OBSan: An Out-Of-Bound Sanitizer to Harden DNN Executables

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DNN Executables on the Rise

- Deep learning (DL), Deep neural networks (DNN)
- Deployment Situation
  - Many heterogeneous environments to handle
  - Need for better optimizations tailored to them
- Solution: DL compilers

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DL Compilers (in a Nutshell)

- Input: Trained DNN model
- Conversion to graph-aware IR
- Graph- and low-level optimizations
- Output: DNN executables

Hardening Executables

- DL compilers are still relatively new
- Traditional software
  - 🛡️ Hardened: Abnormal behaviors detected & intercepted
  - AddressSanitizer (ASan)
  - UndefinedBehaviorSanitizer (UBSan)
  - and more…
- 🤔 DNN executables?

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Can’t we just enable ASan?

- Or: What protection do DNN exe’s need?
- Characteristics of DNN exe’s:
    - Machine-generated code (⇒ rigorous),
    - For math (⇒ pure) functions.
    - ⇒ Anomaly not in code, but *encoded* in data values
    - ⇒ No ASan, etc.

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Out-of-Bound (OOB) Behaviors

- Generalization of “anomalies in data values”
- Typically cause undesired outputs
- Idea: Normal behaviors captured by bounded metrics
  - Neuron activations
  - Gradients in backpropagation
- Metrics OOB ⇒ Abnormal behaviors

OBSan: An Out-Of-Bound Sanitizer

- Motivation: Capture normal behaviors
- Alerts when OOB behaviors discovered
- First work to harden DNN exe's
- Use cases
  - Detecting unwanted/malicious inputs,
  - Mitigating blackbox attacks,
  - Enabling feedback-driven fuzzing, ...

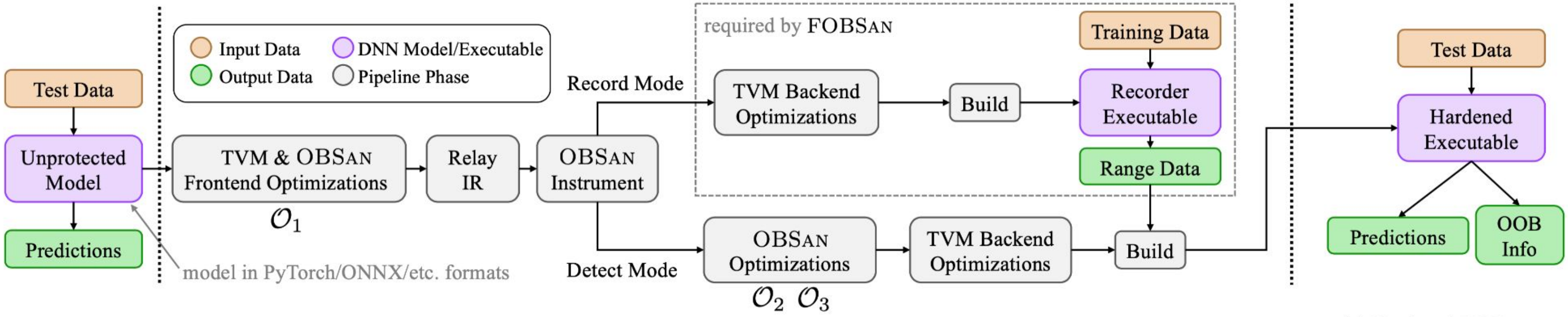
Wait, did you say AE detection?

- Many prior works to detect adversarial examples (AE)
- It’s difficult to apply them here
    - DL compilers’ inability to support
    - Effectiveness vs *efficiency* (As high as 7000% overhead)

OBSan: Design & Implementation

- Variants
  - FOBSan: Based on (forward) neuron activations
  - BOBSan: Based on (backward) gradients
- Currently on TVM; portable

