GEORG-AUGUST-UNIVERSITÄT
GÖTTINGEN

Drebin: Efficient and Explainable Detection of Android Malware in Your Pocket

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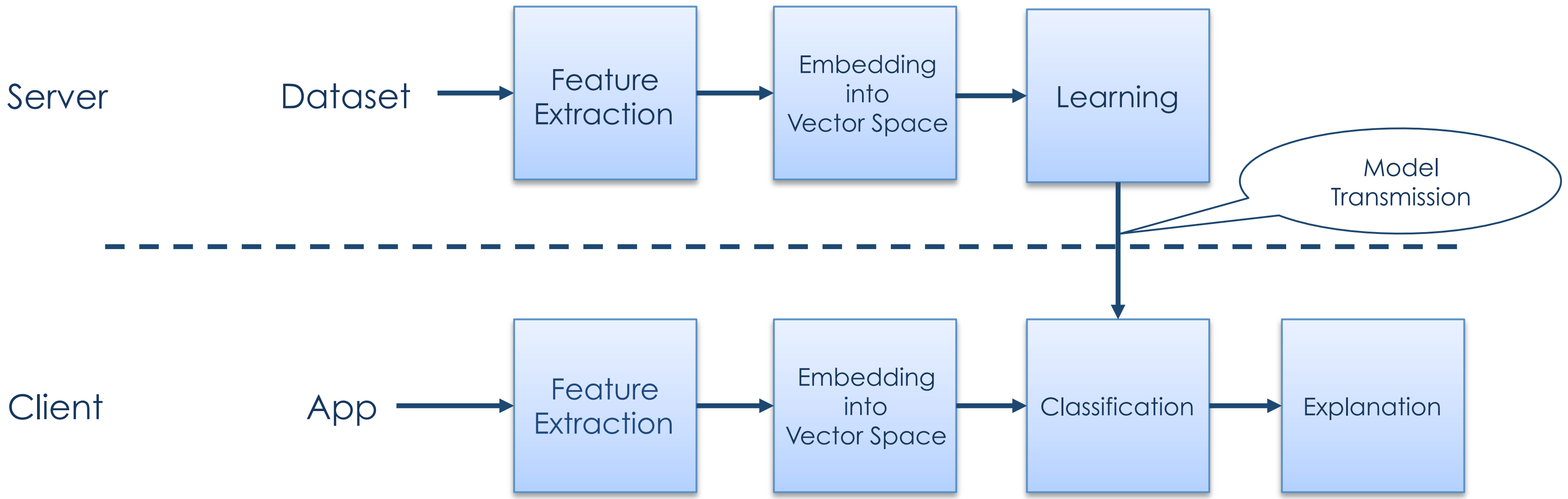
Android-Malware

- Android-Malware
  - Rapid growth in the past few years
  - Mostly distributed through alternative markets
- Mobile Antivirus-Scanners
  - Signature-based detection
  - Unable to identify unknown malware samples

