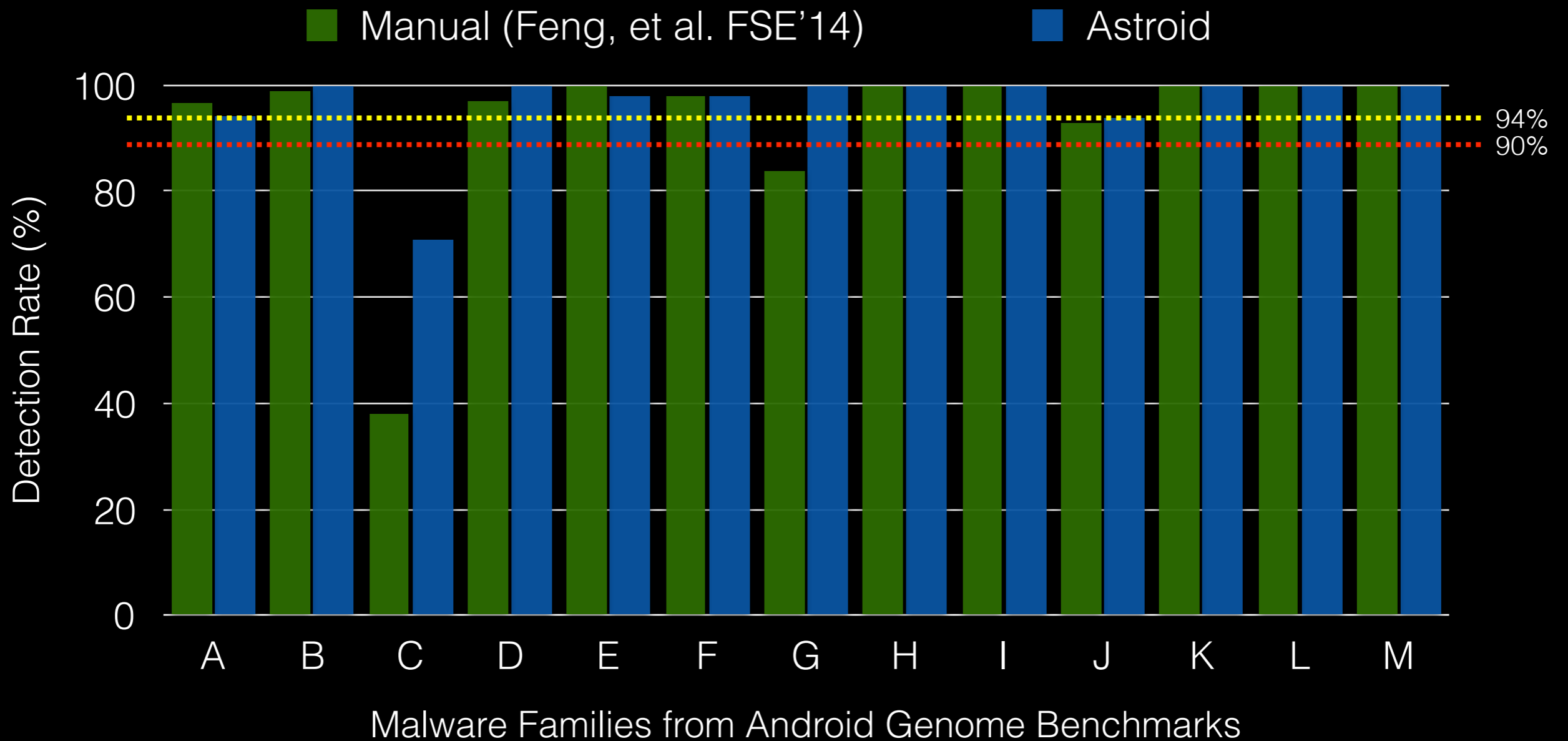
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