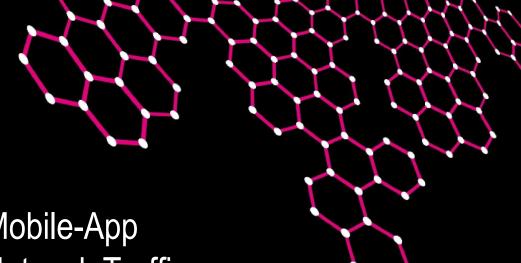
# UNIVERSITY OF TWENTE.



FlowPrint: Semi-Supervised Mobile-App Fingerprinting on Encrypted Network Traffic

**Thijs van Ede**, Riccardo Bortolameotti, Andrea Continella, Jingjing Ren, Daniel J. Dubois, Martina Lindorfer, David Choffnes, Maarten van Steen and Andreas Peter

Contact: t.s.vanede@utwente.nl

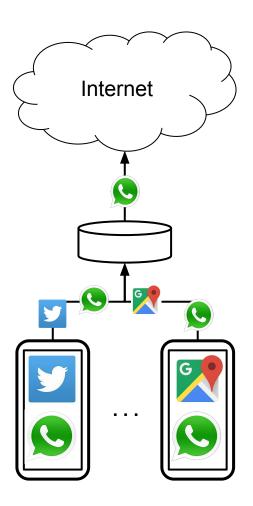




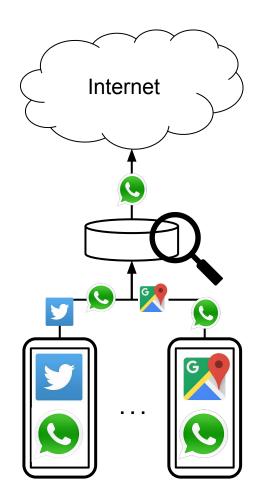




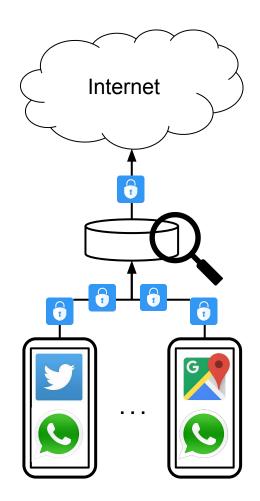
Apps communicate with the internet



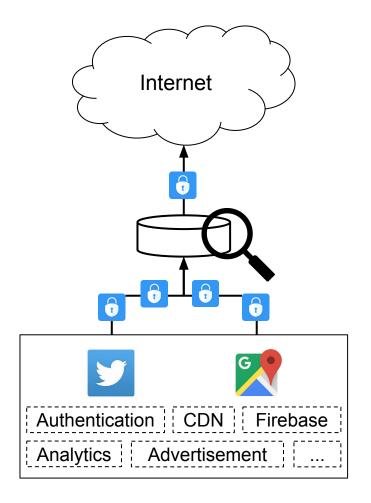
- Apps communicate with the internet
- Can we infer mobile app usage from network traffic?



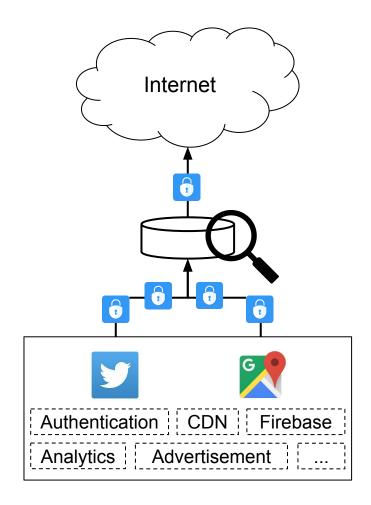
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- Can we infer mobile app usage from network traffic?
- Traffic is encrypted



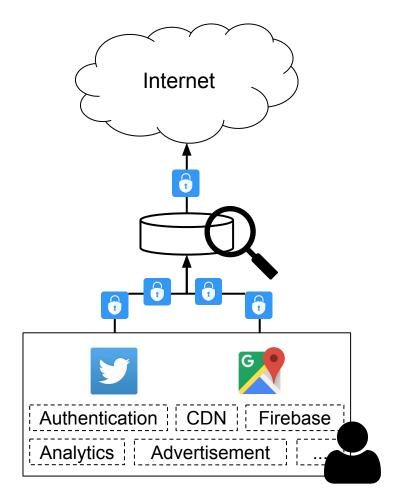
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- Traffic is encrypted
- Apps consist of modules