Drebin

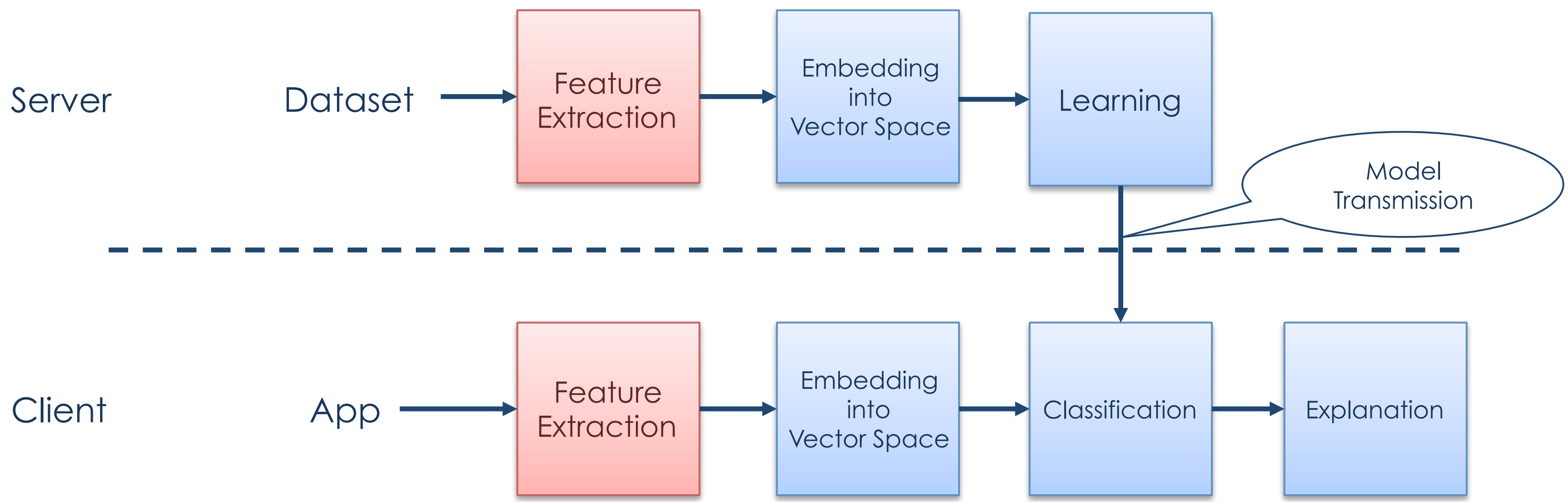
- Detection of unknown malware samples
  - Analysis of known malware
  - Adaptive detection using machine learning techniques
- Detection directly on the smartphone
  - Apps can be installed from many different sources
- Technical Challenges
  - Limited resources of mobile devices

Drebin



Server
Dataset
Feature Extraction
Embedding into Vector Space
Learning
Model Transmission
Client
App
Feature Extraction
Embedding into Vector Space
Classification
Explanation

Drebin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Static Analysis

- Lightweight Analysis of Android Applications
  - Extraction of features (strings) from 8 different categories

APK File

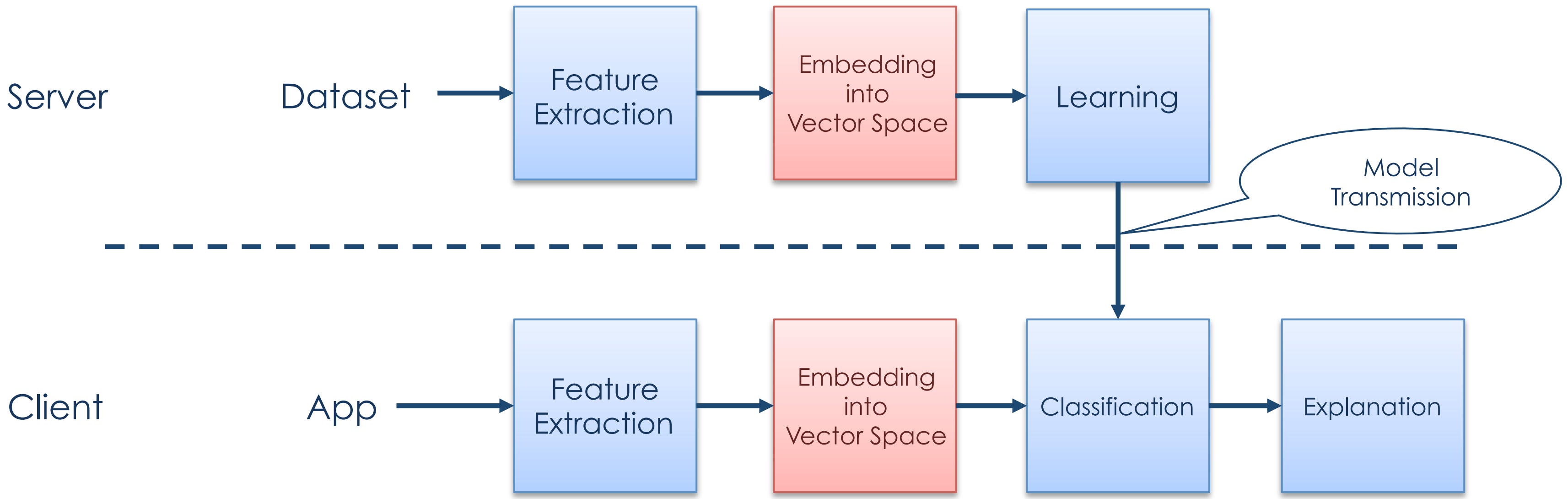
App Components
Filtered Intents
Hardware Components
Requested Permissions

