An Evaluation of the State-of-the-Art Testing Algorithms for Android Mobile Applications

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Motivation

Why does mobile testing matter?

Online experience is becoming **Mobile-First**

- Banking
- Entertainment
- Social apps
- Gaming
- VC
- Health
- Business
- Hobbies

… and more

Problem Statement

SECURITY

USER EXPERIENCE

PRODUCTIVITY

Research Methodology

IDENTIFY	Identify commonly used approaches in industry and research
UNDERSTAND	Literature review to deep dive into different testing methodologies
BENCHMARK	Establish standard benchmark
COMPARE	Compare **CODE COVERAGE** and **FAULT DETECTION** of different approaches against the benchmark.

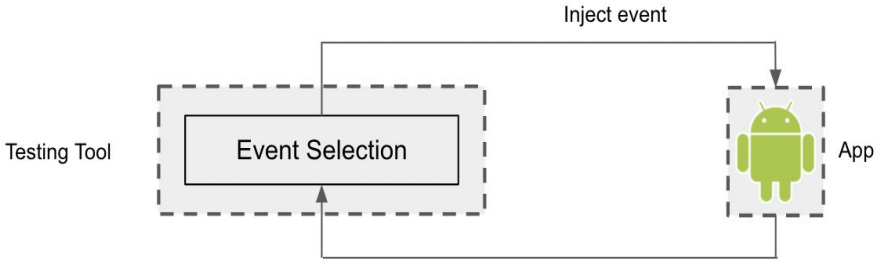
Android has 70+% of mobile OS market share. We use it to do the comparisons

Approaches to Testing

Random Testing

Send random, independent inputs to the app

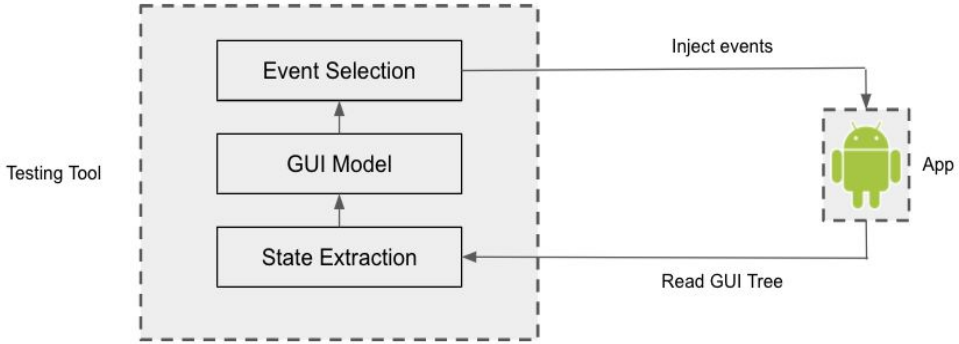
- ✓ Fully blackbox
- ✗ Difficult to reproduce crashes
- ✗ Prior info not leveraged



Model Based Testing

Infer app model and state from GUI, and exploit it

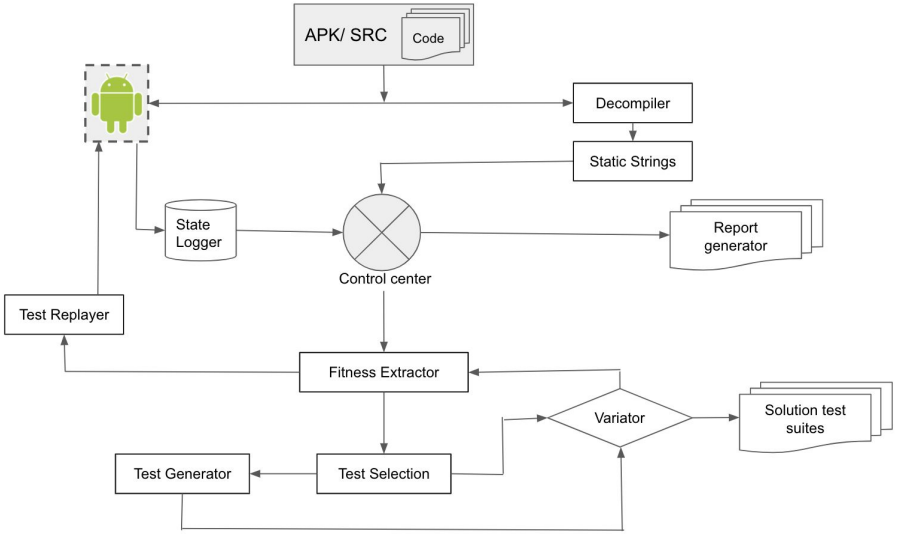
- ✓ Reuses learned information
- ✓ Easy to reproduce crashes
- ✗ Model cannot capture all information