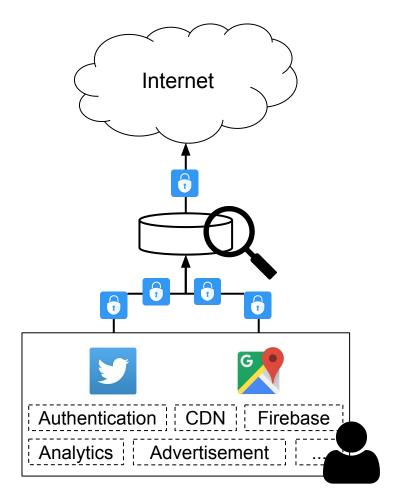
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- Apps consist of modules
- Modules are shared by apps, leading to homogeneous traffic



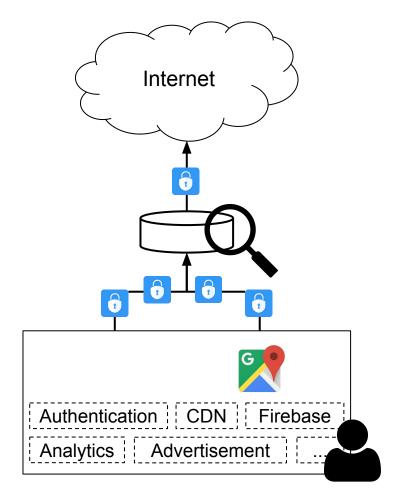
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- Generated traffic depends on dynamic user input



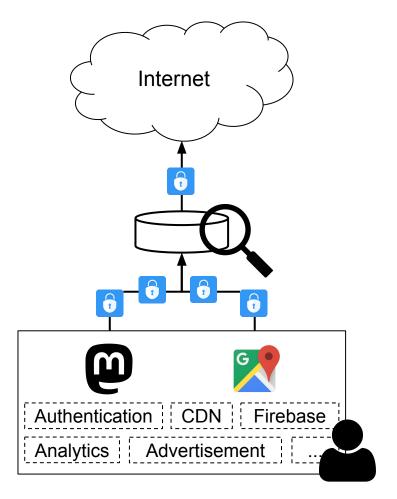
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- Apps on the device evolve over time



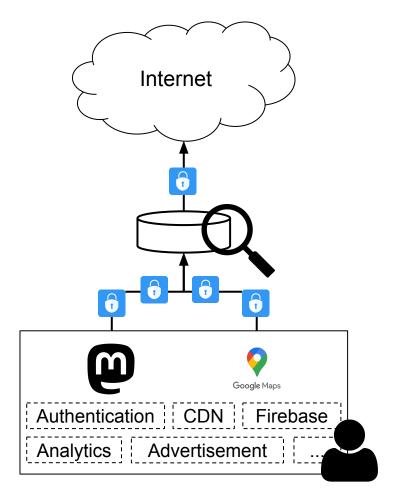
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- Apps communicate with the internet
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- Traffic is e
- Apps cons
- Modules a homogene
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Can we infer mobile app usage from network traffic without prior knowledge of installed apps?

- Apps on the device evolve over time
  - Removal
  - Installation
  - Update

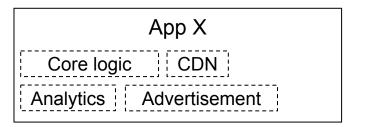


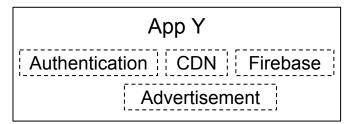
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Internet

Apps are composed of a unique set of modules that each communicate with a relatively invariable set of network destinations