Manifest

Protected API Calls
Used Permissions
Suspicious API Calls
Network Addresses

Dexcode

Drebin



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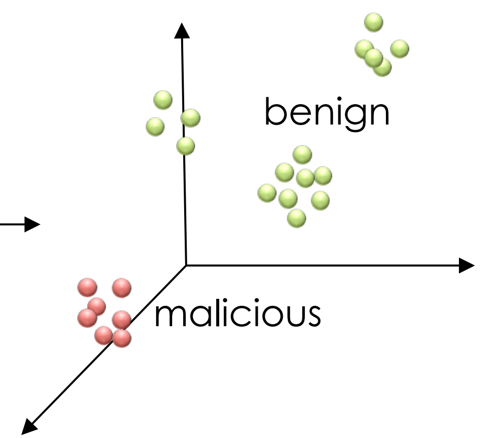
Embedding in Vector Space

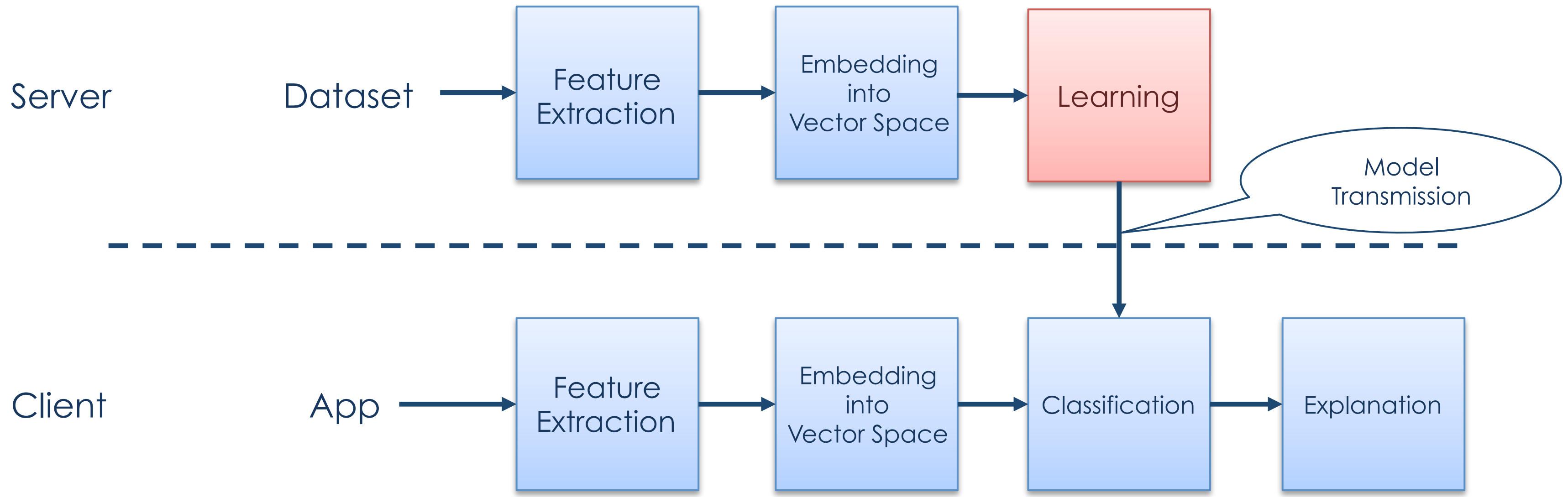
- Embedding of Apps into a vector space

- Vector representation of an App
  - Extracted features are set to 1
  - Small distance between Apps with similar characteristics

$$\xrightarrow{\varphi(x)} \begin{array}{cl} \left[\begin{array}{c} \cdots \\ 0 \\ 0 \\ \cdots \\ 1 \\ 0 \\ \cdots \end{array}\right] & \begin{array}{l} \cdots \\ \textit{hardware :: android.hardware.wifi} \\ \textit{hardware :: android.hardware.telephony} \\ \cdots \\ \textit{permission :: SEND\_SMS} \\ \textit{permission :: DELETE\_PACKAGES} \\ \cdots \end{array} \end{array} \longrightarrow$$



