

Synthesising the semantics of obfuscated code

Tim Blazytko
⟨tim.blazytko@rub.de⟩

Ruhr-Universität Bochum

24th January 2017

Joint work

Chair for Systems Security, Ruhr-Universität Bochum

- Tim Blazytko
- Moritz Contag
- Cornelius Aschermann
- Thorsten Holz

Today

- How does code obfuscation work?
- What is Monte Carlo Tree Search (MCTS)?
- How does MCTS-based program synthesis work?
- How to deobfuscate assembly code with program synthesis?

Code analysis

How do we analyse code?

- static analysis
 - disassembler
 - control-flow graphs
- dynamic analysis
 - debugging
 - instruction traces
- automated analysis

Obfuscation

Make analysis more difficult

Code obfuscation

Techniques 1/2

- disassembler/debugger traps
- packers, self-modifying code
- opaque predicates (cf. next slides)
- control-flow flattening (cf. next slides)

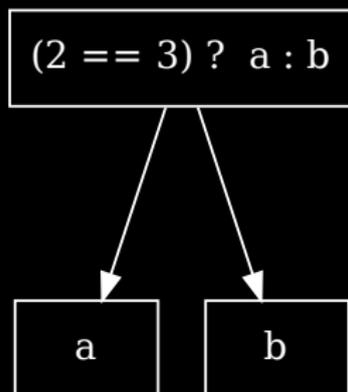
Code obfuscation

Techniques 2/2

- mixed Boolean-arithmetic (cf. next slides)
- data encoding
- virtual machine-based obfuscation (cf. next slides)
- white-box cryptography

Code obfuscation

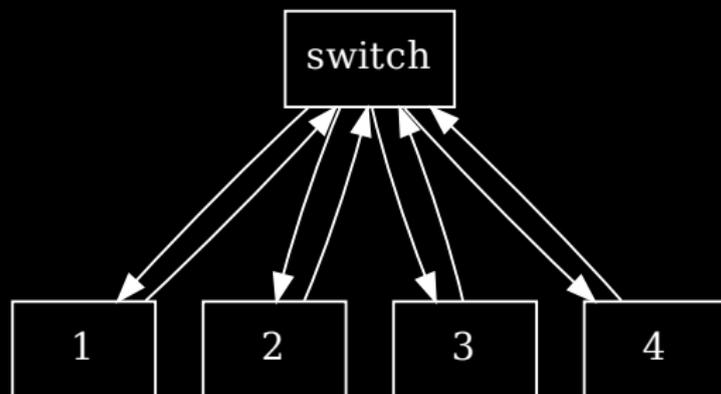
Opaque predicates



- always evaluate to either true or false

Code obfuscation

Control-flow flattening



- obfuscate control-flow structure

Code obfuscation

Mixed Boolean-arithmetic

$$x + y$$

$$(x \oplus y) + 2 \cdot (x \wedge y)$$

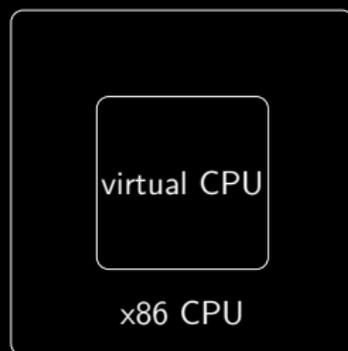
$$x + y + z$$

$$(((x \oplus y) + ((x \wedge y) \ll 1)) \vee z) + (((x \oplus y) + ((x \wedge y) \ll 1)) \wedge z)$$

hard to simplify symbolically

Code obfuscation

Virtual machine-based obfuscation



- virtual CPU with custom instruction set (VM instruction handler)
- obfuscated code is interpreted by virtual CPU

Code deobfuscation

Techniques 1/2

- abstract interpretation
 - analysis in an abstract domain
- SMT-based analysis
 - detection of unsatisfiability paths
- taint analysis
 - tracking the dependencies of an input

Code deobfuscation

Techniques 2/2

- symbolic execution
 - CAS-like assembly code calculation
- program synthesis
 - learning the semantics of traces
- side-channel attacks
 - DPA, fault injection on white-box cryptography

Code deobfuscation

State-of-the-art

- works on instruction traces
- mixture of taint analysis and symbolic execution
- anti-taint analysis techniques are well known
- recent work on obfuscation attacks symbolic execution

Program synthesis for deobfuscation

Don't care about code analysis

- previous techniques precisely analyse the underlying code
 - ⇒ limited by code complexity
- program synthesis is an orthogonal approach
 - limited by the complexity of the underlying semantics
 - ⇒ works for code and expressions of arbitrary complexity

Oracle-guided synthesis

Given: input/output black-box oracle



What happens inside?