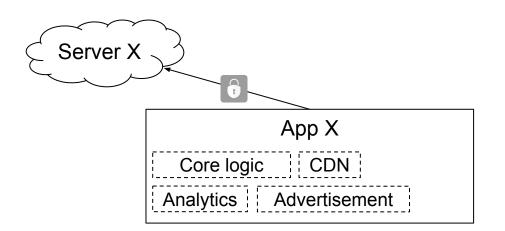
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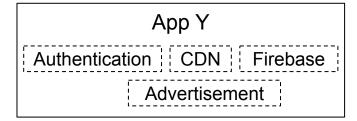




Apps are composed of a unique set of modules that each communicate with a relatively invariable set of network destinations







Apps are composed of a unique set of modules that each communicate with a relatively invariable set of network destinations App Y App X

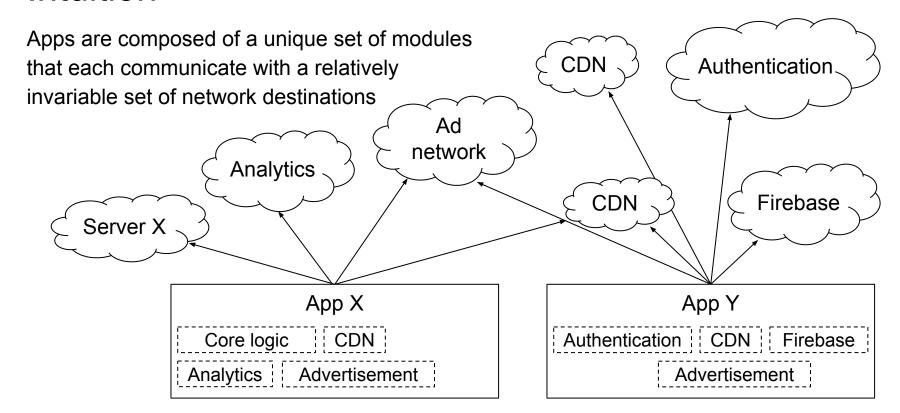
CDN

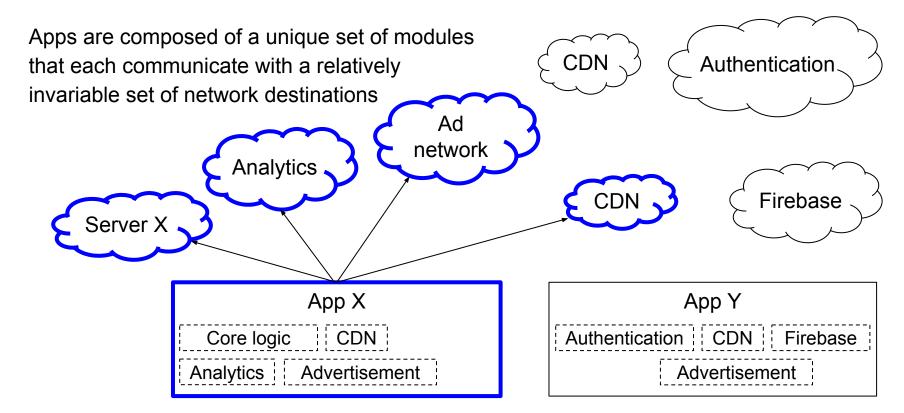
Analytics : Advertisement

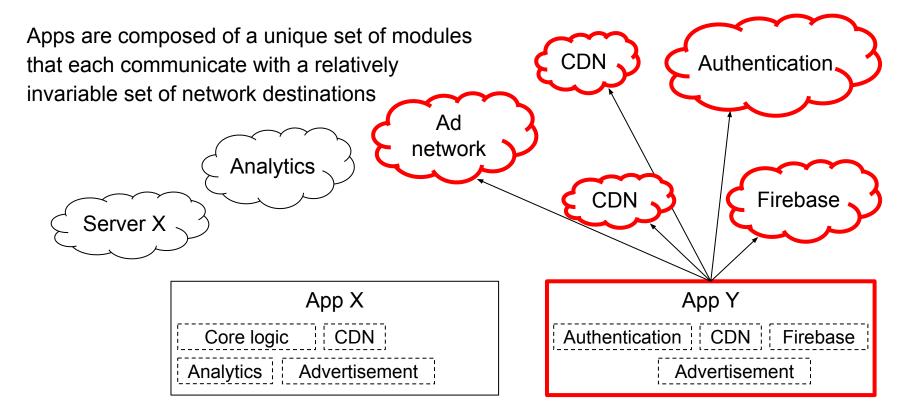
Core logic

Authentication | CDN | Firebase

Advertisement

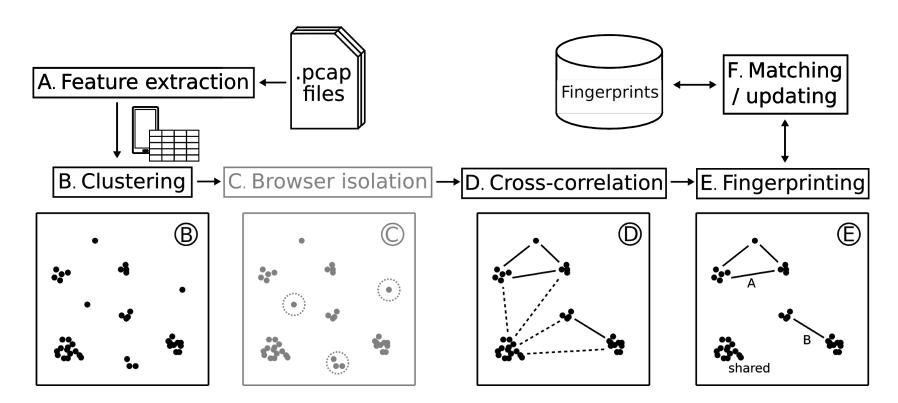






Apps are composed of a unique set of modules **Authentication**, that each communicate with a relatively invariable set of How do we **extract** these patterns without prior Firebase knowledge of the apps? Server X App X App Y Core logic CDN Authentication | CDN | Firebase Analytics Advertisement Advertisement