Systematic Testing

Use symbolic execution to get high test coverage

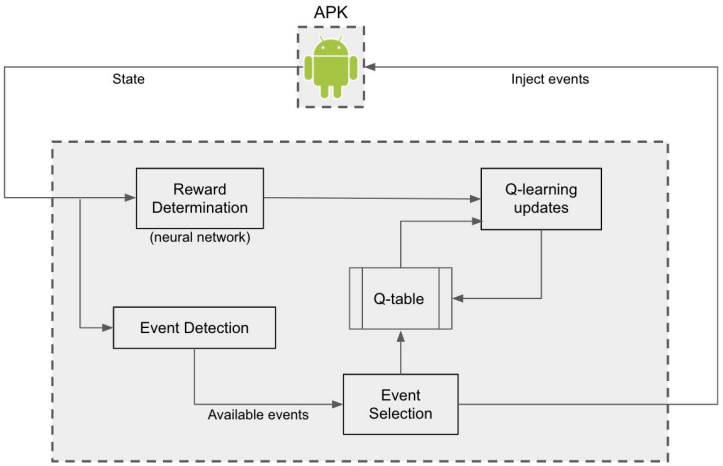
- ✓ Efficient use of internals
- ✗ Not blackbox
- ✗ Path explosion leads to complexity



Machine Learning Based Testing

Train model on many apps to learn app behaviors, and test using that knowledge

Trial/error nature lends to regressive learning algorithms



- ✓ Deep learning about apps
- ✓ Leverage info across apps
- ✗ Complex to build due to variety of events and widgets

Results and Findings

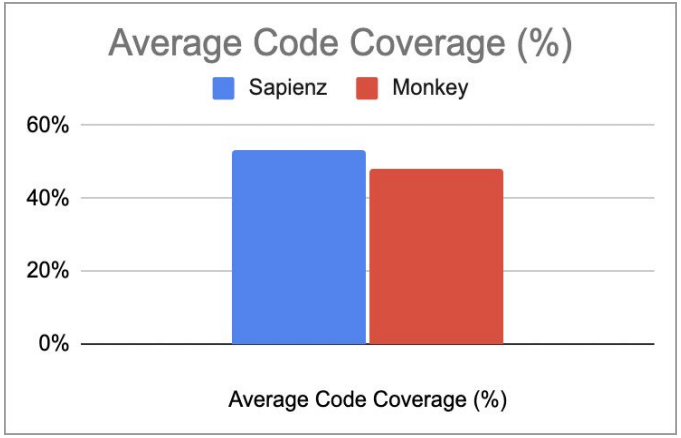
Monkey

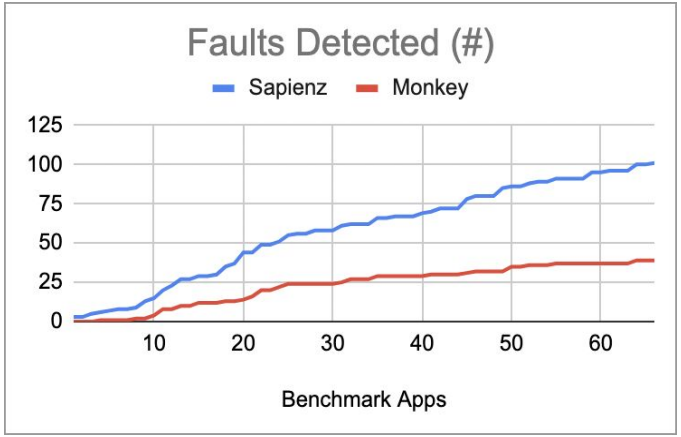
- Google's default Android testing tool
- Random testing, no learning
- Pros
  - Out-of-the-box, simple. Widely used.
- Cons
  - Bug recreation is hard
  - Long execution times
  - No ability of event selection

