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SPRITZ Security & Privacy Research Group

HUMAN INSPIRED TECHNOLOGY Research Centre

DIPARTIMENTO MATEMATICA

ACM SAC ‘19 - Privacy by Design in Practice Track (PDP)

Mind Your Wallet's Privacy

Identifying Bitcoin Wallet Apps and User's Actions through Network Traffic Analysis

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Introduction

- Bitcoin [1] offers pseudo-anonymity, which is, unfortunately, being exploited to commit several financial frauds.
  - E.g., ransomware campaigns.

- Our work primarily aims to identify/filter smartphone-based Bitcoin wallet users.

- We use network traffic analysis using machine learning techniques to achieve our goals.
  - *The governments can ask telecom operators to identify/filter Bitcoin wallet users using our approach, which can assist in the hunt of cyber-criminals.*

[1] S. Nakamoto, “Bitcoin: A Peer-to-Peer Electronic Cash System,” https://bitcoin.org/bitcoin.pdf, 2008.

Introduction

- Our approach works even when the payload is encrypted.

- Using network traffic analysis, we identify:
  - If a user is using a Bitcoin wallet app or not?
    - If so, then which app the user is using?
  - What actions they performing on these apps?
    - Sending, receiving, etc.

- Our work can be extended to other categories of smartphone apps to further improve user profiling.

Smartphone, app, and action selection

- According to Gartner [2], Android and iOS devices together accounted for 99.9% of all smartphone sales by the end of the year 2017. Hence, in our study, we used both Android and iOS devices.

- For the apps, we chose the worldwide most downloaded [3] Bitcoin wallet apps on both Google Play Store and Apple’s App Store in the year 2017.

- For non-Bitcoin apps, we chose the top-10 apps along with additional 20 Internet-dependent apps from each store.

[2] gartner.com/newsroom/id/3859963
[3] sensortower.com/blog/bitcoin-wallet-app-growth

Smartphone, app, and action selection

- We found seven classes of actions relevant to Bitcoin transactions.

- The most important (and common across each app) actions for Bitcoin transactions are:
  a. Send Bitcoin,
  b. Receive Bitcoin,
  c. Open the app (sync data).

App	Action						
	Open app	Receive Bitcoin	Send Bitcoin	Generate addresses	In-app buy/sell	Transaction history	Check balance
BTC.com	✓	✓	✓	✗	✠	❄	❄
BitPay	✓	✓	✓	✓	✓	♣	❄
Bitcoin Wallet (Bitcoin Wallet Devs)	✓	✓	✓	✗	✗	❄	❄
Bitcoin Wallet (Bitcoin.com)	✓	✓	✓	✓	✠	♣	❄
Blockchain	✓	✓	✓	✗	✓	♣	❄
Bread	✓	✓	✓	✗	✓	♣	❄
Coinbase	✓	✓	✓	✗	✓	♣	❄
Copay	✓	✓	✓	✓	✓	♣	❄
Luno	✓	✓	✓	✗	✓	❖	✙
Mycelium	✓	✓	✓	✗	✠	❖	❄
Unocoin	✓	✓	✓	✗	✓	❖	❄
Wirex	✓	✓	✓	✗	✓	❄	❄
Xapo	✓	✓	✓	✗	✓	❖	❄
Zebpay	✓	✓	✓	✗	✓	❖	❄

✓ Available ✗ Not available ❄ On app's home ♣ Under individual wallet/currency
✙ Under dedicated menu for wallets' summary ❖ Under dedicated menu for transaction history
✠ Redirects to an external website, leaving the app

