Software Model Checking via Systematic Testing

Lecture 2: Dealing with Data Inputs

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Software Model Checking

- · How to apply model checking to analyze software?
 - "Real" programming languages (e.g., C, C++, Java),
 - "Real" size (e.g., 100,000's lines of code).
- · Two main approaches to software model checking:



Security is Critical (to Microsoft)

- · Software security bugs can be very expensive:
 - Cost of each Microsoft Security Bulletin: \$Millions
 - Cost due to worms (Slammer, CodeRed, Blaster, etc.): \$Billions
- · Many security exploits are initiated via files or packets
 - Ex: Internet Explorer parses dozens of file formats
- Security testing: "hunting for million-dollar bugs"
 - Write A/V (always exploitable), Read A/V (sometimes exploitable), NULL-pointer dereference, division-by-zero (harder to exploit but still DOS attacks), etc.

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Hunting for Security Bugs

- · Main techniques used by "black hats":
 - Code inspection (of binaries) and
 - Blackbox fuzz testing
- Blackbox fuzz testing:
 - A form of blackbox random testing [Miller+90]
 - Randomly fuzz (=modify) a well-formed input
 - Grammar-based fuzzing: rules that encode "well-formed"ness + heuristics about how to fuzz (e.g., using probabilistic weights)
- · Heavily used in security testing
 - Simple yet effective: many bugs found this way...
 - At Microsoft, fuzzing is mandated by the SDL →

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Blackbox Fuzzing

- · Examples: Peach, Protos, Spike, Autodafe, etc.
- · Why so many blackbox fuzzers?
 - Because anyone can write (a simple) one in a week-end!
 - Conceptually simple, yet effective...
- Sophistication is in the "add-on"
 - Test harnesses (e.g., for packet fuzzing)
 - Grammars (for specific input formats)
- · Note: usually, no principled "spec-based" test generation
 - No attempt to cover each state/rule in the grammar
 - When probabilities, no global optimization (simply random walks)

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Introducing Whitebox Fuzzing

- · Idea: mix fuzz testing with dynamic test generation
 - Symbolic execution
 - Collect constraints on inputs
 - Negate those, solve with constraint solver, generate new inputs
 - → do "systematic dynamic test generation" (=DART)
- Whitebox Fuzzing = "DART meets Fuzz" Two Parts:
 - 1. Foundation: DART (Directed Automated Random Testing)
 - 2. Key extensions ("Whitebox Fuzzing"), implemented in SAGE

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Automatic Code-Driven Test Generation

Problem:

Given a sequential program with a set of input parameters, generate a set of inputs that maximizes code coverage

= "automate test generation using program analysis"

This is not "model-based testing" (= generate tests from an FSM spec)

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How? (1) Static Test Generation

- Static analysis to partition the program's input space [King76,...]
- Ineffective whenever symbolic reasoning is not possible
 - which is frequent in practice... (pointer manipulations, complex arithmetic, calls to complex OS or library functions, etc.)

```
int obscure(int x, int y) {
                                      Can't statically generate
                                      values for x and y that satisfy "x==hash(y)"!
  if (x==hash(y)) error();
  return O:
```

How? (2) Dynamic Test Generation

- Run the program (starting with some random inputs), gather constraints on inputs at conditional statements, use a constraint solver to generate new test inputs
- Repeat until a specific program statement is reached [Korel90,...]
- Or repeat to try to cover ALL feasible program paths: DART = Directed Automated Random Testing = systematic dynamic test generation [PLDI'05,...]
 - detect crashes, assertion violations, use runtime checkers (Purify,...)

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DART = Directed Automated Random Testing

```
Run 1:- start with (random) x=33, y=42
Example:
int obscure(int x, int y) { - execute concretely and symbolically:

if (33!=567) | if (x!=hash(y))
                                       if (33 != 567)
  if (x==hash(y)) error();
                                                      constraint too
  return 0:
                                                       → simplify it: x != 567
                                      - solve: x==567 → solution: x=567
                                      - new test input: x=567, y=42
                                      Run 2: the other branch is executed
                                      All program paths are now covered
```

- Observations:
 - Dynamic test generation extends static test generation with additional runtime information: it is more powerful
 - The number of program paths can be infinite: may not terminate!
 - Still, DART works well for small programs (1,000s LOC)
 - Significantly improves code coverage vs. random testing

DART Implementations

- Defined by symbolic execution, constraint generation and solving
 - Languages: C, Java, x86, .NET,...
 - Theories: linear arith., bit-vectors, arrays, uninterpreted functions,...
 - Solvers: lp_solve, CVCLite, STP, Disolver, Z3,...
- Examples of tools/systems implementing DART:
 - EXE/EGT (Stanford): independent ['05-'06] closely related work
 - CUTE = same as first DART implementation done at Bell Labs
 - SAGE (CSE/MSR) for x86 binaries and merges it with "fuzz" testing for finding security bugs (more later)
 - PEX (MSR) for .NET binaries in conjunction with "parameterized-unit tests" for unit testing of .NET programs
 - YOGI (MSR) for checking the feasibility of program paths generated statically using a SLAM-like tool
 - Vigilante (MSR) for generating worm filters
 - BitScope (CMU/Berkeley) for malware analysis
 - CatchConv (Berkeley) focus on integer overflows
 - Splat (UCLA) focus on fast detection of buffer overflows
 - Apollo (MIT) for testing web applications