Drebin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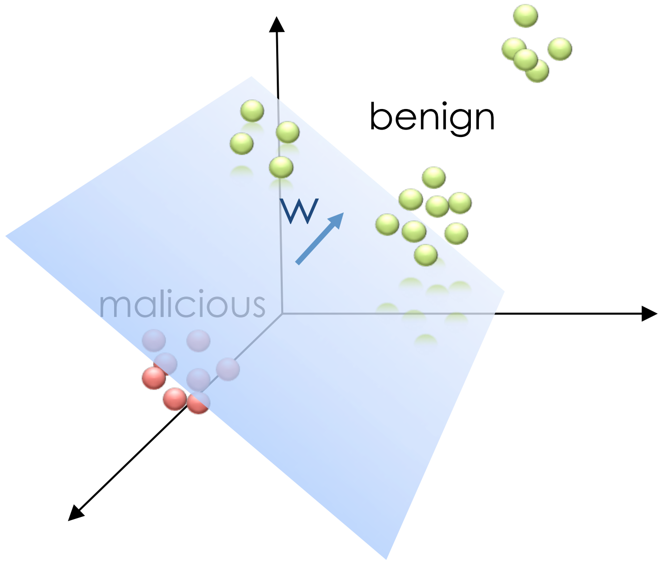
Dataset

- Dataset
  - Training and testing is done on large dataset
  - Collected by Mobile Sandbox project [5]
  - Consists of 123.453 benign and 5.560 malware samples

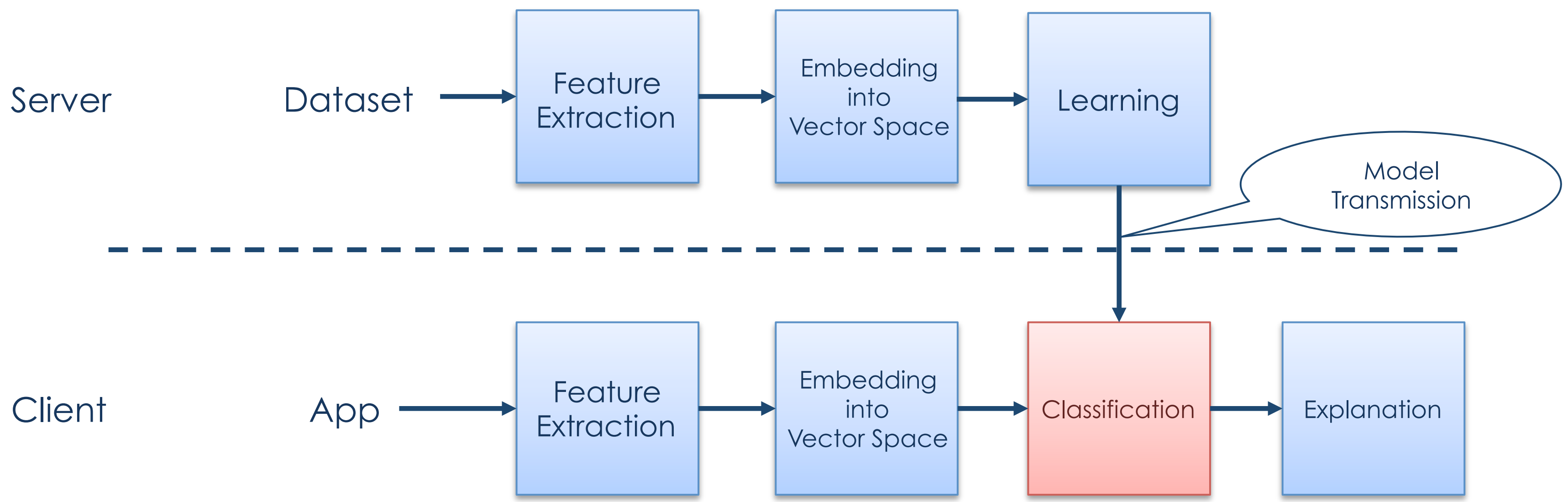
- Malware Samples available at
  - http://user.cs.uni-goettingen.de/~darp/drebin/

Learning

- Linear 2-Class Support Vector Machine
  - Hyperplane, which separates both classes with maximum margin
  - Can be described by model vector w



