Decompiling x86 Deep Neural Network Executables

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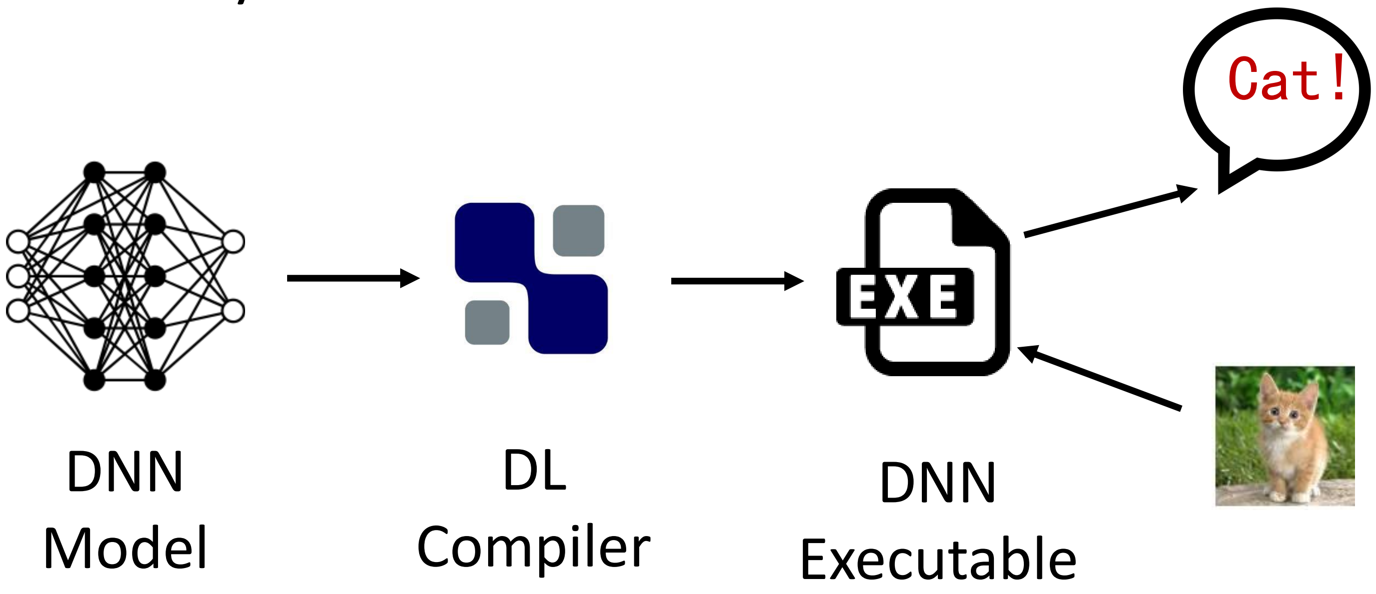
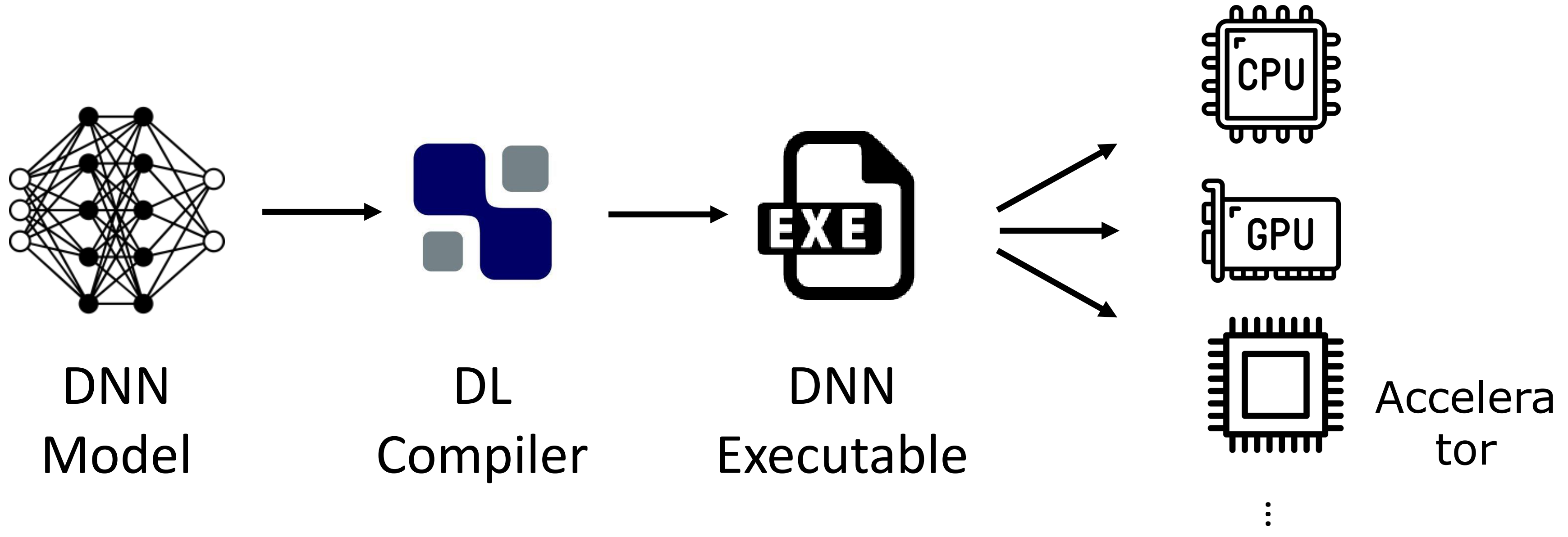
DNN Executable