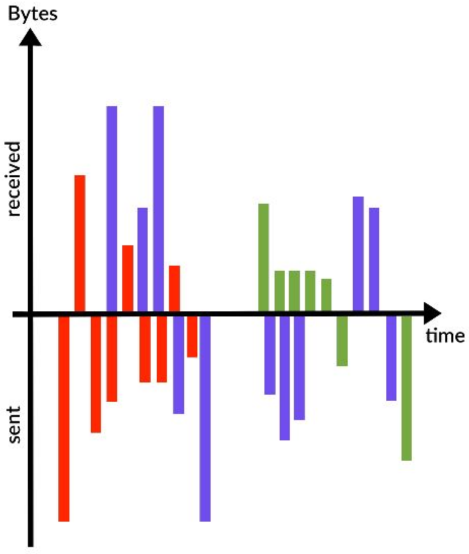
Classifier design

- Our classification procedure consists of the following steps:
  a. Data preprocessing
  b. Feature selection
  c. Machine learning
  d. Training & prediction

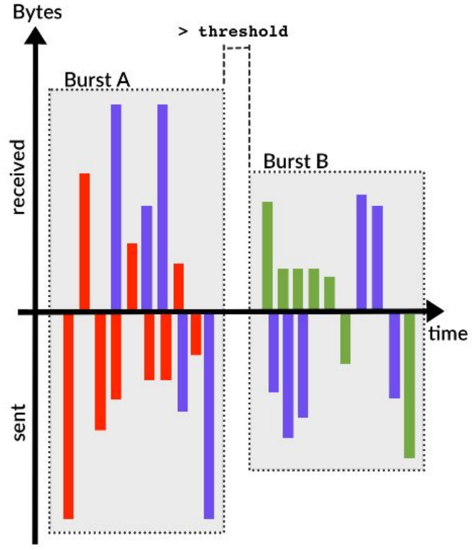
Classifier design

Data preprocessing

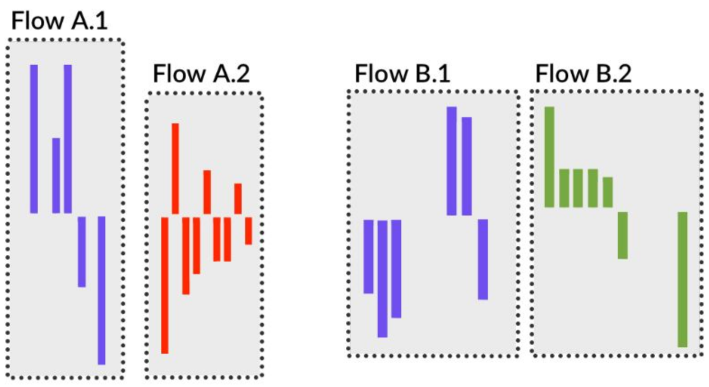
- To handle network traffic traces via machine learning models, we need to perform a preprocessing step, which includes:
  a. Network trace capture
  b. Traffic *burstification* (time/threshold based)
  c. Flows separation



(a) Network traces capture: different colors represent different applications.



(b) Traffic *burstification*: traces are split into bursts.



(c) Flows separation: for each burst, different flows are separated by means of the pairs of source-destination IPs.

Classifier design

Feature selection

- Now, we convert the flows into training instances using following 12 statistics: *length of the series, minimum, maximum, mean, median, mode, variance, skewness, kurtosis, and percentile (25%, 50% and 75%).*

- These statistics are computed for: *the entire sequence, incoming packets only, and for the outgoing packets only.* Hence, the resulting instance has a dimension of 36 (12 × 3).

Classifier design

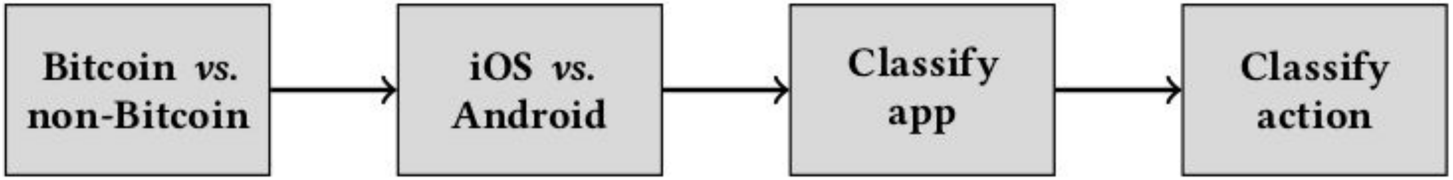
Machine learning

- We employed two most successful machine learning methods for classification:
  a. Random Forest (RF)
  b. Support Vector Machine (SVM)