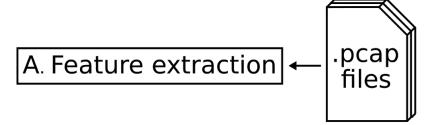
#### FlowPrint - Overview



#### FlowPrint - Feature extraction

For each flow in the network, we extract

- Originating device
- Destination (IP, port)-tuple
- TLS certificate
- Timestamps

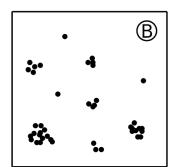


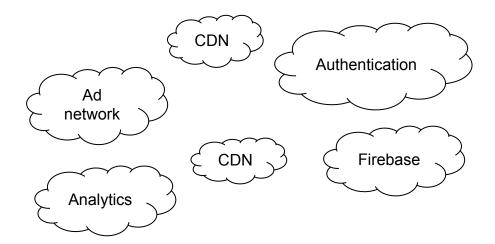
## FlowPrint - Clustering

In 5 minute batches, we cluster flows by network destination:

- Destination (IP, port)-tuple or
- TLS certificate

#### B. Clustering



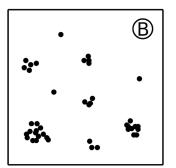


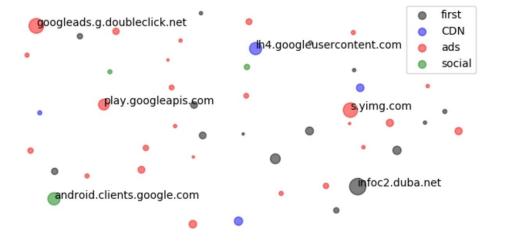
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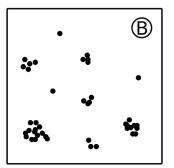


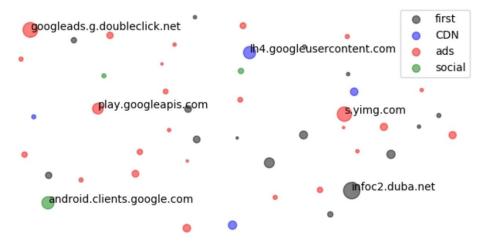
# FlowPrint - Clustering

In 5 minute batches, we cluster flows by network destination:

- Destination (IP, port)-tuple or
- TLS certificate
- Some of these clusters are shared