and more

DART Summary

- DART attempts to exercise all paths (like model checking)
 - Covering a single specific assertion (verification): hard problem (often intractable)
 - Maximize path coverage while checking thousands of assertions all over: easier problem (optimization, best-effort, tractable)
- Better coverage than pure random testing (with directed search)
- DART can work around limitations of symbolic execution
- Symbolic execution is an adjunct to concrete execution
- Concrete values are used to simplify unmanageable symbolic expressions
- Randomization helps where automated reasoning is difficult
- Comparison with static analysis:
 - No false alarms (more precise) but may not terminate (less coverage)

 - "Dualizes" static analysis: static \rightarrow may vs. DART \rightarrow must

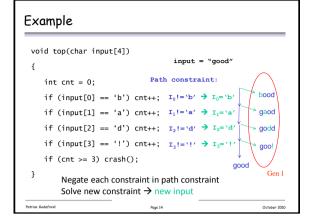
 Whenever symbolic exec is too hard, under-approx with concrete values

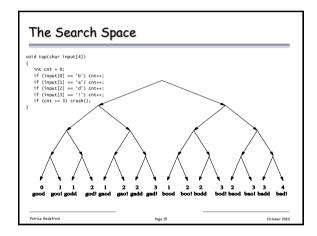
 If symbolic execution is perfect, no approx needed: both coincide!

Whitebox Fuzzing [NDSS'08]

- · Whitebox Fuzzing = "DART meets Fuzz"
- · Apply DART to large applications (not unit)
- · Start with a well-formed input (not random)
- · Combine with a generational search (not DFS)
 - Negate 1-by-1 each constraint in a path constraint
 - Generate many children for each parent run
 - Challenge all the layers of the application sooner
 - Leverage expensive symbolic execution
- Search spaces are huge, the search is partial... yet effective at finding bugs!

Gen 1

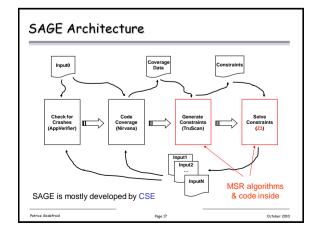


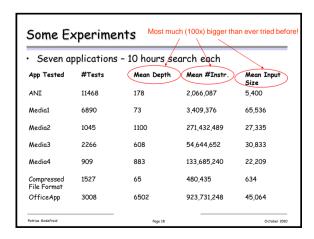


SAGE (Scalable Automated Guided Execution)

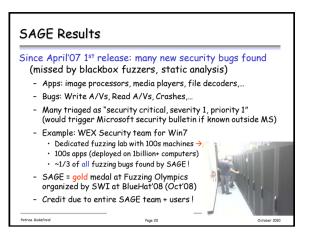
- Generational search introduced in SAGE
- Performs symbolic execution of x86 execution traces
 - Builds on Nirvana, iDNA and TruScan for x86 analysis

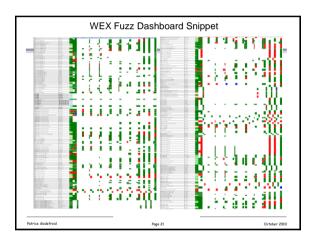
 - Don't care about language or build process
 - Easy to test new applications, no interference possible
- Can analyse any file-reading Windows applications
- Several optimizations to handle huge execution traces
 - Constraint caching and common subexpression elimination
 - Unrelated constraint optimization
 - Constraint subsumption for constraints from input-bound loops
 - "Flip-count" limit (to prevent endless loop expansions)

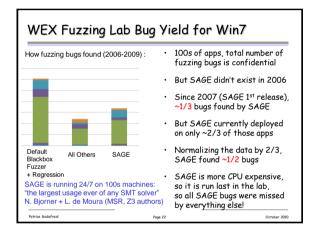


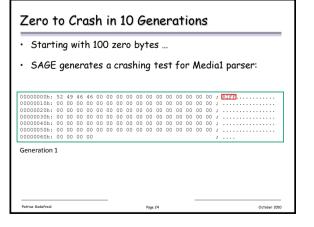


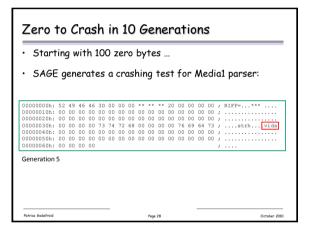
Generational Search Leverages Symbolic Execution • Each symbolic execution is expensive **Test Task** • Yet, symbolic execution does not dominate search time **Testing/Tracing/Coverage** **Testing/Tracing/Tracing/Coverage** **Testing/Tracing/Tr