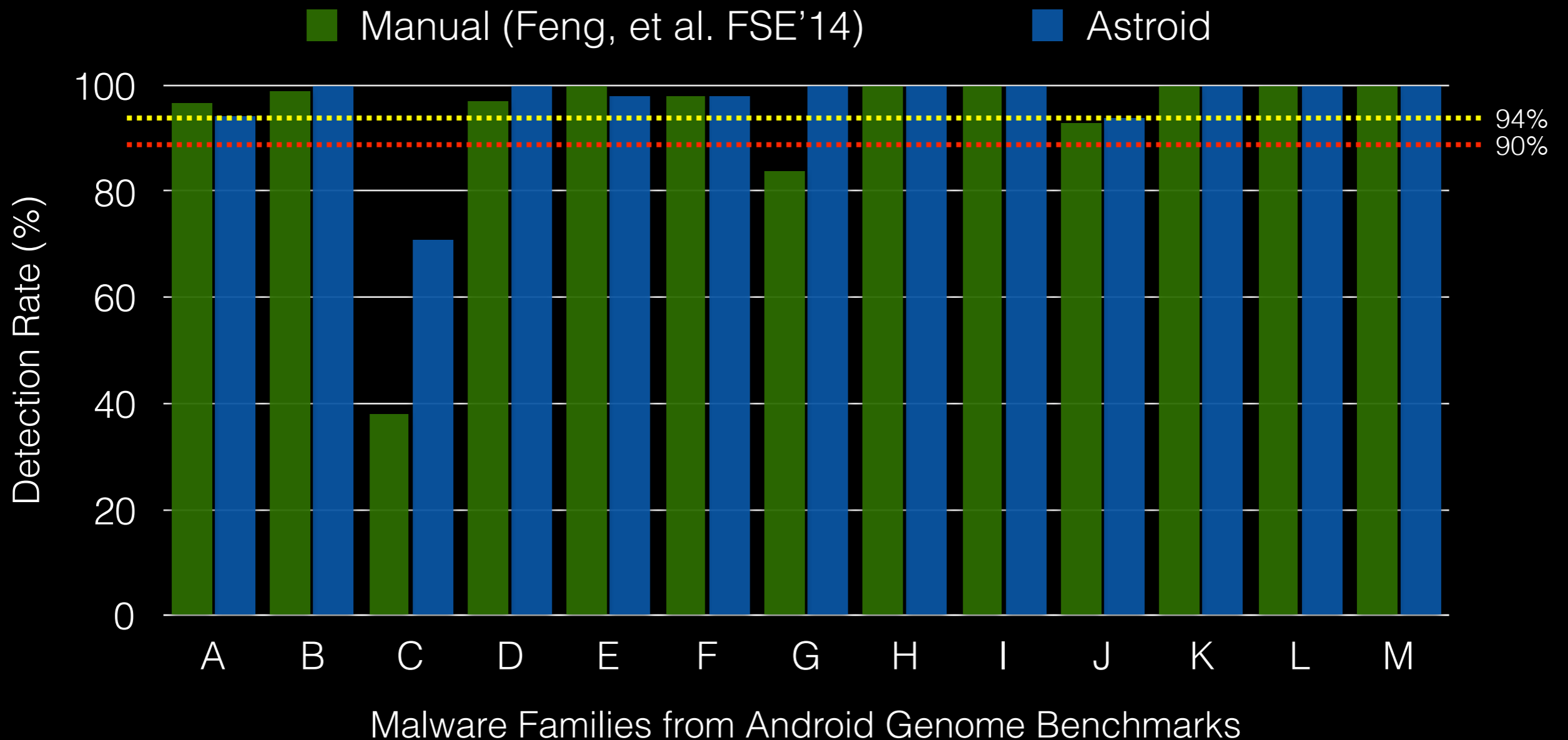


