KANSAS STATE
College of Engineering
Computing and Information Sciences

Scalable Security for Millions of Apps:

Utilizing Tiered-Machine Learning to Scale to Market-wide Solutions

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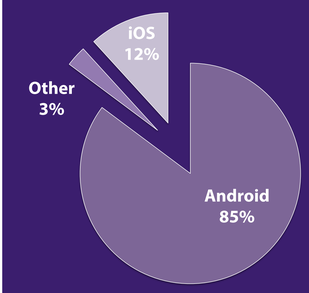
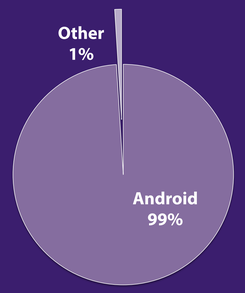
Background

- Android is the most popular platform, both for users (84.7%) and malware (99%)
- Many reasons make it the most common for malware: low protective measures taken by Google, more exploitable APIs, and third-party app stores.
- Google's malware detection tool, Bouncer, performs minimal checks before allowing apps onto the Play Store
- Third-party stores often have no protective measures

Users By Platform



Malware By Platform



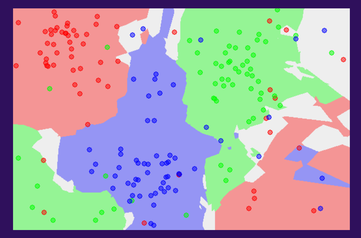
Problem

- The massive amounts of apps developed everyday makes existing solutions ineffective
- Static Analysis Tools are too computationally expensive and not scalable
- Lightweight syntactic approaches are too simple to work with high certainty
- Android Malware continue to evolve and quickly render signature-based systems irrelevant
- A proactive combination of the scalability of lightweight syntactic features with rich semantic features are necessary to provide for scalable security.

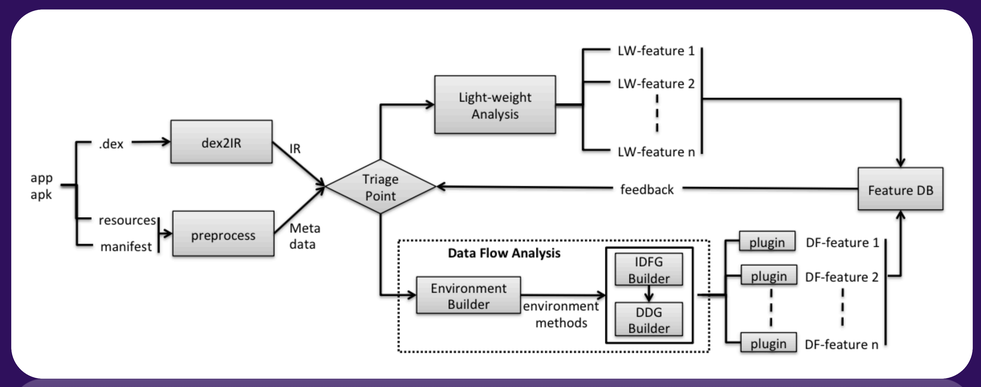
Objectives

- Develop an architecture that can provide the quality and precision of in-depth static analysis, at the speed and scalability of light weight analysis.
- Evaluate the system on realistic datasets symbolic of the magnitude and prevalence of malware in the wild.

Our Approach



- Start with over a million apps classified as either "malware" or "benign"
- Train our classifier on what characteristics relate to maliciousness
- Combine several light features to create a fast and less precise initial point of triage
- Apply more sophisticated and semantic-rich analyses where lightweight analysis were inconclusive
- Bottom line: fast and scalable malware detection with the insights of in-depth analysis where needed

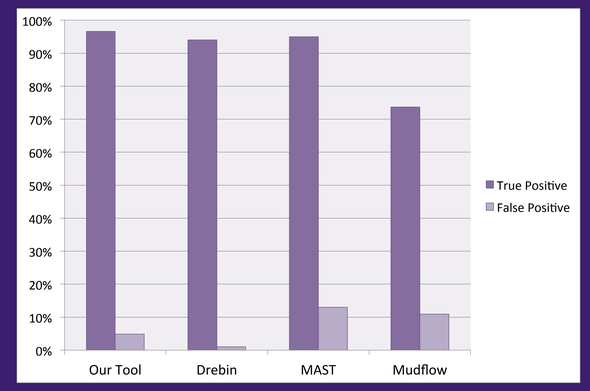


Implementation

- To scale, we utilize Kansas State's high performance computing cluster, Beocat, to extract lightweight feature vectors from millions of apps
- We then feed these characteristics, or feature vectors, to our machine learning classifier to teach it the characteristics of malicious and benign apps
- The system can then detect and classify new apps as either malicious or benign with high certainty
- If the app is marked as possibly malicious, we will apply slower and more precise analyses through our Amandroid framework to make a more accurate decision.

Results

- Our lightweight implementation is able to successfully detect malware 96.6% of the time
- We misclassify benign applications as malicious 4.9% of the time.



Conclusions

- Dataset selection can highly affect results
- Using small, old, or "popular" apps can yield very misleading results
- Our large-scale approach makes our results more real-world but also accuracy

Future Work

- Future work includes devising even newer and more indicative lightweight features
- Examining how detection models change and evolve as the Android ecosystem advances
- Tying in our custom, in-house static analysis framework, Amandroid, to provide more semantic-rich features to learn on

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