Selected as benchmark for wide adoption

Sapienz

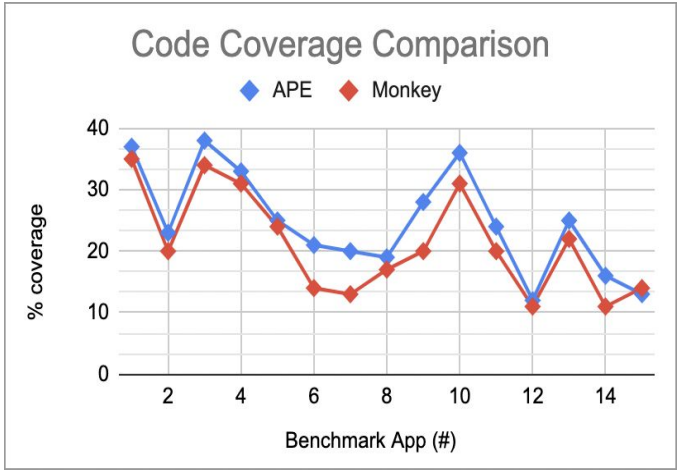
- White box testing by instrumenting the code
- Provides different capabilities depending on level of access
- White box testing is resource intensive and non-leverageable across apps

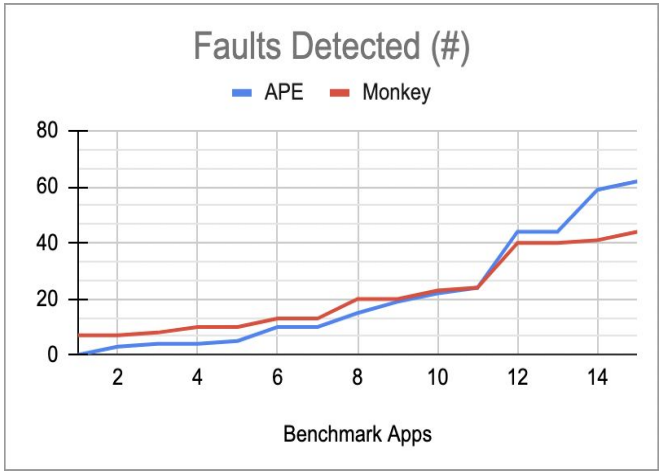




APE

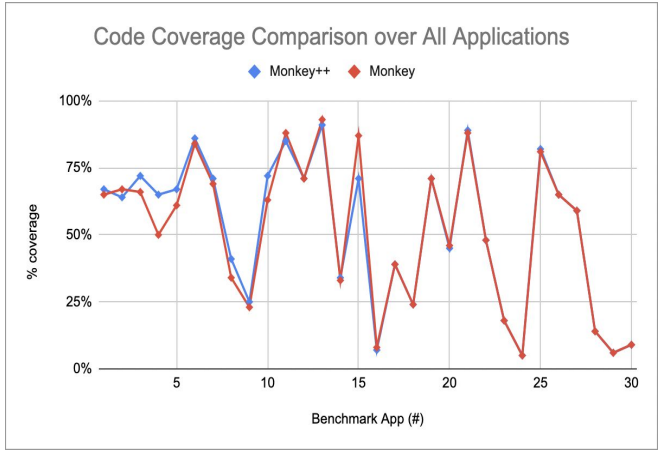
- Starts with an abstract model, and tunes it as it tests and learns.
- Dynamic tuning well suited for complex GUI trees
- Effective blackbox testing