Manual v.s. Automated



Manual v.s. Automated

Outperform manual version!



Zero-day malware

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- 160 malware samples from Symantec and McAfee of which we have no signature
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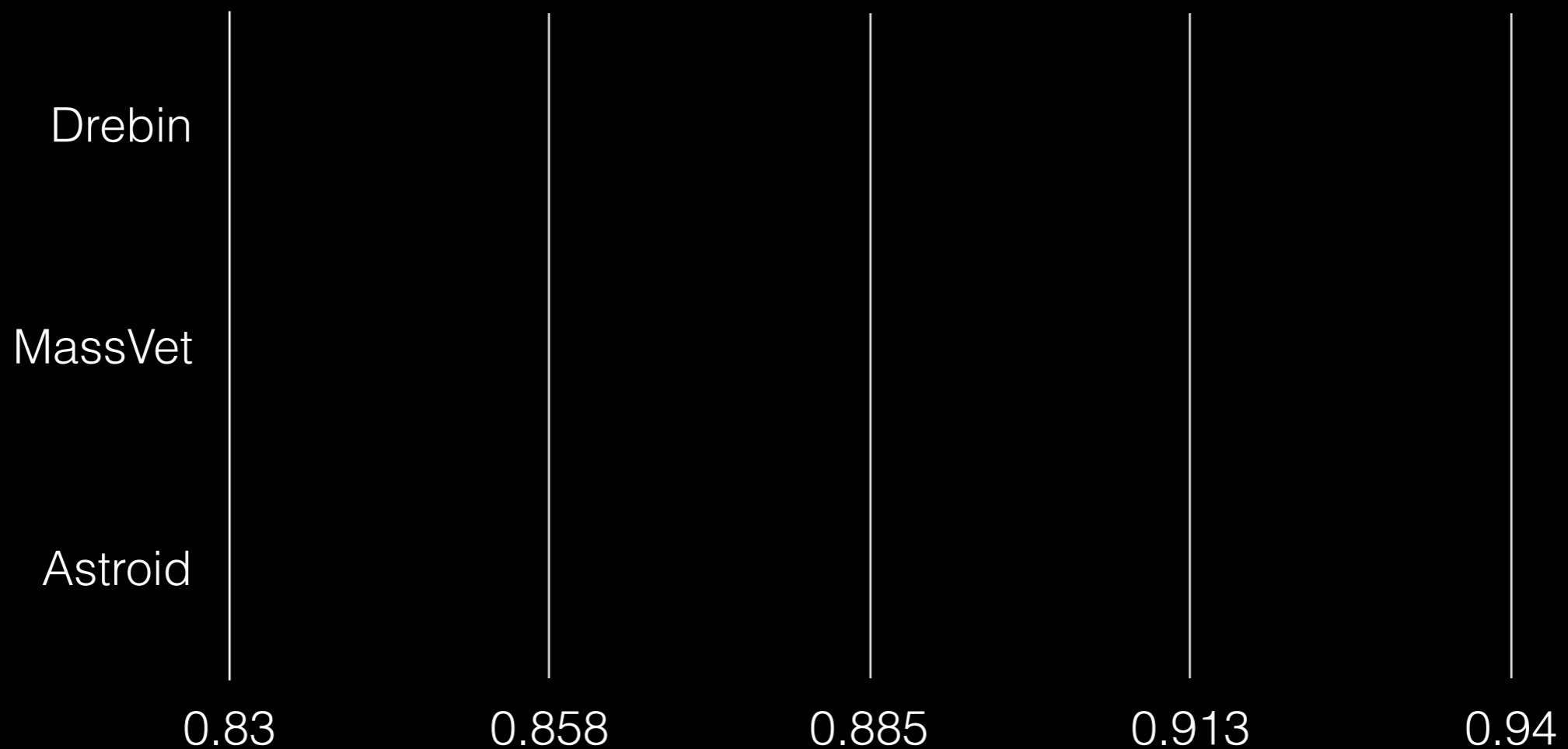
Our approximate matching is effective!

Comparison with other tools

False positive rate: Drebin(NDSS'14): 1%, MassVet (Security'15): 175/503, Astroid: 0.04%