Classifier design

Training & prediction

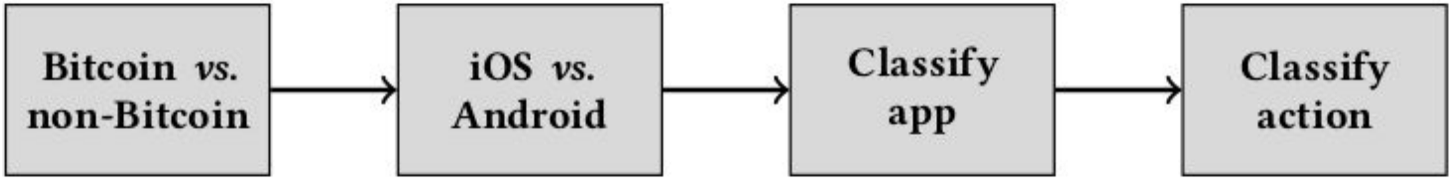
- Training: We tackle our problem at different levels. We identified the following layers of classification:
  a. Classify whether the instance represents a flow of a Bitcoin app;
  b. If so, classify whether it belongs to an Android app or an iOS app;
  c. If it has been categorized as Android/iOS app, classify specific app;
  d. Given the app from the previous step, finally, classify the specific action.



Classifier design

Training & prediction

- Training: We tackle our problem at different levels. We identified the following layers of classification:
  a. Classify whether the instance represents a flow of a Bitcoin app;
  b. If so, classify whether it belongs to an Android app or an iOS app;
  c. If it has been categorized as Android/iOS app, classify specific app;
  d. Given the app from the previous step, finally, classify the specific action.



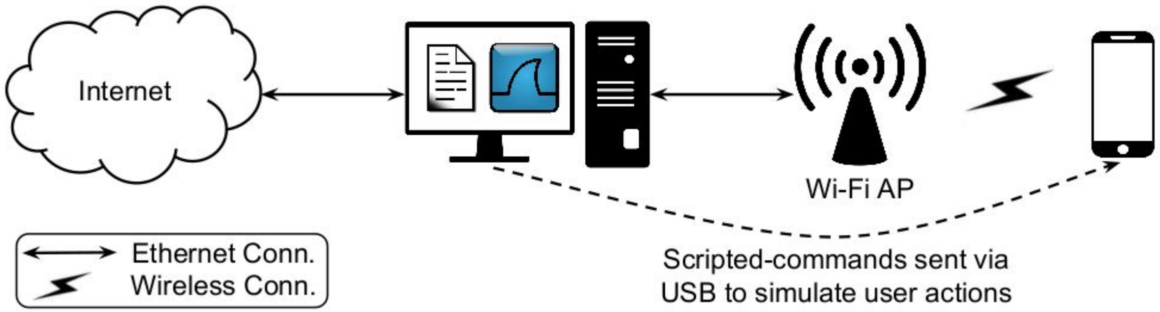
- Prediction: Given a new instance to classify, the prediction is performed using the same steps as in the training phase.
  - Clearly, if a wrong prediction is made in one step, all the following steps will also be wrong.

Equipment setup

- The workstation was equipped with two Ethernet-based (NICs):
  - One for connecting it to the Internet,
  - The other one for connecting it to the Wi-Fi AP

- The workstation was configured to forward traffic between Wi-Fi AP and the Internet.