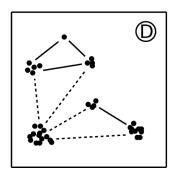
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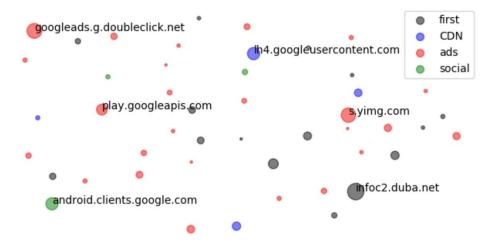




 Network destinations that are active together likely belong to the same app

#### D. Cross-correlation

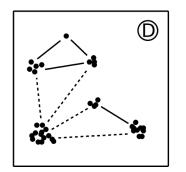


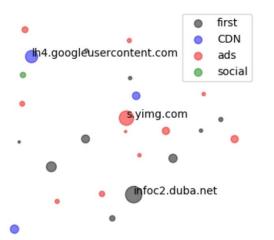


- Network destinations that are active together likely belong to the same app
- Compute correlation based on activity

$$(c_i \star c_j) = \sum_{t=0}^T c_i[t] \cdot c_j[t]$$
 googleads.g.doubleclick.net

#### D. Cross-correlation



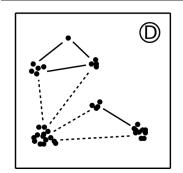


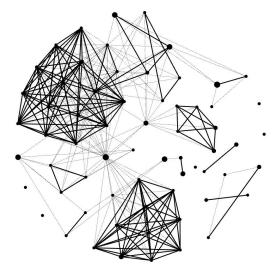
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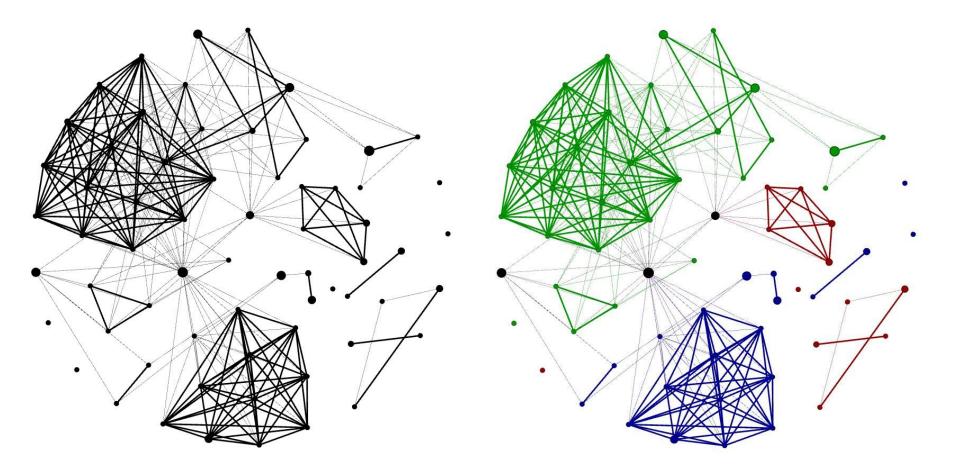
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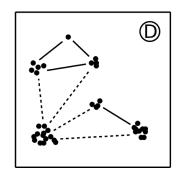


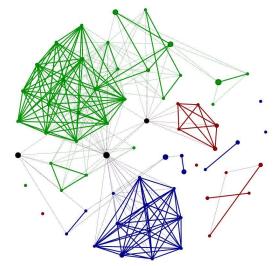


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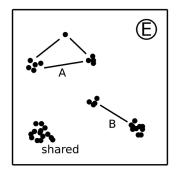


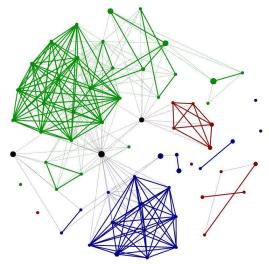


## FlowPrint - Fingerprinting

Remove weak correlations in graph



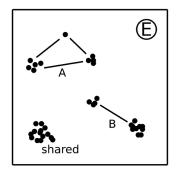


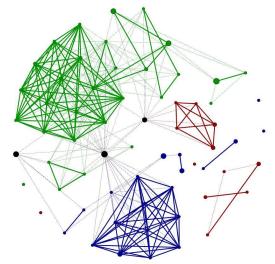


## FlowPrint - Fingerprinting

- Remove weak correlations in graph
- Find cliques of strongly correlated clusters