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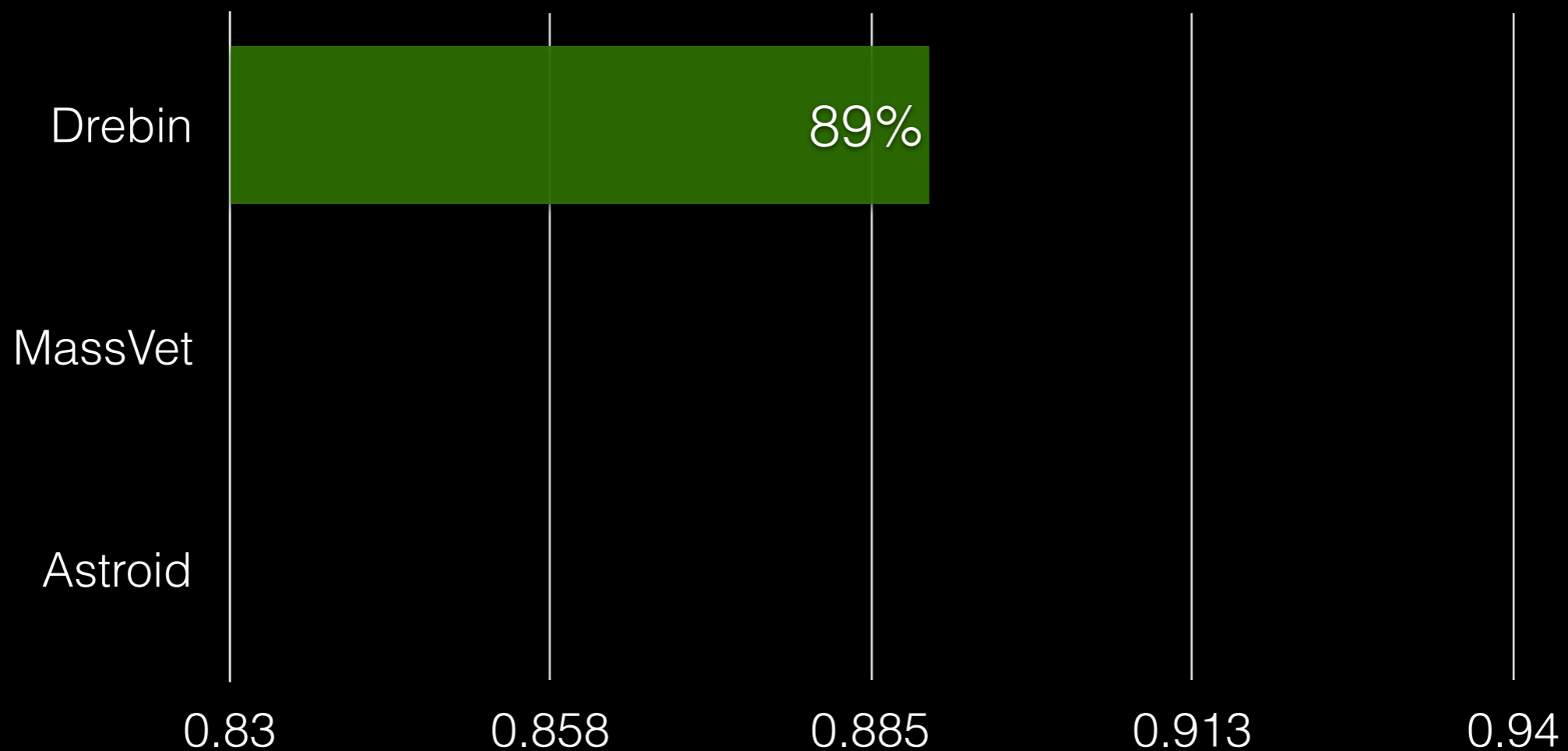
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Detection Rate