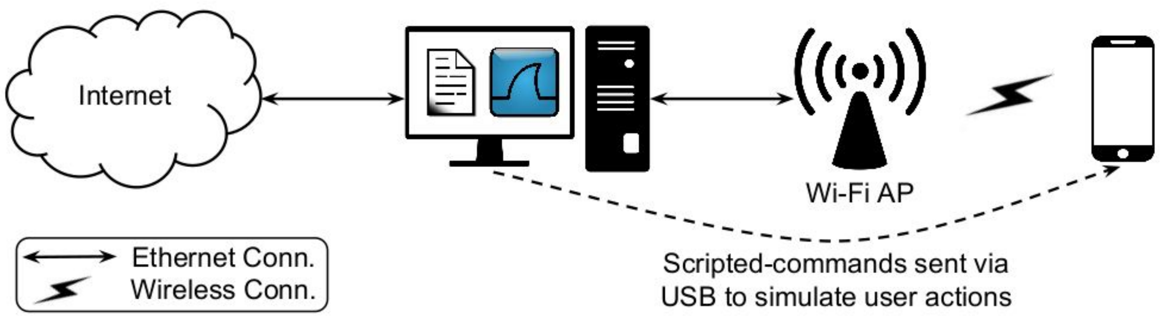
- The smartphones were provided (only one at a time) the Internet via Wi-Fi AP.



Equipment setup

- User actions were simulated on the smartphones using scripted-commands sent via USB or automation.
  - For Android, we used Android Debug Bridge (adb),
  - For iOS, we used Alloy 2.1.1 app that allows to automate the device without jailbreaking it.

- The generated network traffic was captured on the workstation using Wireshark 2.2.6; we discarded the packet's payload.



Evaluation

Evaluation settings

- We performed two different experiments:
  a. **Single classifier assessment:** in this setting, each single classifier is tested independently from the others.
  b. **Full stack classification:** in this setting, the classification is performed following the full-sequence of classification.

- We repeated each experiment **10 times** with a stratified **5-fold** cross validation on **90-10%** training and test splits of our dataset containing a total of **2362** instances.

Evaluation

Results - Single classifier assessment

Bitcoin *vs.* non-Bitcoin app classification

Method	Accuracy	Precision	Recall	F1
RF	0.977 ± 0.005•	0.977 ± 0.005•	0.973 ± 0.005•	0.975 ± 0.005•
SVM	0.930 ± 0.01	0.922 ± 0.01	0.923 ± 0.01	0.922 ± 0.02

App's OS classification

Method	Accuracy	Precision	Recall	F1
RF	0.984 ± 0.01•	0.984 ± 0.01•	0.983 ± 0.01•	0.983 ± 0.01•
SVM	0.956 ± 0.01	0.955 ± 0.02	0.955 ± 0.02	0.955 ± 0.02

Bitcoin app classification on Android

Method	Accuracy	Precision	Recall	F1
RF	0.966 ± 0.01•	0.968 ± 0.01•	0.968 ± 0.01•	0.968 ± 0.01•
SVM	0.945 ± 0.02	0.948 ± 0.02	0.948 ± 0.02	0.948 ± 0.02

Evaluation

Results - Single classifier assessment

Classification of user actions in Bitcoin apps on Android

Method	Bitcoin Wallet (Bitcoin.com)	BTC.com	Coinbase	Mycelium
RF	0.8 ± 0.15	0.98 ± 0.03•	0.991 ± 0.01•	0.971 ± 0.03•
SVM	0.85 ± 0.1•	0.975 ± 0.03	0.988 ± 0.02	0.958 ± 0.05

Bitcoin app classification on iOS

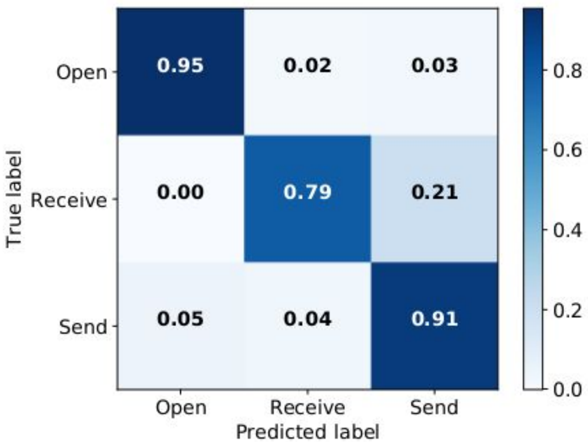
Method	Accuracy	Precision	Recall	F1
RF	0.962 ± 0.02•	0.964 ± 0.02•	0.963 ± 0.02•	0.963 ± 0.02•
SVM	0.935 ± 0.02	0.938 ± 0.02	0.935 ± 0.02	0.935 ± 0.02