#### E. Fingerprinting

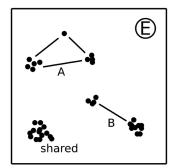


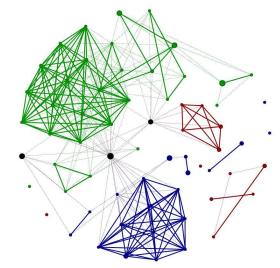


# FlowPrint - Fingerprinting

- Remove weak correlations in graph
- Find cliques of strongly correlated clusters
- Extract fingerprints as the set of destinations
  - Destination (IP, port)-tuple
  - TLS certificate

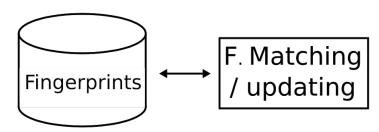
#### E. Fingerprinting





# FlowPrint - Fingerprint matching

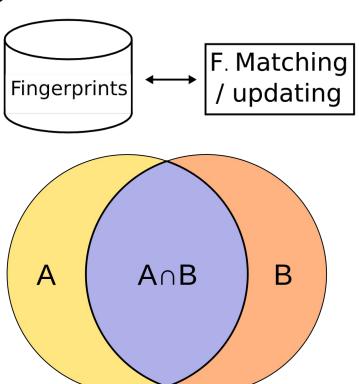
- Fingerprints are a set of destinations
  - Destination (IP, port)-tuple
  - TLS certificate



# FlowPrint - Fingerprint matching

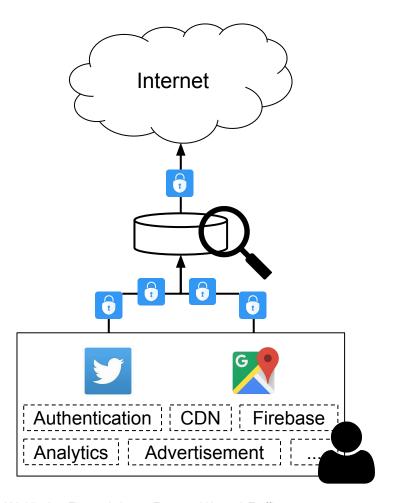
- Fingerprints are a set of destinations
  - Destination (IP, port)-tuple
  - TLS certificate
- Compare using the Jaccard similarity

$$J(F_a, F_b) = \frac{|F_a \cap F_b|}{|F_a \cup F_b|}$$



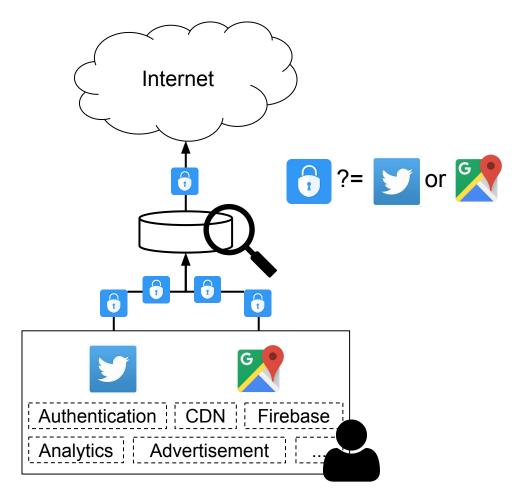
## **Evaluation**

How well does our approach work?



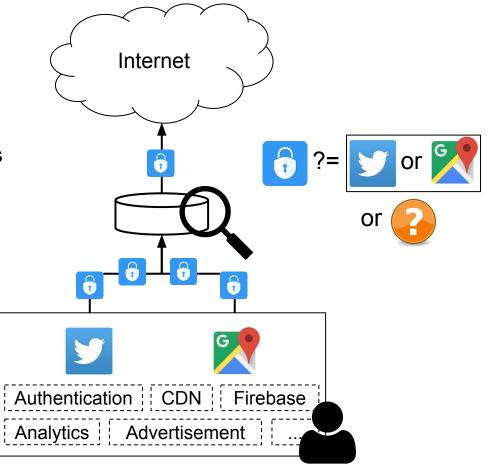
### **Evaluation**

- How well does our approach work?
  - Recognizing known apps



### **Evaluation**

- How well does our approach work?
  - Recognizing known apps
  - Detecting previously unseen apps