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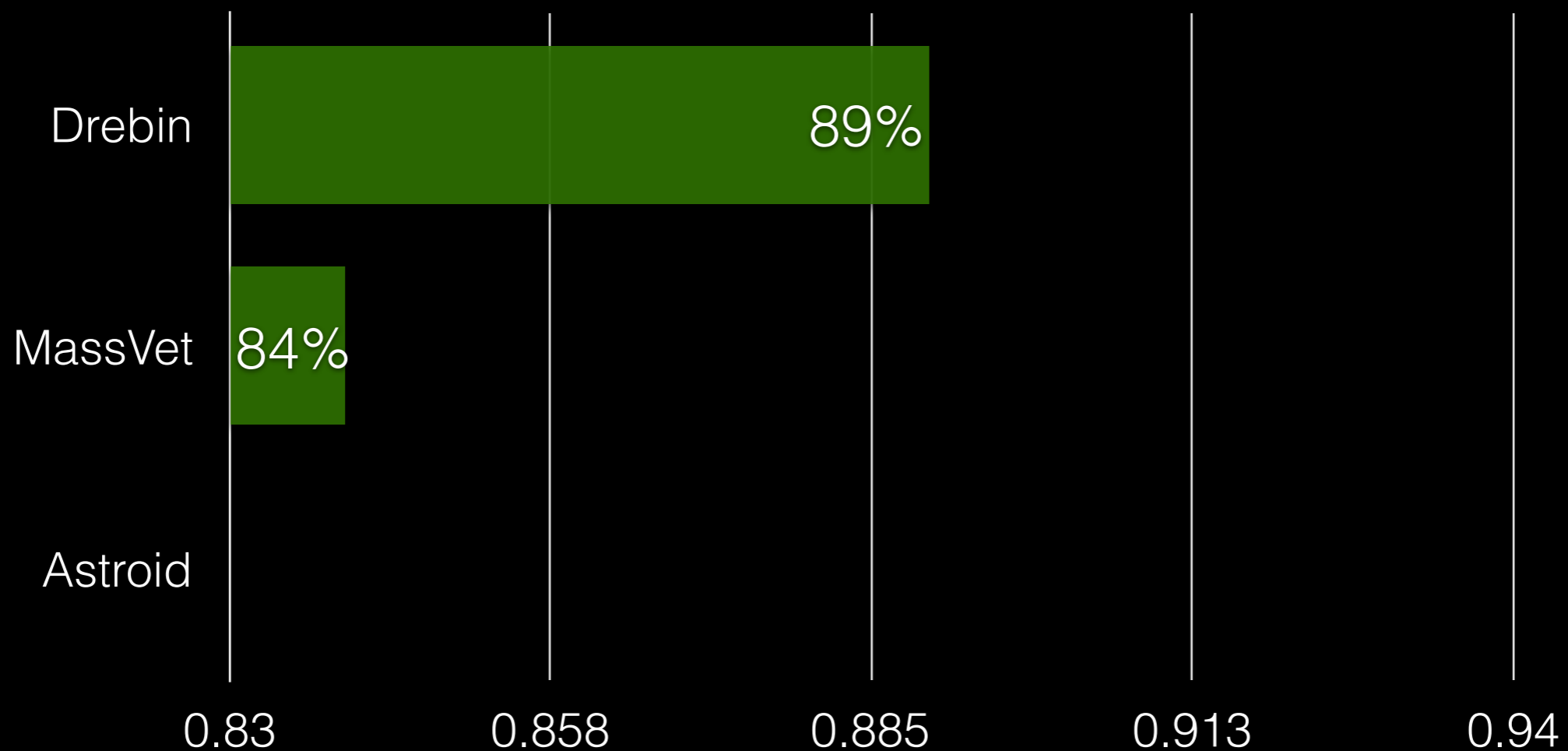
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Comparison with other tools

