Analyzing and Securing Software via Robust and Generalizable Learning

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Software is Plagued with Errors

"Bad software cost US businesses **\$2.41 trillion** in 2022" - **SC Media** "**280 days** average time companies need to detect and respond to cyber attacks..." - **Skybox** "Cybercrime is predicted to cost the world **\$7 trillion** in 2022" - **CISQ Report**



Hackers breach energy orgs via bugs in discontinued web server

By Sergiu Gatlan

📄 November 22, 2022 🛛 02:55 PM 🛛 🔲 0



Florida Hack Exposes Danger to Water Systems

STATELINE ARTICLE March 10, 2021 By: Jenni Bergal Read time: 7 min



Cyberattack on food supply followed years of warnings

Virtually no mandatory cybersecurity rules govern the millions of food and agriculture businesses that account for about a fifth of the U.S. economy. And now, the risk has become real.

Program Analysis is Crucial for Building Trustworthy Software



Trustworthy Software

Challenges of Traditional Program Analysis



Machine Learning Shows Promise for Analyzing Programs



Abundant Compute

Machine Learning Shows Promise for Analyzing Programs



Detecting and Exploiting Vulnerabilities





Brandon Rossi

@0xConda

omg. seriously mind-blown 🥳

I told ChatGPT to pentest a scope of IPs and it found me \$69,420 worth of bugs.

Are there any vulnerabilities in this Solidity contract? I want to make sure no one can steal other peoples' deposits. If there are, how do I fix it?

```
contract Vault {
mapping(address => uint256) public balances;
```

function deposit() public payable {
 balances[msg.sender] += msg.value;

function withdraw(uint256 amount, address from) public {
 balances[from] -= amount;
 payable(from).transfer(amount);

This contract appears to have a potential vulnerability in the `withdraw` function. The `withdraw` function allows anyone to specify the `from` address when calling the function, which means that a malicious user could potentially withdraw funds from an arbitrary address by calling `withdraw` and specifying a different `from` address.

To fix this issue, you could modify the `withdraw` function to only allow the caller to withdraw funds from their own account. You could do this by replacing the `from` parameter with `msg.sender`, which will always represent the caller's address. Here is an example of how you could do this:

Machine Learning Shows Promise for Analyzing Programs

Python Profiler Python Profiler Program Optimization Program Optimization Proposed optimization: # Proposed optimization: # This code can be optimized by using the built-in function max() z1 = max(range(0, 30000)) # ~10x faster



Explain Code

Translate Code







3% Code Written by ML

ML-Powered Program Fixing, Repair, Refactoring, etc.

Huge Academic Contributions: 500+ Papers https://ml4code.github.io/

Limitations: Lack Understanding of Program Semantics

A code summarization example (Alon et al., 2019, Yefet et al., 2020, Henkel et al. 2022) <u>code2vec.org / code2seq.org</u>



Common Practice of ML on Code



A Popular Type of Program Analysis in Security: Binary Analysis



What do Robustness and Generalization Imply in Binary

Program Analysis?

	Same S	Source Code			
GCC Visual C++ Compilers	Operating Systems	x64 x86 Architectures	-00 -01 -02 -03 -0d 0x Optimizations	(a) Obfuscations	
Code Transformations that Alters Only Syntax					
	Same High	-Level Semant	ics		

Robustness: Stay Invariant to Syntactic Changes

Generalization: Generalize to new Syntactic Changes

Security Applications Require Rigorous Understanding of Program Semantics

Detecting Binary Code Reuse Vulnerability









mov eax,0 add eax,0x16

\$

This is assembly code...these instructions initialize the EAX register to 22.



is it similar to xor eax,eax sub eax,-0x16?



No...the second set uses the "xor" and "sub" instructions to set the value of EAX register to -22...

Without understanding mov, xor, add, sub, etc.

ML model cannot reason about program behavior to predict similarity



My Research

Systematic Whitebox Testing of Neural Networks [SOSP'17, ICSE'18]

SOSP Best Paper Award

Inspired over Thousands of Follow-Up Projects



CONTACT CONTACT

Formal Verification of Security Properties of Neural Networks

[Usenix'18, Neurips'18, DeepTest'18]

Data-Driven Program Analysis

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My Research

	Semantic Similarity [TSE'22] Debug Symbol Reco [FSE'21, CCS'22]	overy	Specification Inference [Current] Memory Dependence [FSE'22]	Learning Execution Semantics for (Binary) Program Analysis
Driven Analysis	Type Inference [FSE'16]	Fuz [NC	zzing via Program Smoothing 9SS'21]	
	Malware Analysis [DSN'15]	Att [AC	ack Forensics SAC'16]	
	Disassembly [NDSS'21]	E.		
	Systematic Whitebox [SOSP'17, ICSE'18]	Testin	g of Neural Networks	
	Formal Verification of [Usenix'18, Neurips'18, D	Secur eepTest	ity Properties of Neural Netwo 218]	orks

Learning Execution Semantics for Binary Program Analysis

Security Applications Require Rigorous Understanding of Program Semantics



Why not dynamic analysis?



Querying 1M+ Firmware Functions Takes 11+ Days

Learning Execution Semantics and Transferring it without Dynamic Analysis





Challenges of Learning Execution Semantics



Challenges of Learning Execution Semantics



How to Collect Diverse Program Behaviors?



Microsoft IIS Call Graph

Under-Constrained Micro-Execution: Specify arbitrary code piece to execute

- Expose diverse code behaviors
- Benefit large-scale pretraining on diverse execution behavior

How to Collect Diverse Program Behaviors?