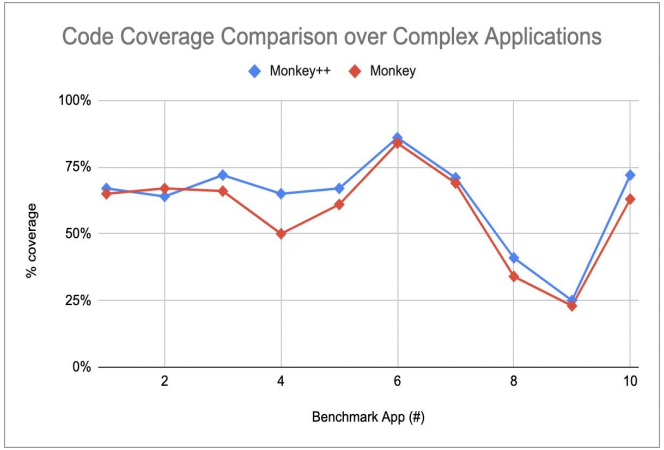




DeepGUI/Monkey++

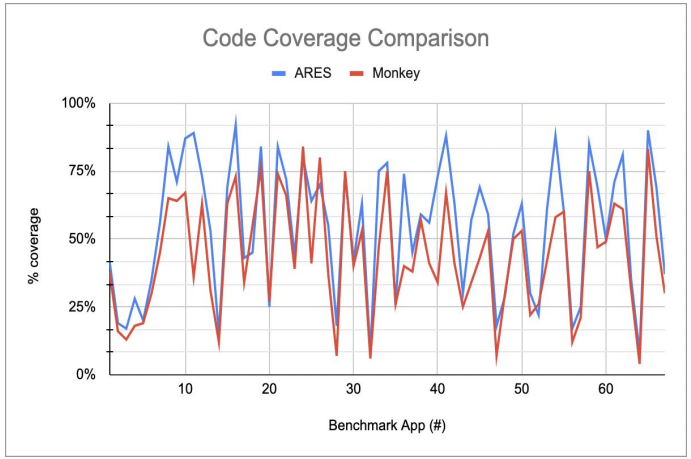
- Uses machine learning to create heat map of pixels likely to be widgets
- Sophisticated event selection process
- Implemented in Monkey, creating Monkey++

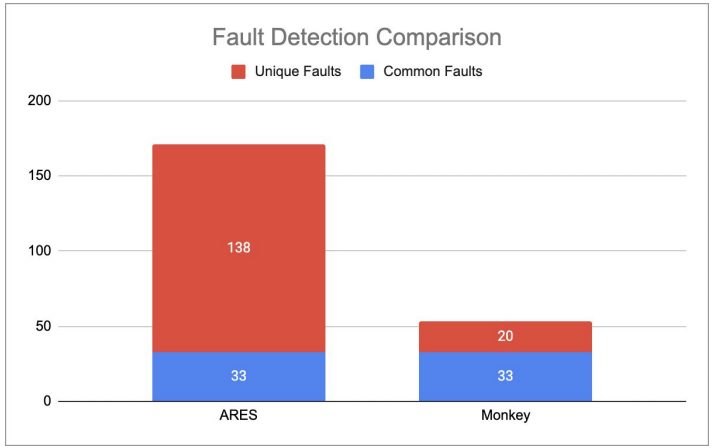




ARES

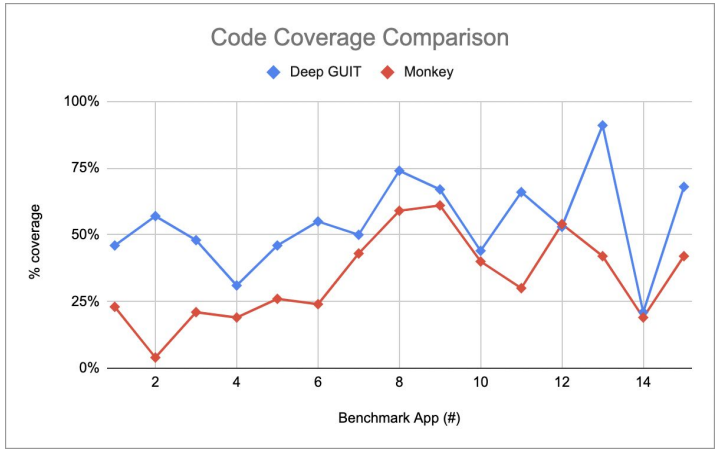
- Generic, black box testing tool that learns and evolves
- Neural network semantics - trial and error testing with reward system
- Users can plug in any of the neural learning algorithms