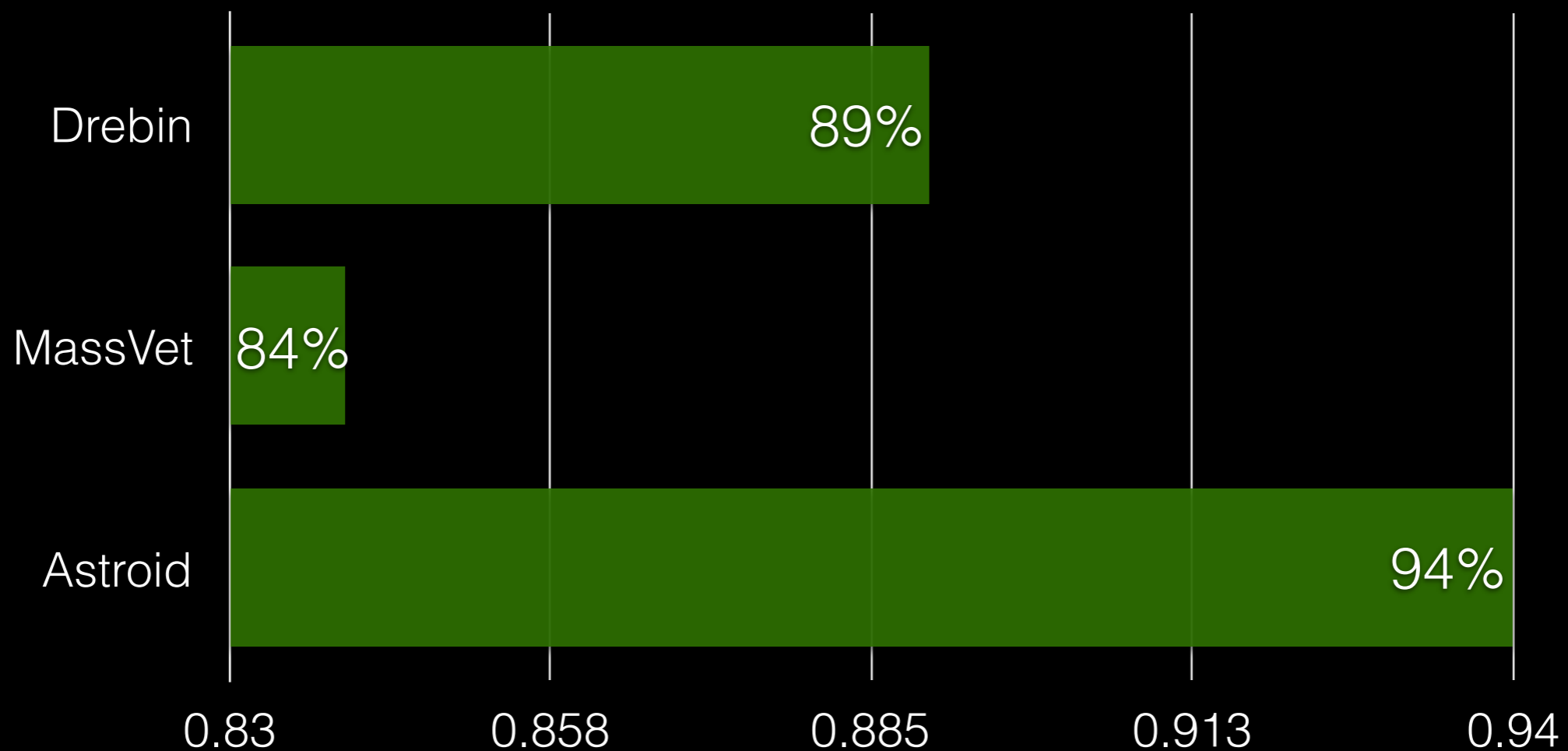
False positive rate: Drebin(NDSS'14): 1%, MassVet (Security'15): 175/503, Astroid: 0.04%