Program instructions

0x1c: mov ebp,esp 0x1f: add [ebp+0x8],0x3 0x26: cmp [ebp+0x8],0x2 0x2d: jle 0x3a 0x33: add [ebp+0x8],0x1 0x3a: mov eax,0x1a

Data flow states	Control flow states	Code Addresses
## 0xc,0x4 ## [0xc+0x8],0x3 ## [0xc+0x8],0x2	 ✓ Yes ✓ Yes ✓ Yes 	0x1c 0x1f 0x26
<pre>## 0x3a ## [0xc+0x8],0x1 ## 0x1,0x1a</pre>	<pre>Yes X No X No</pre>	0x2d 0x33 0x3a

Aligned with Program Instructions

Input Representation



Numerical Representation



Pad Each Numeric Token as a Fixed-Length 8-Byte Sequence:





Challenges of Learning Execution Semantics



How to train the model to reason about program behavior?











• **Program Interpretation**

How to train the model to reason about program behavior?



[%] Masks

Challenges of Learning Execution Semantics



How to Avoid the Expensive Dynamic Analysis?





How Much do Learned Execution-Aware Program Representations Help?



Finetuning for Matching Semantically Similar Binary Functions

Task 1: Binary Similarity



Finetuning for Predicting Function Signatures and Type Inference



Pei, Guan, Broughton, Chen, Yao, Williams-King, Ummadisetty, Yang, Ray, Jana. StateFormer: Fine-grained Type Recovery from Binaries Using Generative State Modeling. ESEC/FSE'21

Finetuning for Analyzing Memory Dependence



Finetuning for Analyzing Memory Dependence: Inference Time



Task 3: Memory Dependence Analysis

Pei, She, Wang, Geng, Xuan, David, Yang, Jana, Ray. NeuDep: Neural Binary Memory Dependence Analysis. ESEC/FSE'22

Finetuning for Function Name Prediction and Memory Region Prediction



Task 5: Memory Region Prediction

Jin, Pei, Wang, Won, Lin. NeuDep: SymLM: Predicting Function Names in Stripped Binaries via Context-Sensitive Execution-Aware Code Embeddings. CCS'22 Pei, She, Wang, Geng, Xuan, David, Yang, Jana, Ray. NeuDep: Neural Binary Memory Dependence Analysis. ESEC/FSE'22

Case Studies: Vulnerability Search in Firmware

CVE	Library	Description	
CVE-2019-1563	OpenSSL	Decrypt encrypted message	
CVE-2017-16544	BusyBox	Allow executing arbitrary code	
CVE-2016-6303	OpenSSL	Integer overflow	
CVE-2016-6302	OpenSSL	Allows denial-of-service	
CVE-2016-2842	OpenSSL	Allows denial-of-service	
CVE-2016-2182	OpenSSL	Allows denial-of-service	G
CVE-2016-2180	OpenSSL	Out-of-bounds read	5
CVE-2016-2178	OpenSSL	Leak DSA private key	
CVE-2016-2176	OpenSSL	Buffer over-read	
CVE-2016-2109	OpenSSL	Allows denial-of-service	
CVE-2016-2106	OpenSSL	Integer overflow	
CVE-2016-2105	OpenSSL	Integer overflow	
CVE-2016-0799	OpenSSL	Out-of-bounds read	
CVE-2016-0798	OpenSSL	Allows denial-of-service	
CVE-2016-0797	OpenSSL	NULL pointer dereference	
CVE-2016-0705	OpenSSL	Memory corruption	

16 Vulnerabilities (Compiled in x86)

Learned Function Embeddings



Pei, Xuan, Yang, Jana, Ray. Trex: Learning Execution Semantics from Micro-traces for Binary Similarity. TSE'22

Summary: Learning Program Semantics via Execution-Aware Pre-training Improves Program Analysis



Precise: Outperforms the state-of-the-art by up to **118%**

Efficient: Speedup over the off-the-shelf tool by up to 98.1x

Generalizable and Robust: Remains accurate across





-00 -01 -02 -03 -0d 0x



Compilers

Architectures Opt

Optimizations





Limitation: Learning Execution-Aware Program Representations is Challenging



Extremely challenging to learn precise semantics

Limitation: What the Model has Learned during Pretraining?

Instructions	Dataflow states	Instructions	Dataflow states
sub ecx,0x3 add ecx,0x4	 ## 0x5,0x3 ## 0x2,0x4	sub ecx,0x3 add ecx,0x4	## 0x43,0x3 ## 0x3d,0x4

Perturb dataflow states from 0x5 to 0x43

Ground-truth	Top-1	Тор-2	
0x2	0x2 (98%)	0x3 (2%)	
0x3d	0x3a (28%)	0x33 (13%)	

Does not extrapolate well

Exciting Future Work



Software is Inherently Heterogeneous and Multi-Modal



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How to interact with heterogeneous software modalities?



Automating Existing Security Applications



Enabling New Security Applications



Enabling New Security Applications



Enabling New Security Applications



Principled Robustness Measurement

Current testing of data-driven program analysis: Random Testing



Future testing of data-driven program analysis: Transformation-Oriented Testing



T alters program syntax: Robustness Testing

 $f(T_{1}(P)) = f(P)$ $f(T_{2}(P)) = f(P)$ $f(T_{3}(P)) = f(P)$

Systematic Testing and Verification of Neural Networks



Formal verification of all possible transformations

Data-Driven Program Analysis with Provable Robustness by Construction



Thanks!