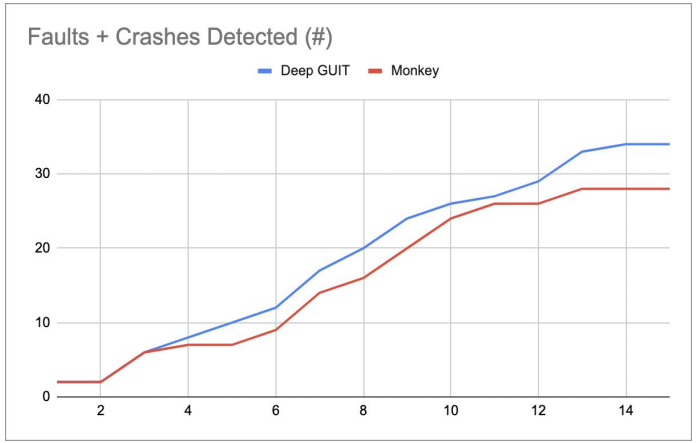




DeepGUIT

- Q-learning: Understand value of an action in a certain state, and try to get to a more "interesting" state from there
- Whitebox testing, needs code instrumentation to be effective
- Can lead to an explosion of # of state-action pairs in complex apps





Conclusion and Implications

Conclusions

- ML-based tools most effective
- Neural algorithms have potential to create intelligent automated tools
- Sapienz has very effective fault detection
- Monkey++ demonstrates significantly more efficient event detection

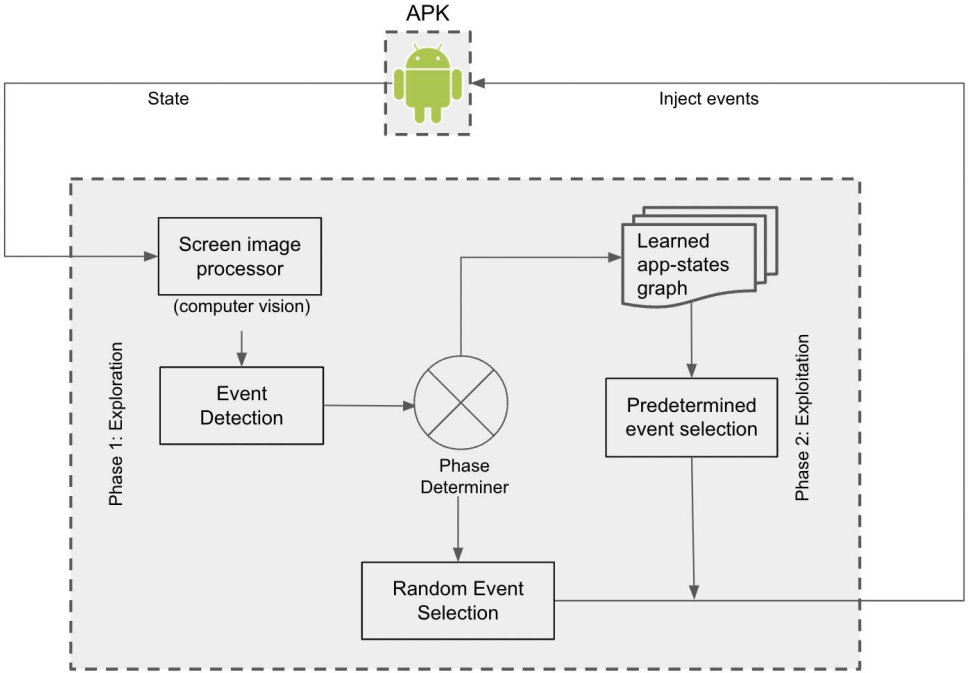
	Effective		Fastest	Best fault detection	Best code coverage
	Sapienz	**APE**	**Monkey++**	**ARES**	**DeepGUIT**
Code coverage improvement	10.4%	16.7%	8.3%	23.4%	**58.8%**
Fault detection improvement	**159.0%**	41.0%	-	**223.0%**	21.4%
Testing modes	Multi-mode	Black-box	Black-box	Black-box	Black-box
Testing Approach	Systematic	Model	Random	ML	ML

But, there are gaps

- Random or model based testing
  - Can't handle complex workflows and states
  - Faults difficult to reproduce in random testing
  - Either low code coverage or long testing times - both lead to poor fault detection
- Neural Self Learning methods
  - Need very a large set of training apps to get trained
  - Time intensive to build. Need specialized skills.
  - Android events and widgets are complex and varied and upsets self learning
  - Runs into memory pressure with complex workflows

My Algorithm

- Create app models for testing
- Use computer vision to understand GUI
- Discover states with many unexplored events to maximize code coverage
- Implements regressive learning to improve event selection
- Adapt reward mechanisms to optimize finding security vulnerabilities



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Thank You

Any Questions?