Classification of user actions in Bitcoin apps on iOS

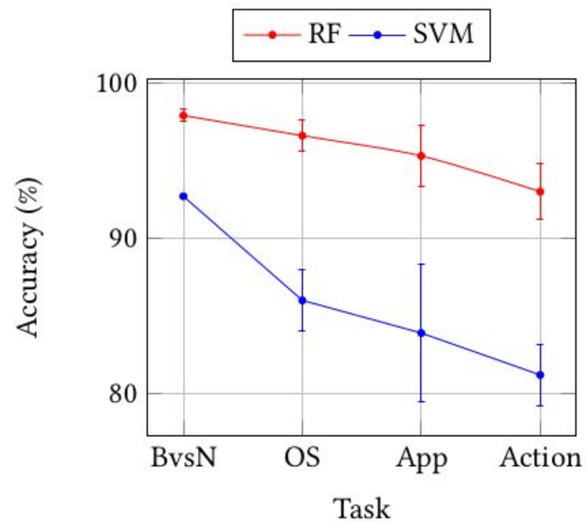
Method	Bitcoin Wallet (Bitcoin.com)	BitPay	Blockchain	Bread	Copay
RF	1.0 ± 0.0•	1.0 ± 0.0•	0.920 ± 0.02•	0.943 ± 0.03	1.0 ± 0.0•
SVM	1.0 ± 0.0•	1.0 ± 0.0•	0.911 ± 0.03	0.958 ± 0.04•	1.0 ± 0.0•

Evaluation

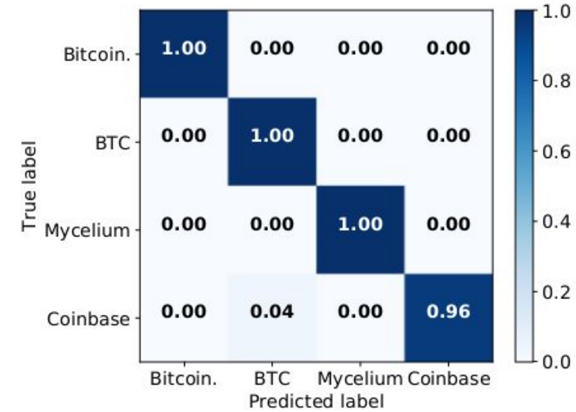
Results - Full stack classification



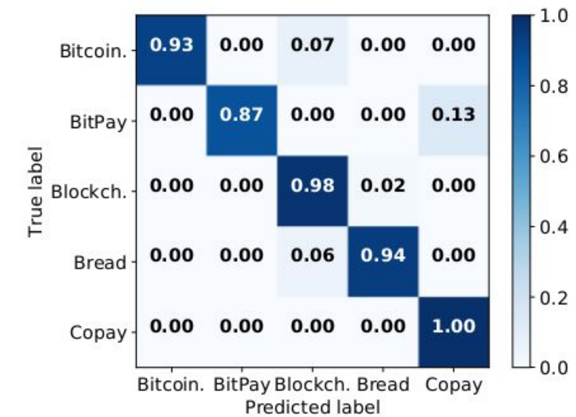
(a) Confusion Matrix



(b) Classification accuracy



(a) Android



(b) iOS

Future works

- In the future, we will investigate the security and privacy implication of transacting on such apps by considering a stronger adversary model.

- We will also explore the possibility to de-anonymize financial transaction placed via wallet apps.

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Thank you!