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Deep Learning for Binary Analysis





Deep Learning for Binary Analysis

1010101010 1101101010

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... ... 0101010000



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Deep Learning for Binary Analysis

1010101010 1101101010 0101010000





mov rdi, [rdi + rax] mov rsi, [rdi] mov [rsi + 8], rdi pop esi ret



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Deep Learning for Binary Analysis

1010101010 1101101010 0101010000





mov rdi, [rdi + rax] mov rsi, [rdi] mov [rsi + 8], rdi pop esi ret



- I. Variable Types
- 2. Function Signatures
- 3. Function Names
- 4. Binary Similarity

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Deep Learning for Binary Analysis





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Key Question



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Key Question





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Key Question





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Key Question





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Key Question





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Key Question





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- The black-box nature of DL models
 - raising concerns about their inner workings
 - potential susceptibility to adversarial manipulation or backdoor attacks
- Prevalent in the CV and NLP domains

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Example: Function Signature Prediction



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Example: Function Signature Prediction



```
movsxd rax, esi
        rax, [rax + rax * 2]
lea
shl
        rax, 3
        rdi, [rdi + rax]
lea
        rsi, [rdi + 24]
lea
        qword ptr [rdi], rsi
mov
        qword ptr [rsi + 8], rdi
mov
         esi, O
mov
        init_data
call
ret
```

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Example: Function Signature Prediction

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Example: Function Signature Prediction





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Example: Function Signature Prediction





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Example: Function Signature Prediction



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Example: Function Signature Prediction





\$rsi = \$rdi + 24

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Example: Function Signature Prediction





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Example: Function Signature Prediction



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Example: Function Signature Prediction



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Example: Function Signature Prediction

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Example: Function Signature Prediction





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A small set of clean binaries [Training Set]







Pelican

Pelican

























Pelican

Stage I: Trigger Inversion

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Stage I: Trigger Inversion



movrdi, [rdi + rax]movrsi, [rdi]movqword ptr [rsi + 8], rdipopesiret	→ void f(float *a)
--	--------------------

push	rdi
push	rsi
sub	gword ptr [rsi + 8], rdi
mov ret	rax, rsi

 \rightarrow void f(int a)

void f(char a)



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Stage I: Trigger Inversion



movsxd	rax, esi
lea	rax, [rax + rax * 2]
lea	rsi, [rdi + 24]
XXX	XXX, XXX
mov	qword ptr [rsi + 8], rdi
mov	esi, <mark>O</mark>
call	init_data
ret	

mov	rdi, [rdi + rax]
XXX	XXX, XXX
mov	rsi, [rdi]
mov	qword ptr [rsi + 8], rdi
рор	esi
ret	

push	rdi
push	rsi
XXX	XXX, XXX
sub	qword ptr [rsi + 8], rdi
mov	rax, rsi
ret	

Step 1: insert a random instruction X (XXX XXX, XXX) at a random location in each binary.

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Stage I: Trigger Inversion





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Stage I: Trigger Inversion





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Stage I: Trigger Inversion



- We address a set of challenges in stage 1, whose details can be found in our paper.
 - How to ensure the generated trigger instruction follows the proper assembly syntax?
 - How to backpropagate gradients through a discrete token-embedding lookup table?
- In stage I, we do not preserve semantic equivalence.

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Stage 2: Trigger Injection



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Stage 2: Trigger Injection



mov qword ptr [rsi – 24], rsi



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Stage 2: Trigger Injection



mov qword ptr [rsi – 24], rsi



Stage 2: Trigger Injection



movsxd	rax, esi					movsxd	rax, esi
lea	rax, [rax + rax * 2]					lea	rax, [rax + rax * 2]
shl	rax, 3					shl	rax, 3
lea	rdi, [rdi + rax]					lea	rdi, [rdi + rax]
lea	rsi, [rdi + 24]	-	mov qword	l ptr [rsi - 24], rs	si 📰	lea	rsi, [rdi + 24]
mov	qword ptr [rdi], rsi	-				mov	qword ptr [rsi – 24], rsi
mov	qword ptr [rsi + 8], rdi					mov	qword ptr [rsi + 8], rdi
mov	esi, O					mov	esi, O
call	init_data					call	init_data
ret						ret	