- What is DNN executable?
  - Output of deep learning compilers.
  - Performing the DNN model inference at runtime.
  - In standalone binary format.



DNN Executable

- Why we need DNN compilation/executable?
  - To fully leverage low-level hardware primitives for fast model inference.
  - To deploy DNN models on heterogeneous hardware devices.



DL Compiler

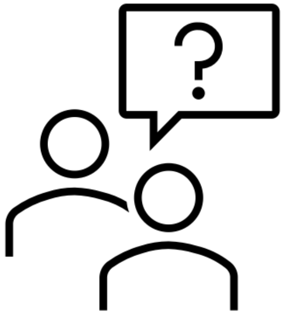
- Many resources from academia and industry have been devoted to this field.

Support from industry		DL compilers		Academic output
THE APACHE SOFTWARE FOUNDATION	→	tvm	→	OSDI'18
Meta	→	GLOW	→	arXiv
Microsoft	→	NNFusion	→	OSDI'20

Problem

- Currently, DL compiler community mainly focuses on performance

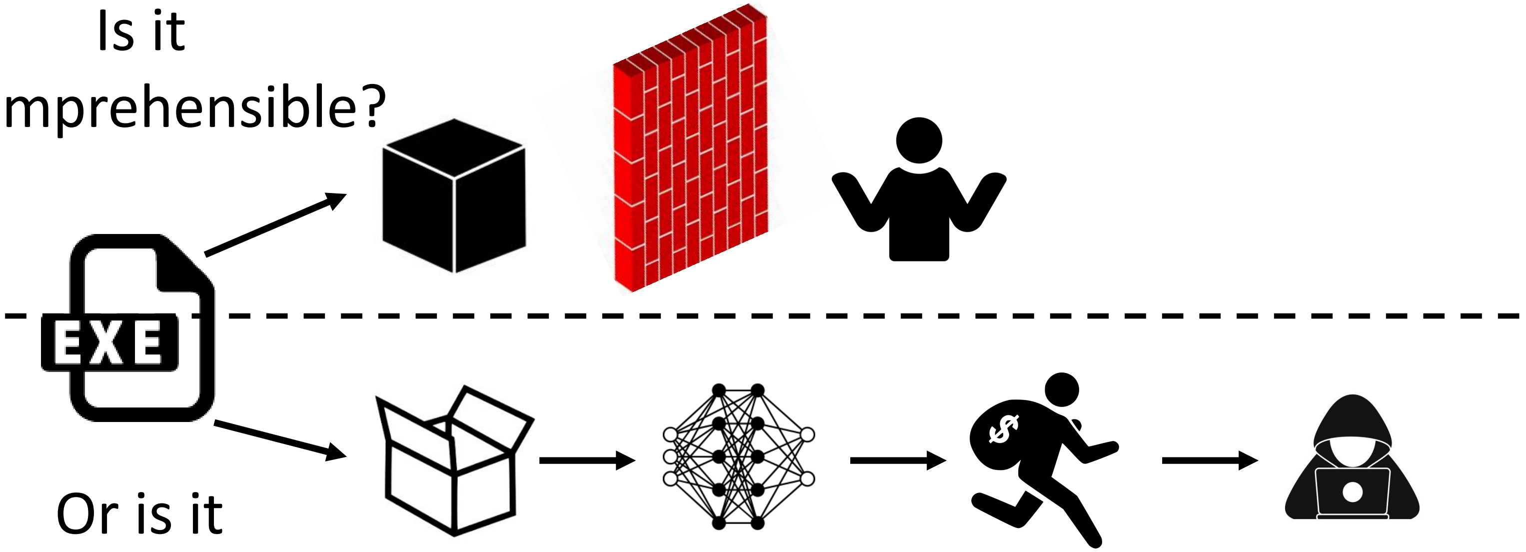
- Our questions:
  - What is the difference between DNN exe and traditional exe?
  - Can we do reverse engineering on DNN executable?



Problem

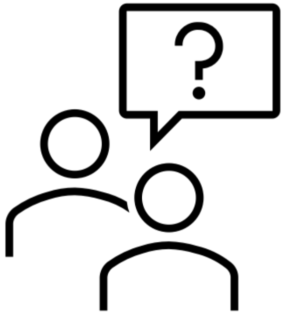
- Specifically, should we view a DNN executable as a black-box or a white-box?

Is it incomprehensible?



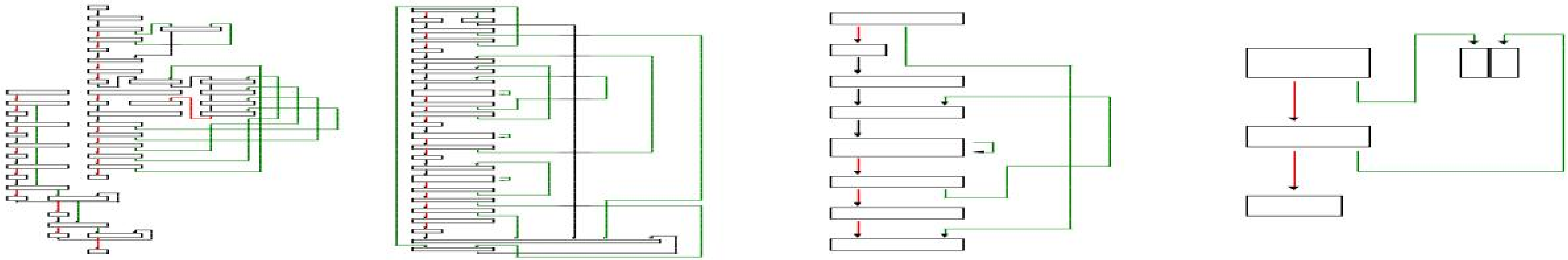
Or is it vulnerable?

Which assumption is true?



Challenges

- The traditional software reverse engineering techniques are unable to tackle DNN executables.



(a) Glow (b) TVM -O0 (c) TVM -O3 (d) NNFusion

Figure 2: Compare CFGs of a Conv operator in VGG16 compiled by different DL compilers. TVM refers to enabling no optimization as “-O0” while enabling full optimizations as “-O3”. Glow and NNFusion by default apply full optimizations.