Running example

We want to synthesise

$$f(a, b) = a + b \pmod{2^3}$$

We observe

- $f(2, 2) = 4$
- $f(4, 5) = 1$

The set of I/O samples is

$$S = \{(2, 2) \rightarrow 4, (4, 5) \rightarrow 1\}$$

Monte Carlo tree search (MCTS)

Introduction

- general game playing, Computer Go
- reinforcement learning
- does not require much domain knowledge
- efficient tree search for exponential decision trees
- based on random walks and Monte Carlo simulations
- synthesis as stochastic optimisation problem

Monte Carlo tree search (MCTS)

Algorithm

- 1 node selection
 - select best child node (exploration vs. exploitation trade-off)
- 2 node expansion
 - derive new game states
- 3 simulation
 - random playouts
 - a score represents the node's quality
- 4 backpropagation
 - update the path's quality

Monte Carlo tree search (MCTS)

Visualisation

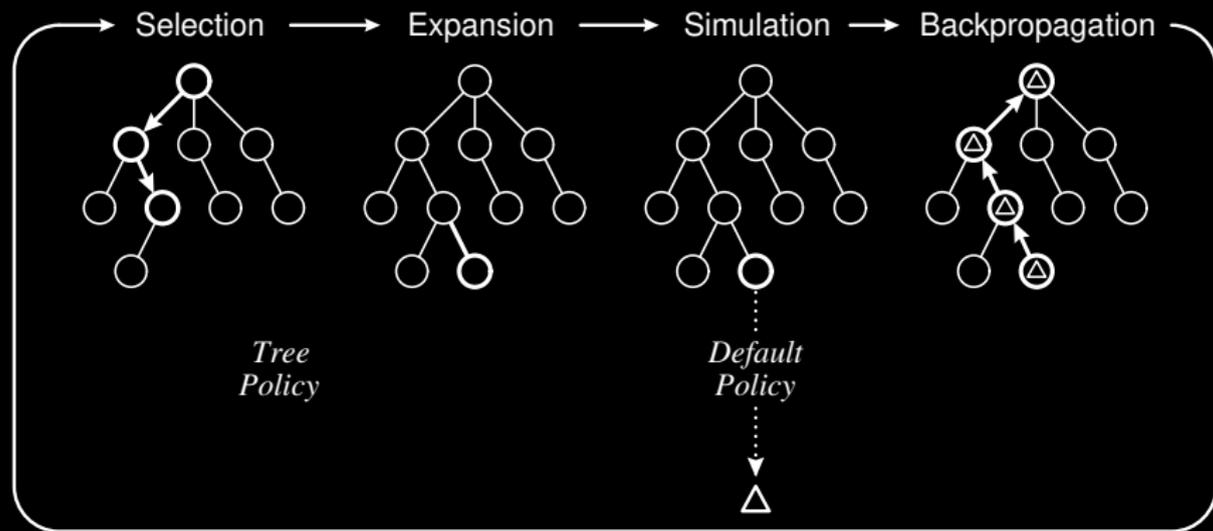


Figure: MCTS algorithm [2]

Selection

Upper confidence bound for trees (UCT)

$$\bar{X}_j + C \sqrt{\frac{\ln n}{n_j}}$$

- average child reward: \bar{X}_j
- number of simulations (parent node): n
- number of simulations (child node): n_j
- exploration-exploitation constant: C

Selection

Simulated Annealing UCT (SA-UCT)

$$\bar{X}_j + T \sqrt{\frac{\ln n}{n_j}}$$

- dynamic parameter: $T = C \frac{N-i}{N}$
- exploration-exploitation constant: C
- maximal MCTS rounds: N
- current MCTS round: i

Focus shifts to exploitation over time.