Drebin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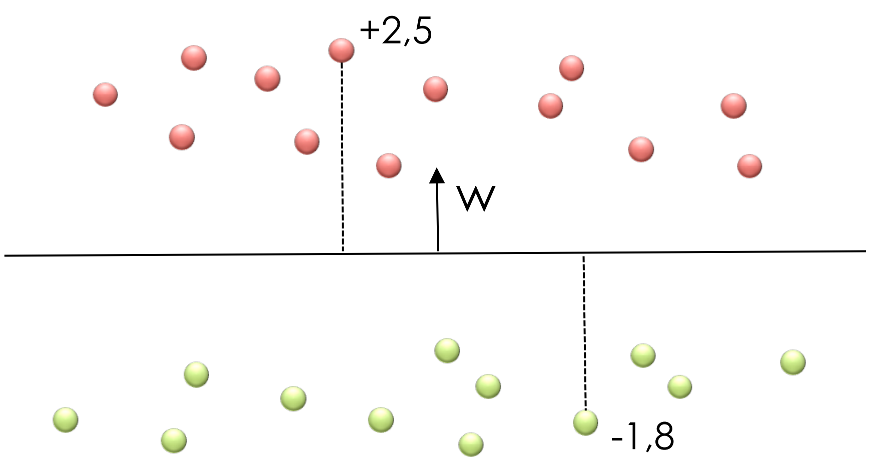
Classification

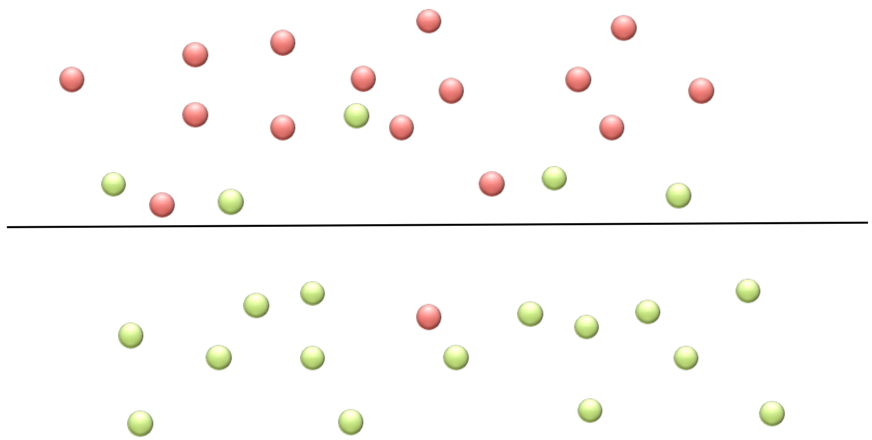
- Classification Score
  - Inner product of model and app vector
  - Sign indicates class of particular sample

$$f(x) = \langle \varphi(x), \vec{w} \rangle$$



Classification

- Detector Calibration
  - FP-Rate should be less than 1%
  - Choice of threshold unequal to zero