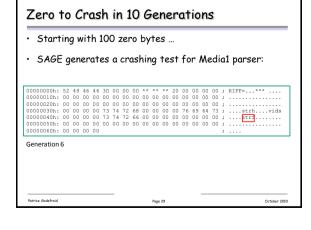


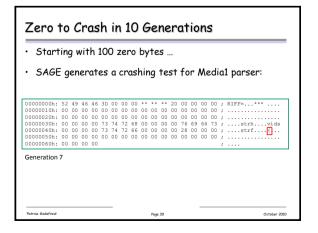












Zero to Crash in 10 Generations

- Starting with 100 zero bytes ...
- · SAGE generates a crashing test for Media1 parser:



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Zero to Crash in 10 Generations

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Zero to Crash in 10 Generations

- · Starting with 100 zero bytes ...
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Different Seed Files, Different Crashes

Bucket	seed1	seed2	seed3	seed4	seed5	100 zero bytes
1867196225	×	×	×	x	х	
2031962117	×	×	×	×	×	
612334691		×	×			
1061959981			×	×		
1212954973			×			х
1011628381			×	×		х
842674295				×		
1246509355			×	×		×
1527393075					x	
1277839407					×	
1951025690			×	For the first time, we	e face bug tri	age issu

SAGE Summary

- SAGE is so effective at finding bugs that, for the first time, we face "bug triage" issues with dynamic test generation
- What makes it so effective?
 - Works on large applications (not unit test, like DART, EXE, etc.)
 - Can detect bugs due to problems across components
 - Fully automated (focus on file fuzzing)
 - Easy to deploy (x86 analysis any language or build process!)
 - · 1st tool for whole-program dynamic symbolic execution at x86 level
 - Now, used daily in various groups at Microsoft

More On the Research Behind SAGE

- How to recover from imprecision in symbolic execution? PLDI'05
- How to scale symbolic exec. to billions of instructions? NDSS'08
 Techniques to deal with large path constraints
- How to check efficiently many properties together? EMSOFT08
 Active property checking
- How to leverage grammars for complex input formats? PLDT'08
 Lift input constraints to the level of symbolic terminals in an input grammar
- How to deal with path explosion? POPL'07, TACAS'08, POPL'10
 Symbolic test summaries (more later)
- How to reason precisely about pointers? ISSTA'09

 · New memory models leveraging concrete memory addresses and regions
- How to deal with floating-point instructions? ISSTA'10
 Prove "non-interference" with memory accesses
- + research on constraint solvers (Z3, disolver,...)

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Conclusion: Impact of SAGE (In Numbers)

- · 100+ machine-years
 - Runs in the largest dedicated fuzzing lab in the world
- · 100+ million constraints
 - Largest computational usage ever for any SMT solver
- · 100s of apps, 100s of bugs (missed by everything else)
- Bug fixes shipped to 1 Billion+ computers worldwide
- · Millions of dollars saved
 - for Microsoft + time/energy savings for the world
- DART, Whitebox fuzzing now adopted by (many) others (10s tools, 100s citations)

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Conclusion: Blackbox vs. Whitebox Fuzzing

- · Different cost/precision tradeoffs
 - Blackbox is lightweight, easy and fast, but poor coverage
 - Whitebox is smarter, but complex and slower
 - Note: other recent "semi-whitebox" approaches
 - Less smart (no symbolic exec, constr. solving) but more lightweight: Flayer (taint-flow, may generate false alarms), Bunny-the-fuzzer (taint-flow, source-based, fuzz heuristics from input usage), etc.
- · Which is more effective at finding bugs? It depends...
 - Many apps are so buggy, any form of fuzzing find bugs in those!
 - Once low-hanging bugs are gone, fuzzing must become smarter: use whitebox and/or user-provided guidance (grammars, etc.)
- · Bottom-line: in practice, use both! (We do at Microsoft)

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Future Work (The Big Picture)

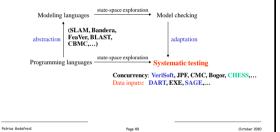
- During the last decade, code inspection for standard programming errors has largely been <u>automated</u> with static code analysis
- · Next: automate testing (as much as possible)
 - Thanks to advances in program analysis, efficient constraint solvers and
- · Whitebox testing: automatic code-based test generation
 - Like static analysis: automatic, scalable, checks many properties
 - Today, we can exhaustively test small applications, or partially test large applications
 - Biggest impact so far: whitebox fuzzing for (Windows) security testing
 Improved security for a billion computers worldwide!
 - Next: towards exhaustive testing of large applications (verification)
 - How far can we go?

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Conclusion

- Software Model Checking via Systematic Testing
 - Lecture 2: Dealing with Data Inputs



Acknowledgments: SAGE

- · Joint work with Michael Levin (CSE) and others:
 - Chris Marsh, Lei Fang, Stuart de Jong (CSE)
 - interns Dennis Jeffries (06), David Molnar (07), Adam Kiezun (07), Bassem Elkarablieh (08), ...
- Thanks to the entire SAGE team and users!
 - MSR: Ella Bounimova,...
 - Z3: Nikolaj Bjorner, Leonardo de Moura,...
 - WEX (Windows): Nick Bartmon, Eric Douglas,...
 - Office: Tom Gallagher, Octavian Timofte,...
 - SAGE users all across Microsoft!

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