A Systematic Study of Comparing Traditional Machine Learning and Deep Learning for Security Vetting of Android Apps

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Award #1717862,#1717871,#1718214 SaTC: CORE: Small: Collaborative: Data-driven Approaches for Large-scale Security Analysis of Mobile Applications. \$200K, \$200K, \$100K, 8/15/2017-7/31/2020.

Datasets – for both DL and classical ML experiments

- ✓ Data collection lasted one and half years
- Solution Labeled 1,456,350 apps released between 2016 and 2018
- ✓ Labeled 339,853 apps between 2018 and 2019



- ✓ AMD malware dataset (2010 2016): 24,553
- ✓ Newer benign (After 2016): 370,701
- ✓ Newer malicious (After 2016): 24,868

Traditional ML Based Vetting System

- Uses specific apk features to classify benign and malicious apps
- The ML system used in our experiment is based on 471 features
- We built our datasets with real-life malicious:benign ratio (less than 0.05)

extracted from permissions, intent actions, discriminative APIs, obfuscation signatures, and native code signatures



Main Challenges

- Feature engineering has to keep up with evolving app trends
- Feature extractor has to keep up with changing app format

DL Shows Advantage over Traditional ML for Highly Unbalanced Data



- We use the area under the precision-recall curve (auPRC) to evaluate the classifier's performance for real-world application
- Experimented with Bernoulli Naïve Bayes, k-nearest neighbors, support vector machines, and random forest classifiers
- Traditional ML model meets challenges on highly unbalanced dataset



- Feeds raw apks into preprocessing layer; then generates API call sequence
- Treats each API call as a word; it uses the first 4000 API calls for each app
 Applies different embedding techniques such as Word2vec, GloVe, ELMo and BERT
 Each app, represented as a vector, is fed into an LSTM neural network layer with 4000 neurons



DL vs. Traditional ML Results

- Both traditional ML and DL models have good performance on balanced data
- Both models' performance decreases on unbalanced data
- DL model has better performance on highly unbalanced data
- 10 09 09 0.8 0.7 0.6 ML_Prediction 0.6 DL_Prediction_132k 0.3 0.2 0.1 0.067 0.05 0.02 0.01 Malicous/Benign Ratio

Benefits & Challenges

- Automated feature capability of DL could benefit mobile app vetting systems
- Efficiently applying DL for largescale malware detection comes with significant challenges