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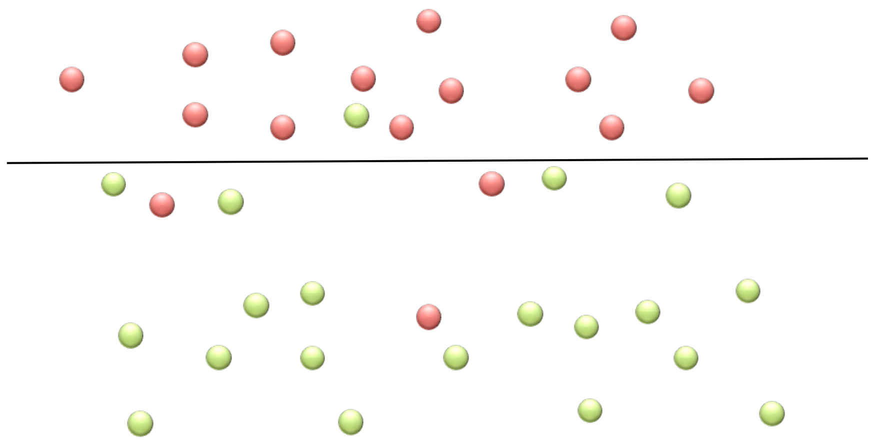
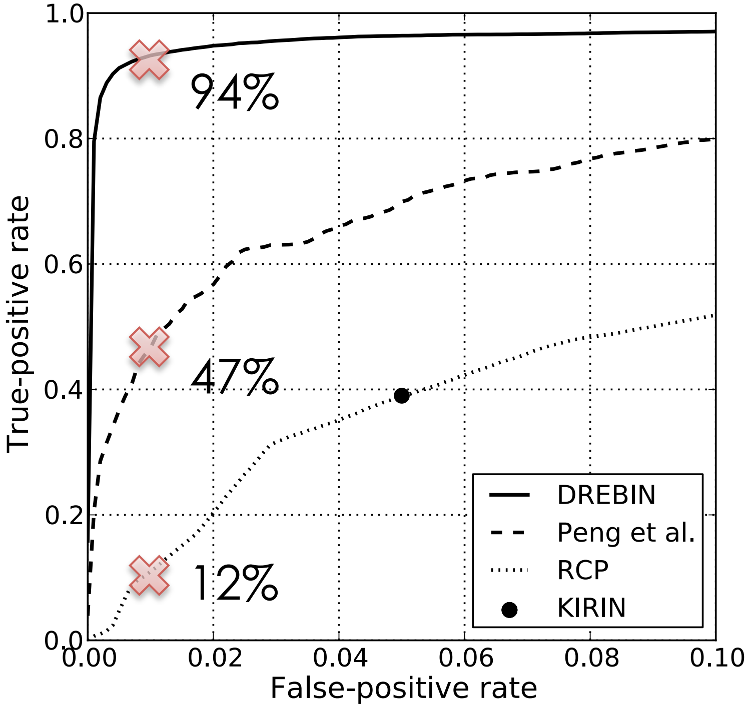
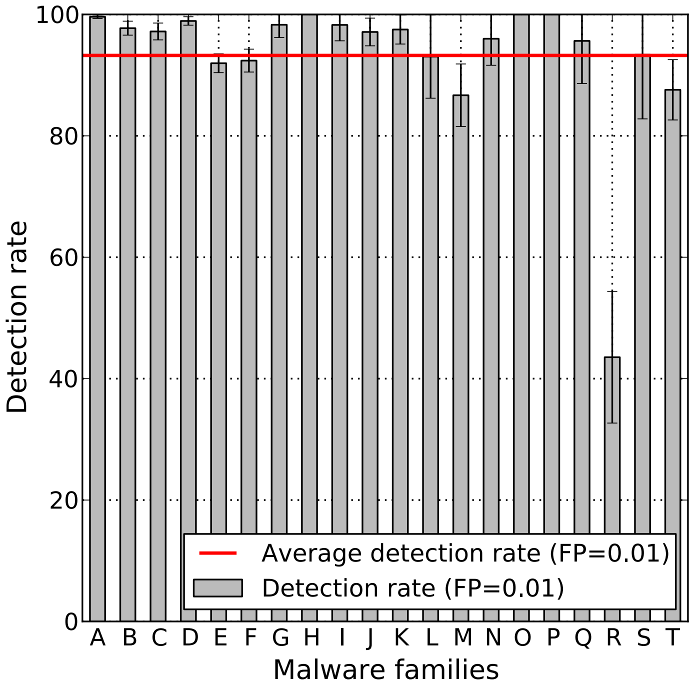