Detection Rate

Comparison with other tools

False positive rate: Drebin(NDSS'14): 1%, MassVet (Security'15): 175/503, Astroid: 0.04%

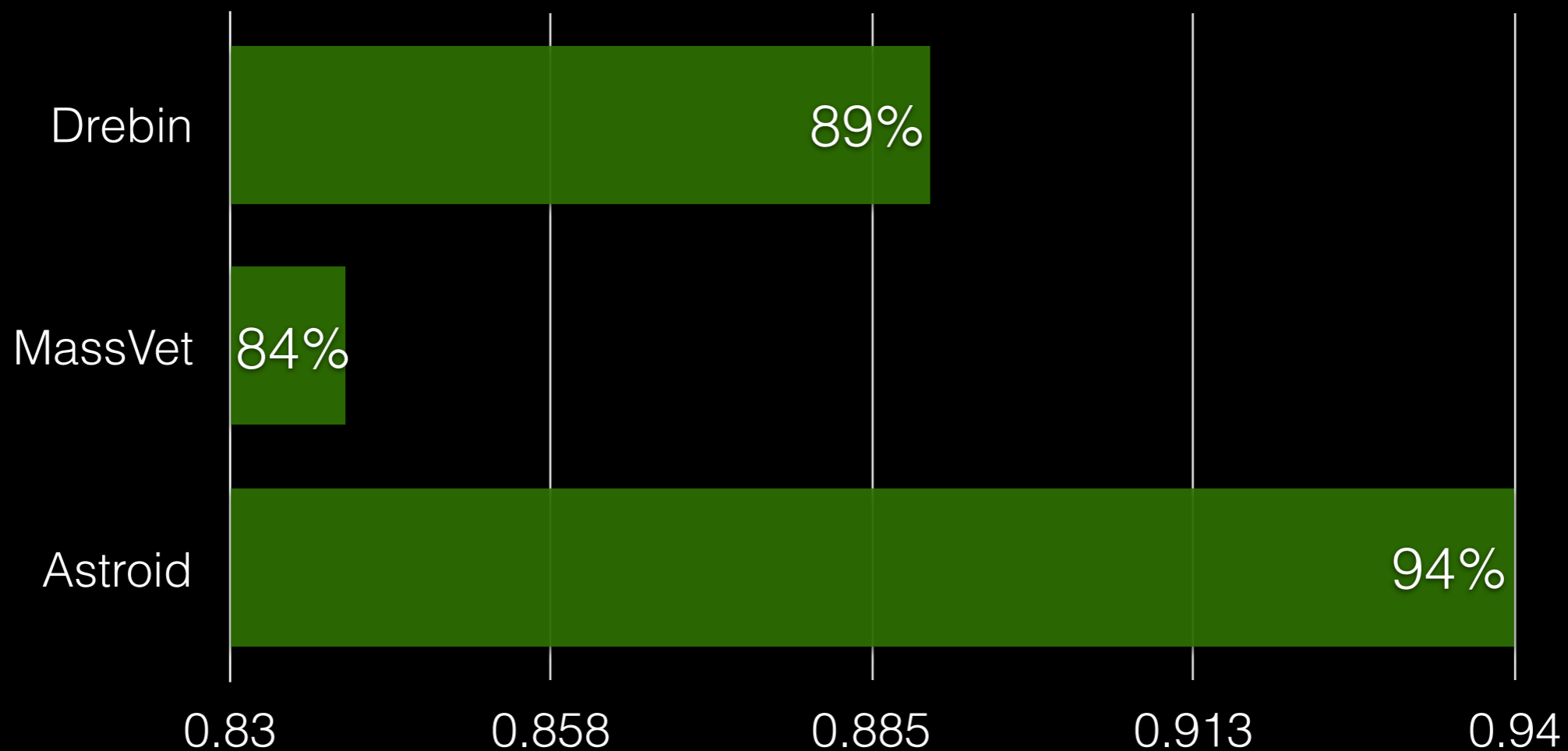


Detection Rate

Comparison with other tools

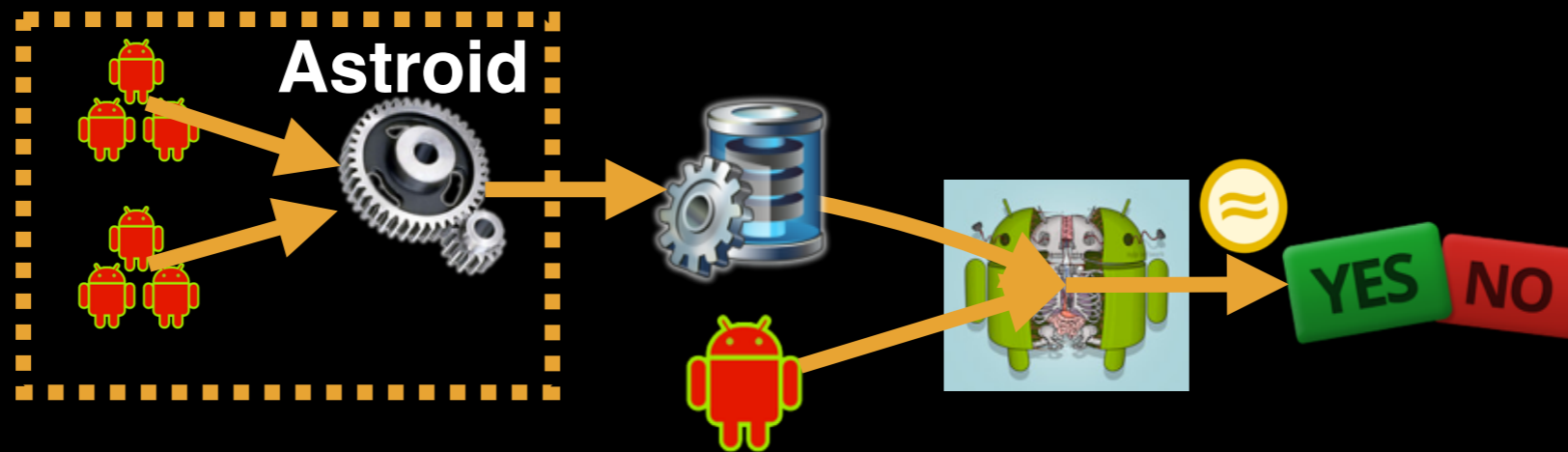
False positive rate: Drebin(NDSS'14): 1%, MassVet (Security'15): 175/503, Astroid: 0.04%

Astroid achieves high detection rate with low FP!