Context-free grammar

$$U \rightarrow U U + \mid U U * \mid a \mid b$$

- non-terminal symbol U
- a terminal symbol for each input
- expressions: game states (nodes)
- production rules: moves in the game
- root node U
- terminal nodes: end states of the game

$$U \Rightarrow U U + \Rightarrow U a + \Rightarrow b a +$$

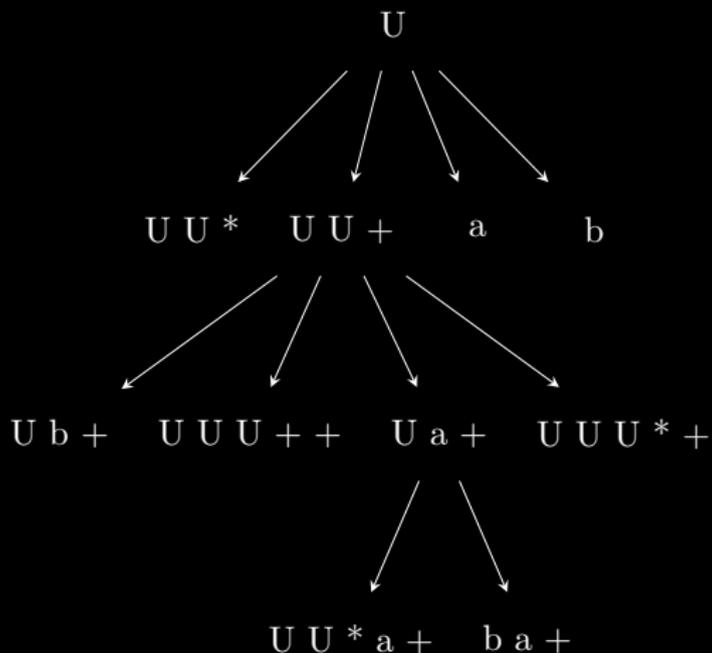
Expression derivation

$$U U U * + \Leftrightarrow (U + (U * U))$$



- apply random production rule to **top-most-right-most** U

Synthesis tree



Grammar components

- addition, multiplication
- unary/binary minus
- signed/unsigned division
- signed/unsigned remainder
- logical and arithmetic shifts
- unary/binary bitwise operations

Random payout

Algorithm

Algorithm

Input: Set of I/O samples S

- 1 randomly derive terminal expression T from current node
- 2 $reward := 0$
- 3 for all $\vec{I}, O \in S$
 - 1 evaluate terminal expression $O' := T(\vec{I})$
 - 2 $reward := \text{similarity}(O, O') + reward$
- 4 return $\frac{reward}{|S|}$

Random payout

Example: random derivations for two different nodes

$$S = \{(2, 2) \rightarrow 4, (4, 5) \rightarrow 1\}$$

- $U U * \Rightarrow U U U * * \Rightarrow U U + U U * * \Rightarrow \dots \Rightarrow a a + b a * *$

$$\Rightarrow g(a, b) = ((a + a) * (b * a)) \bmod (2^8)$$

$$\Rightarrow g(2, 2) = 0$$

- $U U + \Rightarrow \dots \Rightarrow a b b + +$

$$\Rightarrow h(a, b) = (a + (b + b)) \bmod 2^8$$

$$\Rightarrow h(2, 2) = 6$$

Similarity of outputs

Metrics

Arithmetic mean of the following metrics:

- trailing zeros
- leading zeros
- trailing ones
- leading ones
- hamming distance
- numeric distance

Similarity of outputs

Example: hamming distance and leading zeros

$$\text{similarity}(O, O') := \frac{\text{hamming}(O, O') + \text{clz}(O, O')}{2}$$

$U U *$

$$\text{similarity}(4, 0) := \frac{0.67+0}{2} = 0.335$$

$U U +$

$$\text{similarity}(4, 6) := \frac{0.67+1.0}{2} = 0.835$$

$U U +$ has a higher reward than $U U *$

Backpropagation

Algorithm

Input: current node n

- 1 WHILE $n \neq root$
 - 1 update the nodes average reward
 - 2 increment the nodes playout count
 - 3 $n := n.parent$