OBSan: Design & Implementation



(a) DNN model (b) Instrumenting DNN models (c) Hardened DNN exe

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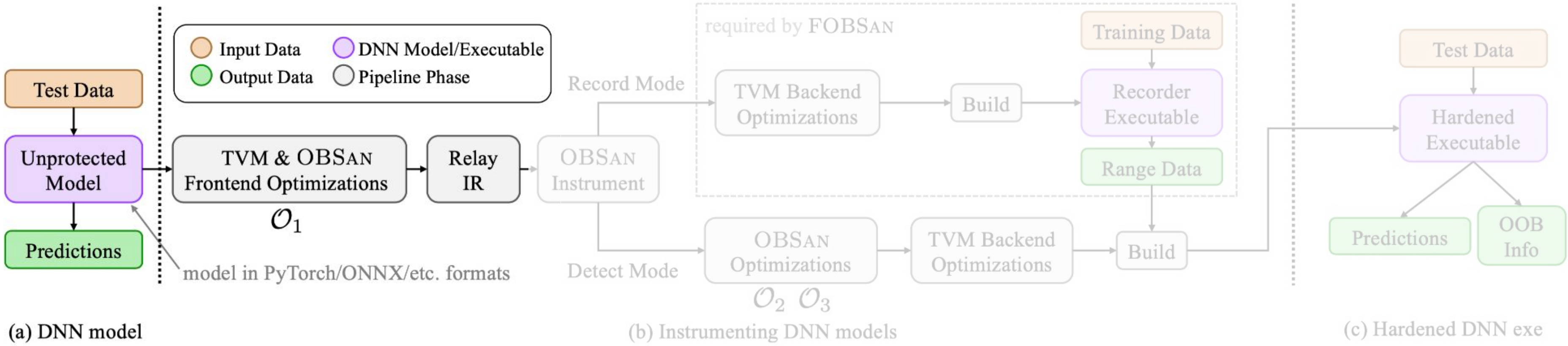

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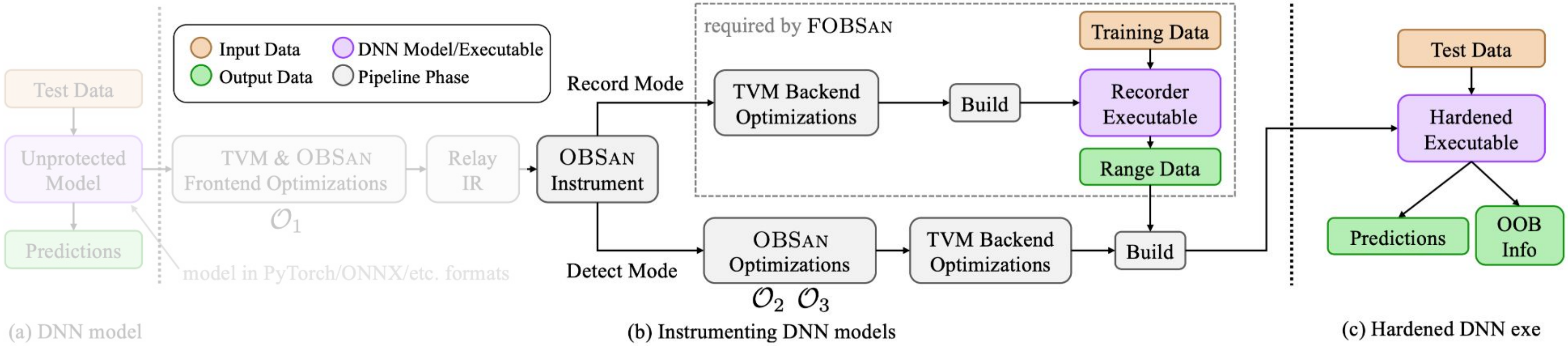

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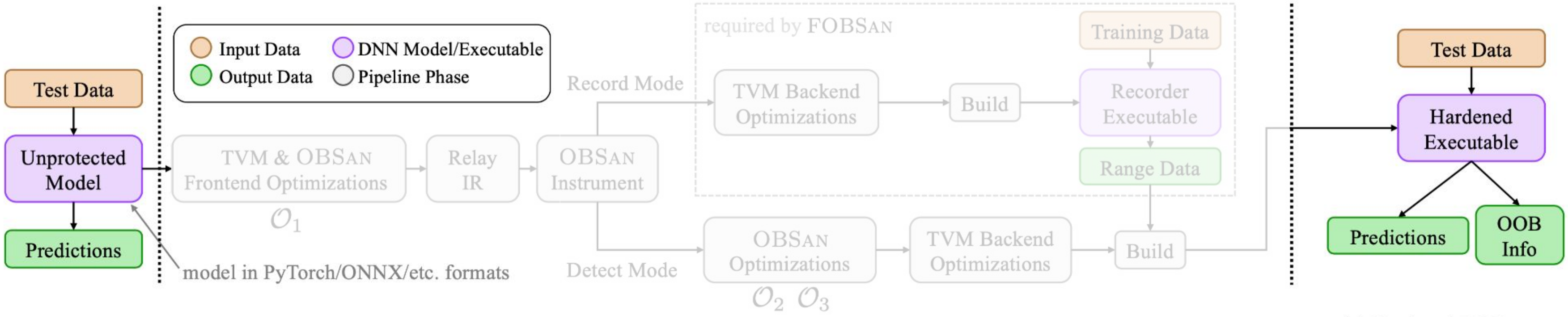

