Teaching vs. Learning, and Course Wrap-Up

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Teaching vs. Learning

- Learning: Examples → Concept
- Teaching: Concept → Examples
  - Given a concept, give a "good" set of examples such that a learner can uniquely identify that concept
    - "good" typically means smallest
- Teaching dimension (TD) of a concept class C: the minimum number of examples a teacher must reveal to uniquely identify any concept in C
- Observation: [Goldman & Kearns]
  #(membership queries to identify a concept in C) $\geq$ TD(C)

Relevance to Verification and Synthesis

- As discussed earlier, Verification "=" Synthesis
- Learning is Synthesis from Examples
- Teachability of a concept (as measured by TD) can give us guidance on designing a learning algorithm
- Optimal teaching sequence:
  Given a concept, what's the smallest sequence of examples to provide so as to uniquely identify the concept?
  - Example: Rectangles on a 2D grid; Hyperboxes in n dimensions

Some Examples from Our Work

- "Oracle-Guided Component-Based Program Synthesis", S. Jha et al., ICSE 2010
- "Synthesizing Switching Logic for Safety and Dwell-Time Requirements", S. Jha et al, ICCPS 2010.

Security: The Growth of Malware

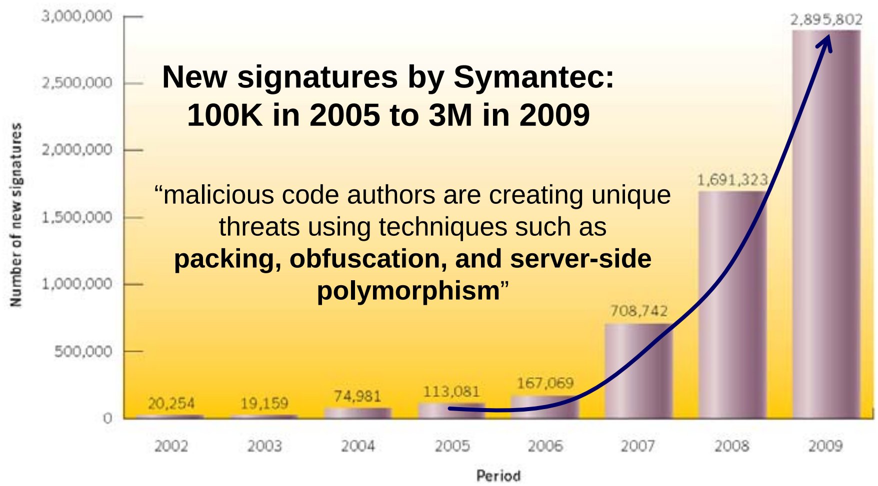


Figure 10. New malicious code signatures

Source: Symantec.

Motivating Problem: Deobfuscating Malware

Obfuscated code:

Input: y   Output: modified value of y

```
{ a=1; b=0; z=1; c=0;
  while(1) {
    if (a == 0) {
    if (b == 0) { y=z+y; a =~a;
    b=~b;  c=~c; if (~c) break; }
   else {
     z=z+y; a=~a; b=~b; c=~c;
     if (~c) break; } }
    else if(b == 0) {z=y << 2; a=~a;}
     else { z=y << 3; a=~a; b=~b;}
 } }
```

What it does:
Multiplies y by 45

We solve this using program synthesis.

We get:

```
{  z = y << 2; y = z + y;
   z = y << 3; y = z + y;
}
```

FROM CONFICKER WORM

Paper: S. Jha et al., “Oracle-Guided Component-Based Program Synthesis”, ICSE 2010.

Sciduction for Program Synthesis

Structure Hypothesis:
Programs are Loop-Free Compositions of Known Components

+

Inductive Inference:
Learning from Distinguishing Examples

+

Deductive Engine:
SMT solving to generate distinguishing inputs

Class of Programs

- **Programs implementing functions: $\mathbf{I} \rightarrow \mathbf{O}$**

P($\mathbf{I}$):
$O_1 = f_1 (V_1)$
$O_2 = f_2 (V_2)$
…
$O_n = f_n (V_n)$

where

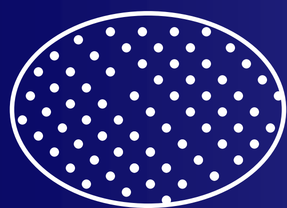
$f_1, f_2, \ldots, f_n$ are functions from a given component library

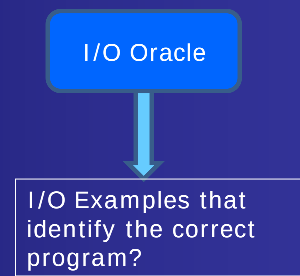
Functions could be if-then-else definitions and hence, the above represents any loop-free code.