Monte Carlo tree search (MCTS)

Now it should make sense

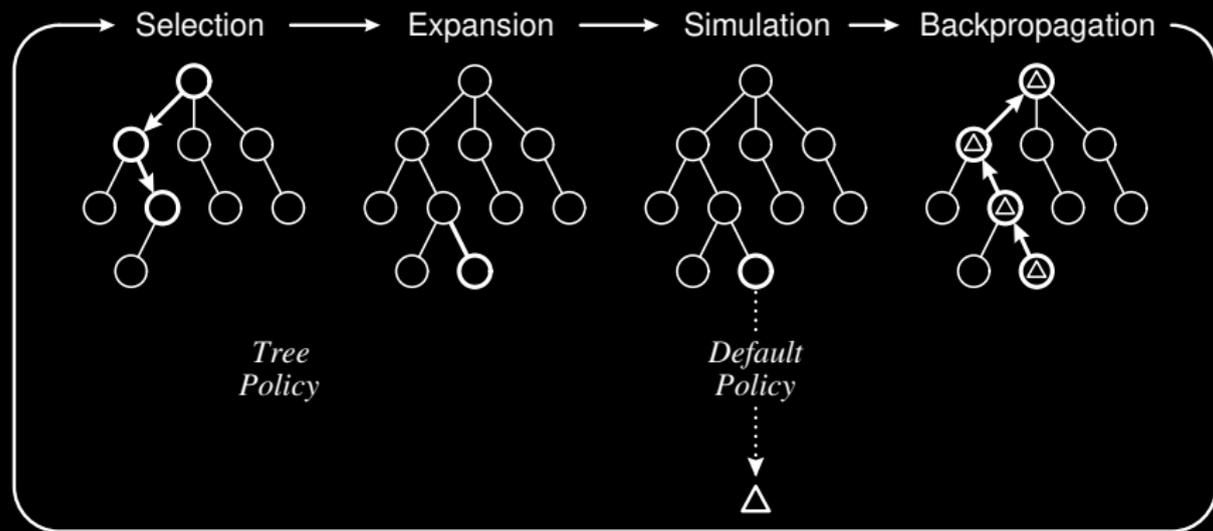


Figure: MCTS algorithm [2]

Simplification of instruction traces

Overview

Procedure

- 1 dissecting trace into trace windows
- 2 random sampling of each trace window
- 3 synthesis of trace windows

Trace dissection

How to determine trace window boundaries?

- trace window boundaries impact synthesis results
 - $x \oplus y$
 - $(x \oplus y) + 2 \cdot (x \wedge y)$
- split traces at indirect control-flow transfers

Trace dissection

Example

```
1 mov rax, 0x8
2 add rax, rbx
3 jmp rdx
4 inc rax
5 ret
6 mov rdx, 0x1
7 ret
```

Instruction trace

```
1 mov rax, 0x8
2 add rax, rbx
3 jmp rdx
```

Trace window 1

```
1 inc rax
2 ret
```

Trace window 2

```
1 mov rdx, 0x1
2 ret
```

Trace window 3

Random sampling

Generating I/O pairs

- trace memory modifications in a window
- derive inputs and outputs
 - read-before-write principle
 - inputs: memory reads, registers
 - outputs: memory writes, registers
- generate random inputs and calculate outputs

Random sampling

Example

```
1 mov rax, [rbp + 0x8]
2 add rax, rcx
3 mov [rbp + 0x8], rax
4 add [rbp + 0x8], rdx
```

- inputs: $\vec{I} = (M_0, rcx, rdx)$
- outputs: O_0, O_1
- $O_0 = M_0 + rcx$
- $O_1 = (M_0 + rcx) + rdx$
- $(2, 5, 7) \rightarrow (7, 14)$
- $(1, 7, 10) \rightarrow (8, 18)$