### **Evaluation**

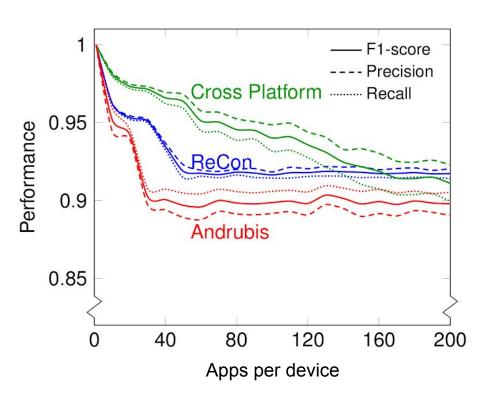
- How well does our approach work?
  - Recognizing known apps
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#### Datasets

Dataset	Encrypted	Homogeneous	Dynamic	Evolving	Malicious
Cross Platform	<b>V</b>	<b>V</b>	<b>V</b>		
ReCon	V	V		V	
Andrubis	V	V			<b>V</b>

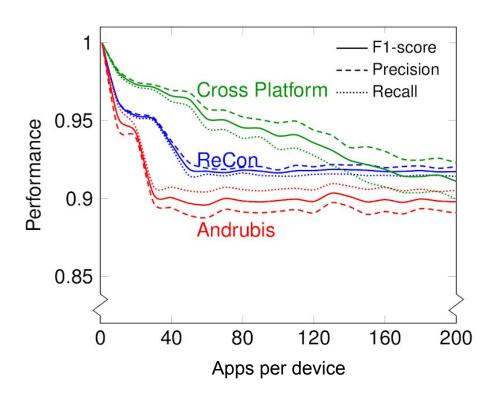
# Evaluation - Recognizing known apps

 Stable performance if number of apps increase



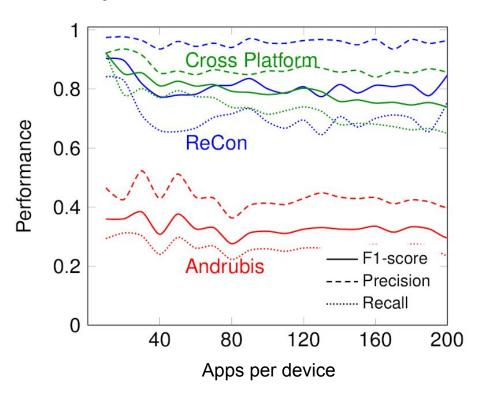
# Evaluation - Recognizing known apps

- Stable performance if number of apps increase
- Compared FlowPrint with supervised approach AppScanner
  - F1-score of **0.89** vs 0.58
  - Precision of **0.92** vs 0.88
  - Recall of **0.89** vs 0.50



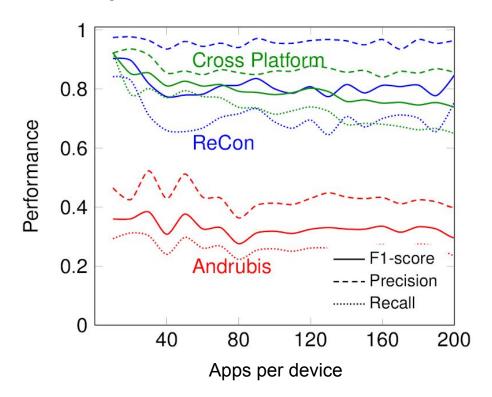
# Evaluation - Detecting previously unknown apps

 Good performance in detecting and isolating previously unseen apps



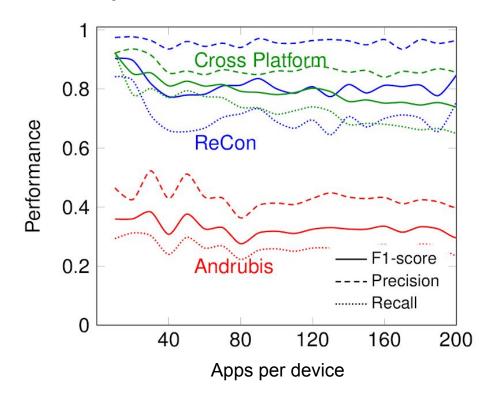
# Evaluation - Detecting previously unknown apps