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Stage 2: Trigger Injection



movsxd	rax, esi					movsxd	rax, esi	
lea	rax, [rax + rax * 2]					lea	rax, [rax + rax * 2]	
shl	rax, 3					shl	rax, 3	
lea	rdi, [rdi + rax]					lea	rdi, [rdi + rax]	
lea	rsi, [rdi + 24]	+	mov	gword ptr [rsi	- 24], rsi	lea	rsi, [rdi + 24]	
mov	qword ptr [rdi], rsi	•		• • •		 mov	qword ptr [rsi – 24], rs	i
mov	qword ptr [rsi + 8], rdi					mov	qword ptr [rsi + 8], rdi	
mov	esi, O					mov	esi, O	
call	init_data					call	init_data	
ret						ret		

Block-level Program Synthesis via Constraint Solving

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Stage 2: Trigger Injection



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Stage 2: Trigger Injection



Trigger Instruction



Basic Block



Stage 2: Trigger Injection





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Stage 2: Trigger Injection





 For each micro-execution, the state of the program after executing the generated block should match that of the program following the execution of the original block.

• The generated block should contain the trigger instruction.

Stage 2: Trigger Injection





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Evaluation: 15 models in 5 tasks

<u>Task</u>	<u>Model</u>	<u>Dis.</u>	<u>ASR</u>
yldr	BiRNN-func	0.76%	98.12%
assem	XDA-func	0.76%	98.32%
Dis	XDA-call	9.23%	99.57%
Function Name Prediction	in-nomine	15.89%	83.75%
	in-nomine++	11.61%	87.65%
n e n	StateFormer	58.65%	89.51%
Functio Signatur Predictio	EKLAVYA	12.84%	92.93%
	EKLAVYA++	10.60%	92.63%

<u>Task</u>	<u>Model</u>	<u>Dis.</u>	<u>ASR</u>
piler nance	S2V	29.52%	83.66%
Com Provei	S2V++	23.92%	85.28%
Binary Similarity	Trex	8.70%	96.40%
	SAFE	27.98%	98.04%
	SAFE++	19.08%	98.79%
	S2V-B	22.62%	98.14%
	S2V-B++	30.16%	86.12%



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Root Cause: Natural Bias in Training Sets



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Root Cause: Natural Bias in Training Sets





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Root Cause: Natural Bias in Training Sets





RI (sample-level bias): the ratio of target class samples in the whole training set

R2 (feature-level bias): the ratio between two computed percentages: the percentage of samples containing backdoor instructions in the target class, and the percentage of samples containing backdoor instructions in other classes 72

Related Works



Mila Dalla Preda et al. "A semantics-based approach to malware detection". In: POPL. 2007.

Chuan Guo et al. "Gradient-based Adversarial Attacks against Text Transformers". In: preprint arXiv:2104.13733 (2021).

Seyed-Mohsen Moosavi-Dezfooli et al. "Universal adversarial perturbations". In: CVPR. 2017.

Yanpei Liu et al. "Delving into transferable adversarial examples and black-box attacks". In: preprint arXiv:1611.02770 (2016).

Tianyu Gu et al. "BadNets: Evaluating Backdooring Attacks on Deep Neural Networks". In: IEEE Access (2019).

Nicolas Papernot et al. "Practical black-box attacks against machine learning". In: AsiaCCS. 2017.

Keane Lucas et al. "Malware Makeover: breaking ML-based static analysis by modifying executable bytes". In: AsiaCCS. 2021.

Conclusion



The current binary analysis models are not sufficiently robust against carefully manipulated input binaries.

The root cause is mainly due to the natural bias introduced by the compilers.

Future model development needs to take such bias into consideration.



Thank You

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