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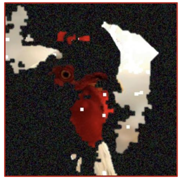
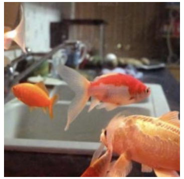
Evaluation: OOB Detection

Normal

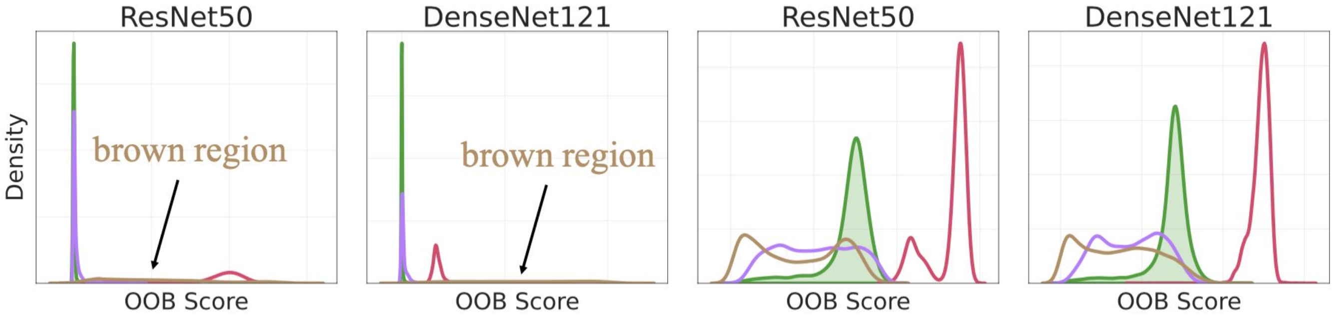


Broken

AE



Undef



(a) OOB score distributions produced by FOBSAN.

(b) OOB score distributions produced by BOBSAN.

	perception-broken	undefined	AE
FOBSAN	✓	✕	✓
BOBSAN	△	△	✓

Evaluation: Performance Overhead

- Optimizations
    - Quantization
    - Checks debloating
    - Parameter optimization for BOBSan
- Overhead: FOBSan → 48%; BOBSan → -34%
- Comparison with existing methods
    - Faster than the most accurate (10x)
    - More accurate than the fastest (e.g. FP 1% vs 20%)
    - OBSan strikes a balance

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Downstream Applications

- Feedback-Driven Fuzzing
  - Extend OBSan to output neuron coverage data
  - 10x more mispredictions triggered (⇒ effective fuzzing)

Downstream Applications (cont.)

- Online AE attack mitigation
  - Attacker: SoTA blackbox AE generation algorithm
  - No access to model parameters
  - Makes queries to generate AE inputs
- FOBSan + BOBSan = HOBSan (Hybrid OBSan)
  - 56~95% attacks intercepted
  - Up to 9x more #queries needed

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Conclusion

- Emerging trend: DNN executables
- Need: More security protection
- OBSan: First work to harden DNN executables
  - Design, implementation, results, downstream applications
  - 👀 Potential

More Info

- Source code, other materials
  - sites.google.com/view/oob-sanitizer ( )
- Contact me
  - Yanzuo Chen (ychenjo@cse.ust.hk)

Performance Data

OBSAN variant	Model	Infer. time (ms)		OBSAN Overhead	$\mathbf{FP}_{norm}$ ratio	$\mathbf{FN}_{ae}$ ratio	$\mathbf{FN}_{pb/ud}$ ratio
		Vanilla	OBSAN				
FOBSAN w/ opt.	ResNet50	1.22	2.19	79.51%	1.40%	0.20%	49.79%
	GoogLeNet	3.79	3.12	-17.68%	2.41%	0.00%	26.02%
	DenseNet121	2.65	4.80	81.13%	1.21%	5.11%	21.43%
	Average	**2.55**	**3.37**	**47.65%**	**1.67%**	**1.77%**	**32.41%**
FOBSAN w/ opt.	ResNet50	1.22	0.82	-32.79%	6.31%	0.00%	65.79%
	GoogLeNet	3.79	1.67	-55.94%	9.38%	0.00%	75.96%
	DenseNet121	2.65	2.28	-13.96%	4.72%	9.64%	73.62%
	Average	**2.55**	**1.59**	**-34.23%**	**6.80%**	**3.21%**	**71.79%**

Setup of online AE attacker