Synthesis

$$(M_0, rcx, rdx) \rightarrow (O_0, O_1)$$

$$(2, 5, 7) \rightarrow (7, 14)$$

$$(1, 7, 10) \rightarrow (8, 18)$$

We synthesise each output separately:

$$S_{O_0} := \{(2, 5, 7) \rightarrow 7, (1, 7, 10) \rightarrow 8\}$$

$$S_{O_1} := \{(2, 5, 7) \rightarrow 14, (1, 7, 10) \rightarrow 18\}$$

Evaluation

Generic approach

- synthesis of arithmetic instruction handlers
 - VMProtect
 - Themida VMs
- simplification of mixed Boolean-arithmetic
 - Tigress Obfuscator
- ROP gadget analysis

Mixed Boolean-arithmetic

Overview

```
int p10 (int v0, int v1, int v2, int v3, int v4)
{
    int r = ((~ v0) - v4);

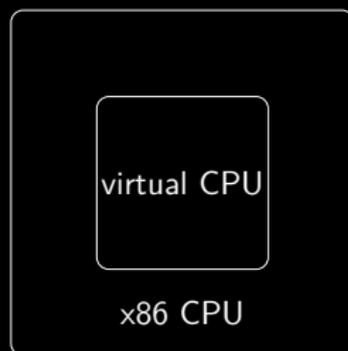
    return r;
}
```

- generated 500 *random* expressions (layer 3 to 5)
- 5 input variables per expression
- two stages of arithmetic encoding (average layer 156)
- synthesised 442 expressions (88.4%) in 30 minutes
- less than 4 seconds per synthesis task

DEMO

Code obfuscation

Virtual machine-based obfuscation



- virtual CPU with custom instruction set (VM instruction handler)
- obfuscated code is interpreted by virtual CPU

VMProtect

Overview

- basis of Denuvo
- stack-based VM
- performs bitwise operations with NOR gates
- 48 instructions per handler
- 2 inputs and outputs per handler

DEMO

VMProtect

Results

- 12,577 trace windows on instruction trace
- 449 of them unique
- 1123 synthesis tasks finished in less than one hour
- 3 seconds per synthesis task on average
- synthesised 19.2% of the whole trace
- synthesised 93.8% of all 184 arithmetic handlers

Themida

Overview

- register-based VM architecture
- 258 instructions per handler on average
- 10 to 15 inputs/outputs per handler

Themida

Results

- 2448 trace windows on instruction trace
- 106 unique trace windows
- synthesis finished in 77 minutes for 1092 tasks
- 4.1 seconds per synthesis task
- learned the semantics of 34 out of 36 (94.4%) arithmetic handlers

ROP gadget analysis

- 78 unique gadgets
- 3 inputs and 2 outputs on average
- synthesised partial semantics for 91% of the gadgets
- successful in 72% of the 178 synthesis tasks

Conclusion

- obfuscation and deobfuscation techniques
- Monte Carlo Tree Search
- MCTS-based program synthesis
- simplification of instruction traces
- evaluation on commercial obfuscators

References I

-  David Silver et al. 'Mastering the Game of Go with Deep Neural Networks and Tree Search'. In: *Nature* (2016).
-  Cameron B Browne et al. 'A Survey of Monte Carlo Tree Search Methods'. In: *IEEE Transactions on Computational Intelligence and AI in Games* (2012).
-  Maarten PD Schadd et al. 'Single-player Monte-Carlo Tree Search for SameGame'. In: *Knowledge-Based Systems* (2012).
-  Hilmar Finnsson. 'Generalized Monte-Carlo Tree Search Extensions for General Game Playing'. In: *AAAI Conference on Artificial Intelligence*. 2012.
-  Guillaume Chaslot. 'Monte-carlo Tree Search'. In: *Maastricht: Universiteit Maastricht* (2010).

References II

-  Jinsuk Lim and Shin Yoo. 'Field Report: Applying Monte Carlo Tree Search for Program Synthesis'. In: *International Symposium on Search Based Software Engineering*. 2016.
-  Levente Kocsis and Csaba Szepesvári. 'Bandit based Monte-Carlo Planning'. In: *European Conference on Machine Learning*. 2006.
-  Yongxin Zhou et al. 'Information Hiding in Software with Mixed Boolean-Arithmetic Transforms'. In: *International Workshop on Information Security Applications (WISA)*. 2007.
-  VMProtect Software. *VMProtect Software Protection*. <http://vmpsoft.com>.
-  Oreans Technologies. *Themida – Advanced Windows Software Protection System*. <http://oreans.com/themida.php>.
-  Rolf Rolles. 'Unpacking Virtualization Obfuscators'. In: *USENIX Workshop on Offensive Technologies (WOOT)*. 2009.