Detection Performance

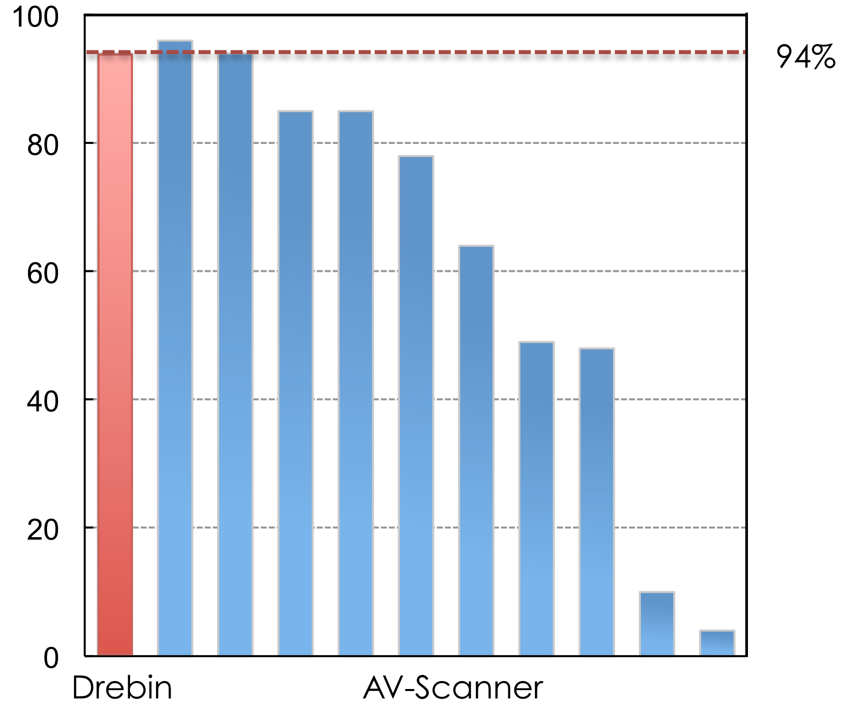


Detection Performance

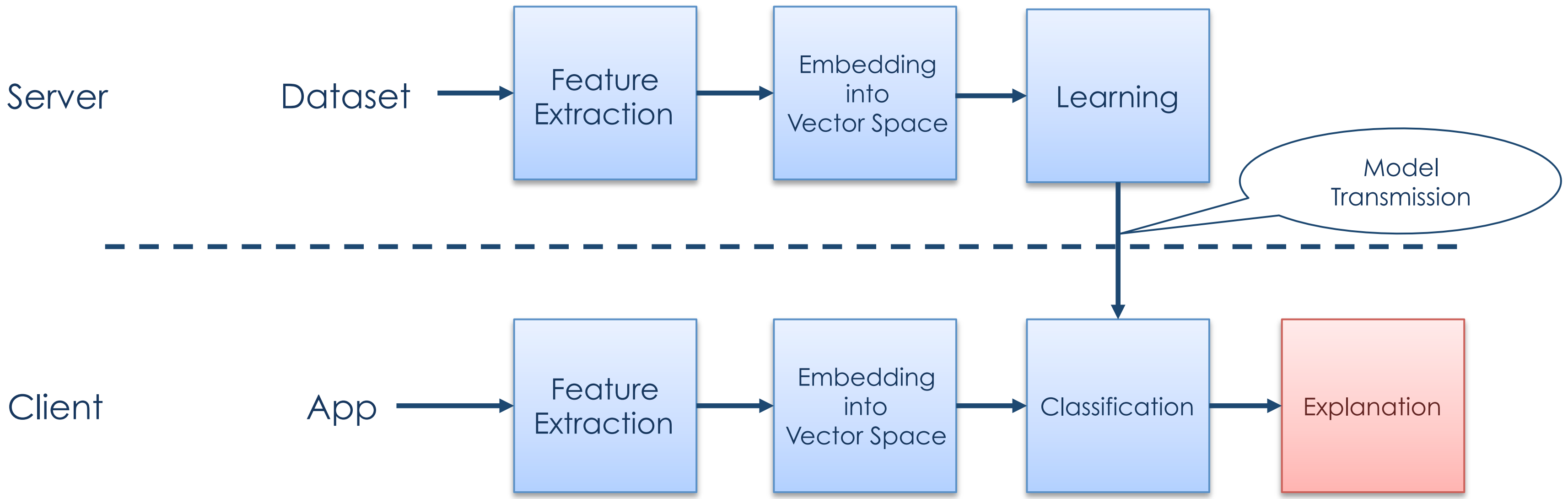


Id	**Family**	**#**	*Id*	**Family**	**#**
A	FakeInstaller	925	*K*	Adrd	91
B	DroidKungFu	667	*L*	DroidDream	81
C	Plankton	625	*M*	LinuxLotoor	70
D	Opfake	613	*N*	GoldDream	69
E	GingerMaster	339	*O*	MobileTx	69
F	BaseBridge	330	*P*	FakeRun	61
G	Iconosys	152	*Q*	SendPay	59
H	Kmin	147	*R*	Gappusin	58
I	FakeDoc	132	*S*	Imlog	43
J	Geinimi	92	*T*	SMSreg	41