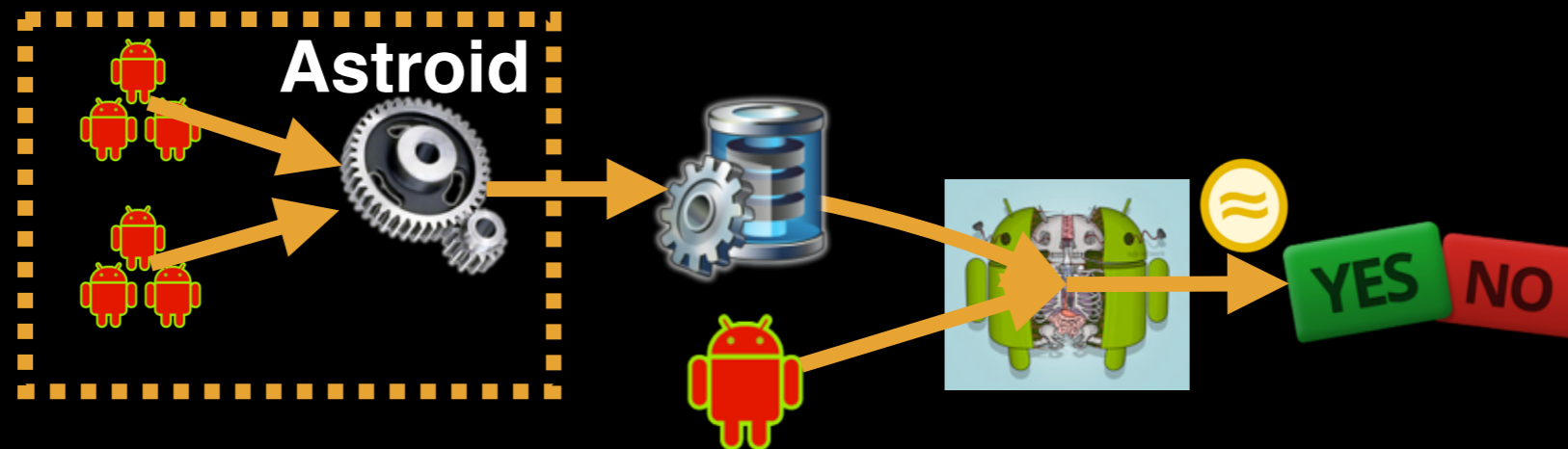
Detection Rate

Conclusion



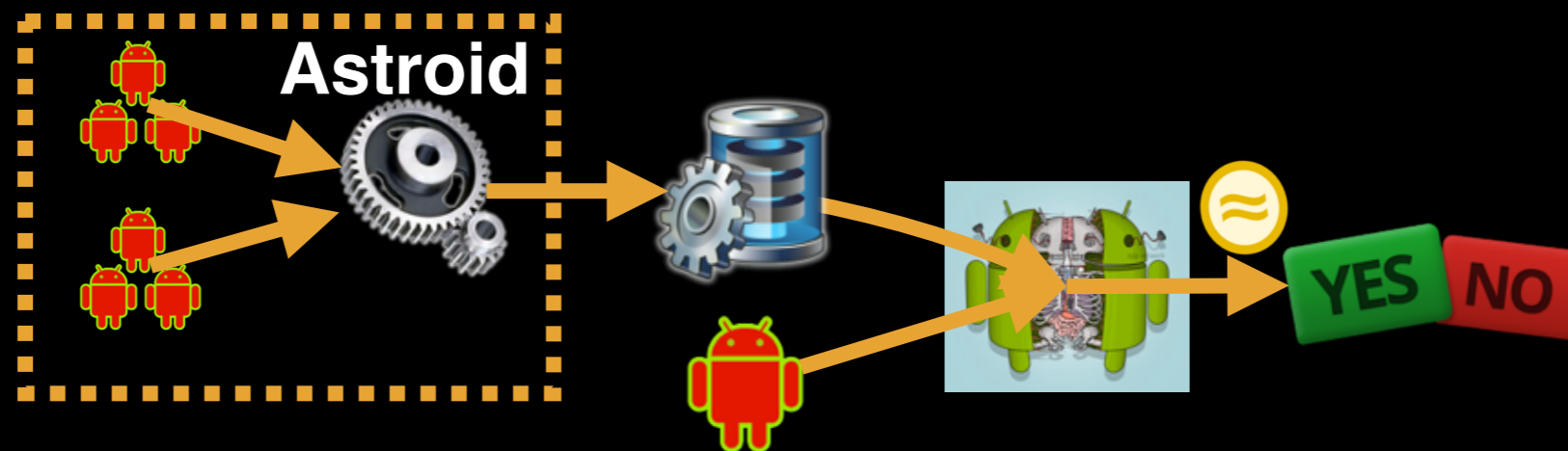
Conclusion

- Automatically infer semantic malware signature from very few samples



Conclusion

- Automatically infer semantic malware signature from very few samples
- Our approximate matching is resilient to semantic obfuscations



Thank you!

Automated Synthesis of Semantic Malware Signatures using Maximum Satisfiability.
Yu Feng, Osbert Bastani, Ruben Martins, Isil Dillig, Saswat Anand. NDSS 2017.

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