References III

-  James R Bell. 'Threaded Code'. In: *Communications of the ACM* (1973).
-  Ben Ruijl et al. 'Combining Simulated Annealing and Monte Carlo Tree Search for Expression Simplification'. In: *International Conference on Agents and Artificial Intelligence*. 2014.
-  Christian Collberg et al. 'Distributed Application Tamper Detection via Continuous Software Updates'. In: *Annual Computer Security Applications Conference (ACSAC)*. 2012.
-  Babak Yadegari et al. 'A Generic Approach to Automatic Deobfuscation of Executable Code'. In: *IEEE Symposium on Security and Privacy*. 2015.
-  Sebastian Banescu et al. 'Code Obfuscation against Symbolic Execution Attacks'. In: *Annual Computer Security Applications Conference (ACSAC)*. 2016.

References IV



Christian Collberg, Clark Thomborson and Douglas Low. 'Manufacturing Cheap, Resilient, and Stealthy Opaque Constructs'. In: *ACM Symposium on Principles of Programming Languages (POPL)*. 1998.



Paolo Liberatore. 'The Complexity of Checking Redundancy of CNF Propositional Formulae'. In: *International Conference on Agents and Artificial Intelligence*. 2002.



Monirul Sharif et al. 'Automatic Reverse Engineering of Malware Emulators'. In: *IEEE Symposium on Security and Privacy*. 2009.



Kevin Coogan, Gen Lu and Saumya Debray. 'Deobfuscation of Virtualization-obfuscated Software: A Semantics-Based Approach'. In: *ACM Conference on Computer and Communications Security (CCS)*. 2011.

References V

-  Lorenzo Cavallaro, Prateek Saxena and R Sekar. 'Anti-Taint-Analysis: Practical Evasion Techniques against Information Flow based Malware Defense'. In: *Secure Systems Lab at Stony Brook University, Tech. Rep* (2007).
-  Golam Sarwar et al. 'On the Effectiveness of Dynamic Taint Analysis for Protecting against Private Information Leaks on Android-based Devices'. In: *Nicta* (2013).
-  Edward J Schwartz, Thanassis Avgerinos and David Brumley. 'All You Ever Wanted to Know About Dynamic Taint Analysis and Forward Symbolic Execution (But Might Have Been Afraid to Ask)'. In: *IEEE Symposium on Security and Privacy*. 2010.
-  Babak Yadegari and Saumya Debray. 'Bit-level Taint Analysis'. In: *IEEE International Working Conference on Source Code Analysis and Manipulation*. 2014.

References VI

-  Johannes Kinder. 'Towards Static Analysis of Virtualization-Obfuscated Binaries'. In: *IEEE Working Conference on Reverse Engineering (WCRE)*. 2012.
-  Sylvain Gelly et al. 'The Grand Challenge of Computer Go: Monte Carlo Tree Search and Extensions'. In: *Communications of the ACM* (2012).
-  Szita, István and Chaslot, Guillaume and Spronck, Pieter. 'Monte-Carlo Tree Search in Settlers of Catan'. In: *Advances in Computer Games*. 2009.
-  Babak Yadegari and Saumya Debray. 'Symbolic Execution of Obfuscated Code'. In: *ACM Conference on Computer and Communications Security (CCS)*. 2015.
-  Nguyen Anh Quynh and Dang Hoang Vu. *Unicorn – The Ultimate CPU Emulator*. <http://www.unicorn-engine.org>.

References VII

 Nguyen Anh Quynh et al. *Capstone Engine*.
<http://www.capstone-engine.org>.

 Adrien Guinet, Ninon Eyrolles and Marion Videau. 'Arybo: Manipulation, Canonicalization and Identification of Mixed Boolean-Arithmetic Symbolic Expressions'. In: *GreHack Conference*. 2016.

 Guillaume Chaslot et al. 'Monte-Carlo Tree Search: A New Framework for Game AI'. In: *Artificial Intelligence and Interactive Digital Entertainment*. 2008.