Detection Performance



Drebin



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Explainability

- Interpretation of Results
  - Insights into characteristics of malware
  - Analysis of false positives

- SVM assigns weight to each feature
  - Features with high weight → characteristic for class
  - Only consider features with high weights
  - Interpretation of malware characteristics

Example: DroidKungFu

Feature	Feature Set	Average Weight
SIG_STR	Filtered Intents	2,02
system/bin/su	Suspicious Calls	1,30
BATTERY_CHANGED_ACTION	Filtered Intents	1,26
READ_PHONE_STATE	Requested Permissions	0,54
getSubscriberId()	Suspicious Calls	0,49

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```
<receiver android:name="com.google.ssearch.Receiver">
    <intent-filter>
        <action android:name="android.intent.action.BATTERY_CHANGED_ACTION" />
        <action android:name="android.intent.action.SIG_STR" />
        <action android:name="android.intent.action.BOOT_COMPLETED" />
    </intent-filter>
</receiver>
```

1. Service is triggered by intent messages

Example: DroidKungFu

Feature	Feature Set	Average Weight
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system/bin/su	Suspicious Calls	1,30
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2. Malware tries to gain root access on the device

Example: DroidKungFu

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SIG_STR	Filtered Intents	2,02
system/bin/su	Suspicious Calls	1,30
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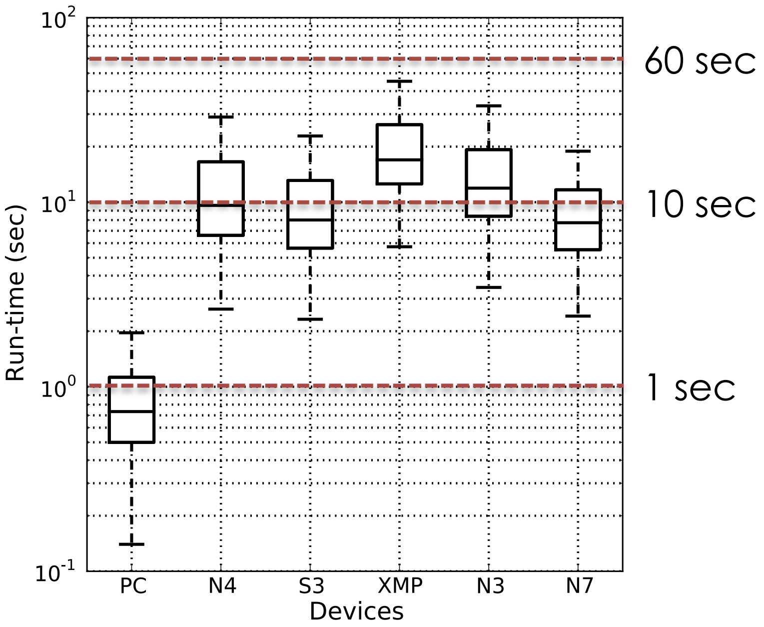
3. Malware steals sensitive data

Run-time Analysis

- Run-time evaluation using prototype implementation
  - Smartphones: Nexus 4, Galaxy S3, Xperia Mini Pro, Nexus i9250
  - Tablets: Nexus 7



Limitations

- Lack of Dynamic Analysis
  - Encryption of payload
  - Loading of malicious code during run-time

- Pollution Attacks
  - Poisoning of dataset by attacker

Conclusion

- Drebin allows reliable detection of Android malware
- Malware can be detected directly on the device
- Explanations are presented to the user

Thanks for your attention!

Questions?

References

- [1] Dissecting Android malware: Characterization and evolution
  - (Zhou and Jiang) (Oakland 2012)
- [2] A study of Android application security
  - (Enck et al.) (USENIX 2011)
- [3] Using probabilistic generative models for ranking risks of Android apps
  - (Peng et al.) (CCS 2012)
- [4] Android permissions: a perspective combining risks and benefits
  - (Sarma et al.) (SACMAT 2012)
- [5] Mobile sandbox: having a deeper look into android applications
  - (Spreitzenbarth et al.) (SAC 2013)

Detection Performance