- Good performance in detecting and isolating previously unseen apps
- Low number of flows gives worse performance
  - Low code coverage



# Evaluation - Detecting previously unknown apps

- Good performance in detecting and isolating previously unseen apps
- Low number of flows gives worse performance
  - Low code coverage
- No observable difference between benign and malicious apps



### Conclusion

FlowPrint isolates apps within encrypted network traffic without requiring prior knowledge

- Performs better than supervised detectors
- Requires no training
- Recognizes known apps
- Isolates and detects previously unseen apps

https://github.com/Thijsvanede/FlowPrint

### Questions?

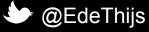
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Thijs van Ede



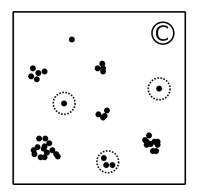


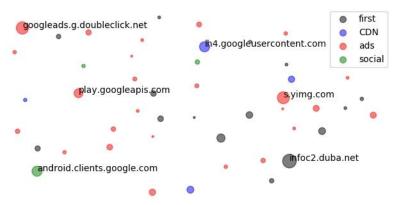


### FlowPrint - Browser Isolation

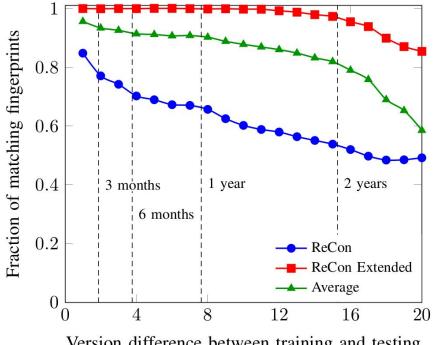
- Browser shows fewer repeatable patterns
- Each website has its own fingerprint
- Isolate browser using Random Forest
  - Relative change in active clusters
  - Relative change in bytes uploaded
  - Relative change in bytes downloaded
  - Relative change in upload/download ratio

#### C. Browser isolation



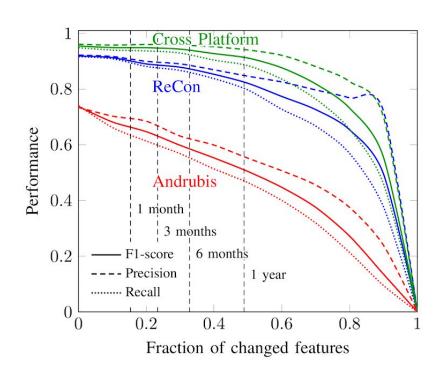


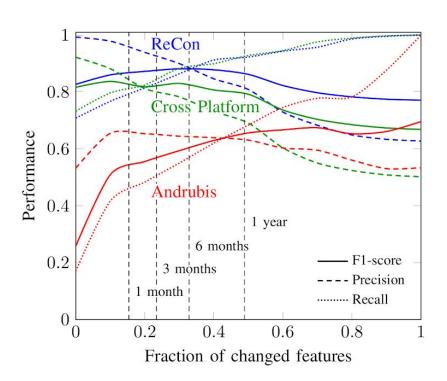
# Different app versions



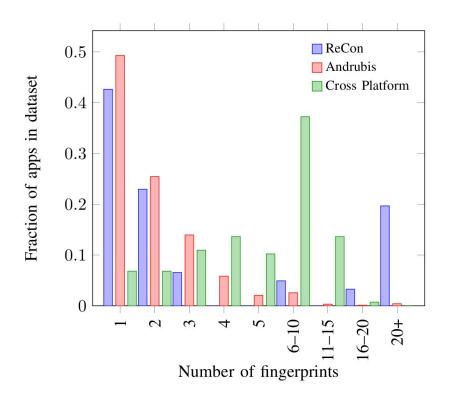
Version difference between training and testing

# Changing features





# Fingerprints per app



### **Execution time**