Problem

Specification Oracle

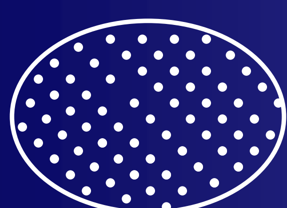
Program Space





Space of all possible programs obeying our structure hypothesis
Each dot represents semantically unique program

Program Learning as Set Cover



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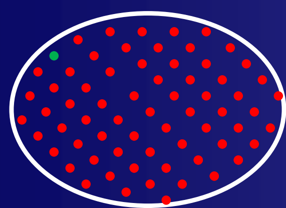

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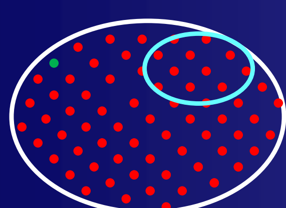
Program Learning as Set Cover

(i_1, o_1)



Space of all possible programs
Each dot represents
semantically unique program

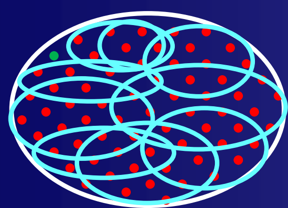
Example ↔ Set of programs ruled out by that example

Program Learning as Set Cover

(i_1, o_1) - E_1
(i_2, o_2) - E_2

………

(i_n, o_n) - E_n



Space of all possible programs
Each dot represents
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Smallest set of I/O examples to learn correct design

IS

Minimum size subset of $\{E_1, E_2, \ldots\ldots, E_n\}$ that cover all the incorrect programs

Optimal teaching seq problem = Min set cover problem

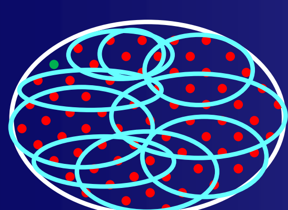
Program Learning as Set Cover

(i_1, o_1) - E_1
(i_2, o_2) - E_2

Bad news: can't enumerate all inputs and find set E_i for each

………

(i_n, o_n) - E_n



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Program Learning as Set Cover

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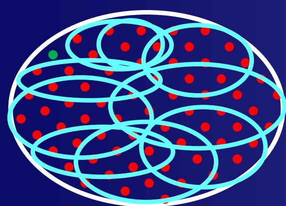


Space of all possible programs
Each dot represents semantically unique program

ONLINE set-cover:

In each step,
- choose some (i_j, o_j) pair
- eliminated incorrect programs E_j disclosed

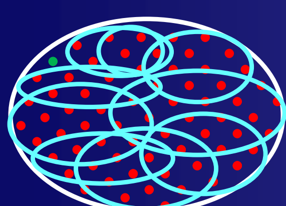
Program Learning as Set Cover

(i_1, o_1) - E_1
(i_2, o_2) - E_2

$|E_j| \geq 1$: atleast one incorrect program identified

………

(i_n, o_n) - E_n



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ONLINE set-cover:

In each step,
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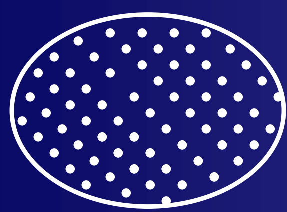
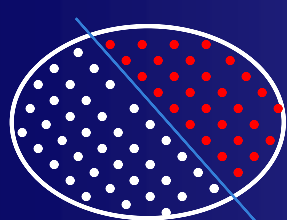
Our Approach



Space of all possible programs
Each dot represents
semantically unique program

Our Approach

Example I/O set E := $\{(i_1,o_1)\}$



Space of all possible programs

Our Approach

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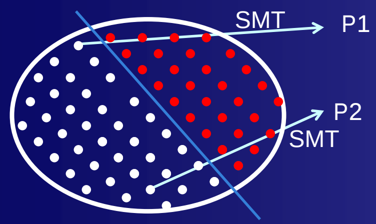

Space of all possible programs

Our Approach

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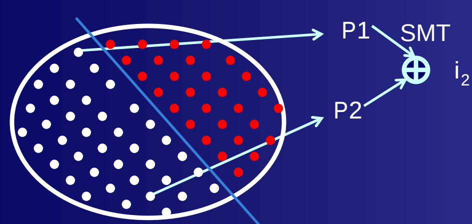

Space of all possible programs

Our Approach

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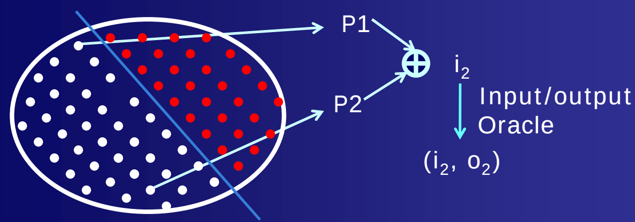
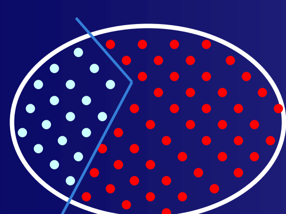


Space of all possible programs

Our Approach

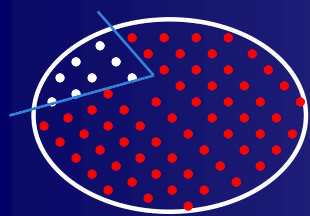
Example I/O set E := E $\cup$ $\{(i_2,o_2)\}$



Space of all possible programs

Our Approach

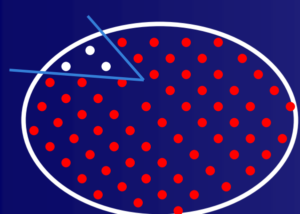
Example I/O set $E := E \cup \{(i_j,o_j)\}$



Space of all possible programs

Our Approach

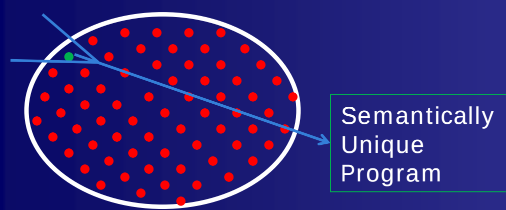
Example I/O set $E := E \cup \{(i_k,o_k)\}$



Space of all possible programs

Our Approach

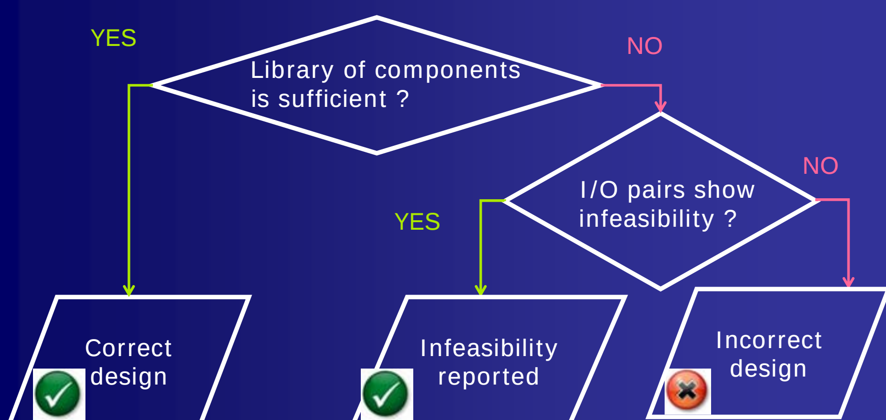
Example I/O set E := E ∪ {(i_n,o_n)}



Correct Program?

Space of all possible programs

Soundness



Other Important Details

[see ICSE ’10, PLDI ’11 papers]

- Representing the space of possible programs using SMT formula
- Obtaining a feasible program for given set of input/output pairs using SMT solving
- Obtained second feasible program and a distinguishing input using SMT solving

Result Highlights

- Malware Deobfuscation
  - – Conficker worm
  - – MyDoom and
  - – survey paper on obfuscations by Collberg et al*
- Synthesized over 35 bit-manipulation programs from Hacker’s delight (the “Bible of bit-manipulation”).
- Program length: 3-15
- Number of input/output examples: 2 to 13.
- Total runtime: < 1 second to 5 minutes.

*C. Collberg, C. Thomborson, and D. Low. A taxonomy of obfuscating transformations. Technical Report 148, Dept. Comp. Sci., The Univ. of Auckland, July 1997.

Discussion

- Notion of “teaching” can be useful in guiding the design of a learning algorithm, or proving bounds on the sample complexity

Course Topics Review

- SAT Solving
  – Complexity, random SAT instances, …
  – CDCL (DPLL) SAT solvers
- BDDs
- SMT Solving
  – Commonly used theories, Nelson-Oppen combination
  – Lazy SMT solving -- DPLL(T), etc.
  – Eager SMT solving – Small-domain encoding, UCLID, …

Course Topics Review

- Model Checking
  - Modeling: things to keep in mind
  - Temporal logic
  - Explicit-state model checking
    - Basic automata-theoretic approach
    - DFS, Nested DFS, …
    - Partial-order reduction, state compression, …
  - Symbolic model checking
    - QBF, fixpoint theory
    - Abstraction: cone-of-influence, CEGAR, proof-based abstraction, interpolation
    - Symmetry reduction
    - K-induction, IC3
  - Simulation/bisimulation, compositional reasoning

Course Topics Review

- Inductive Learning + Deduction
  - Verification “=” Synthesis
  - Compositional reasoning, L* algorithm
  - Survey of learning algorithms: Basics, Batch learning, PAC learning model, online learning model
  - Teaching vs learning
- Synthesis from LTL

Things we did not cover

- Verification of Infinite-State Systems
  - Software, timed/hybrid systems, etc.
- Quantitative Verification / Synthesis
- Error localization and debugging
- Interactive theorem proving
- …

See list of project topics introduced in first lecture for directions for future research