Challenges

- Complex data flow

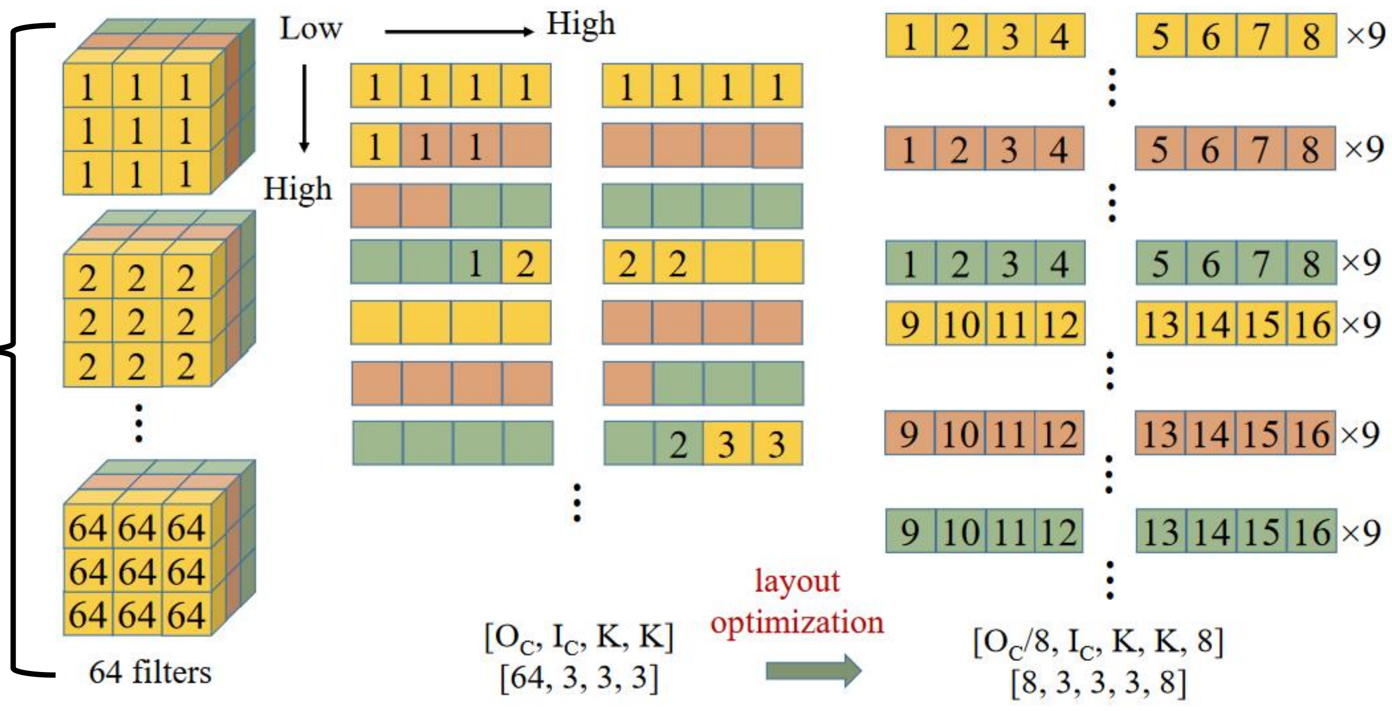
```
v52 = (__m128)*(unsigned int *)(v7 + 4 * v29 + 1024);
v53 = _mm_shuffle_ps(v52, v52, 0);
v159 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v42), v53), v159);
v160 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v45), v53), v160);
v161 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v46), v53), v161);
v162 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v47), v53), v162);
v163 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v48), v53), v163);
v164 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v49), v53), v164);
v165 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v50), v53), v165);
v166 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v51), v53), v166);
v54 = (__m128)*(unsigned int *)(v7 + 4 * v29 + 1536);
v55 = _mm_shuffle_ps(v54, v54, 0);
v167 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v42), v55), v167);
v168 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v45), v55), v168);
v169 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v46), v55), v169);
v170 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v47), v55), v170);
v171 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v48), v55), v171);
v172 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v49), v55), v172);
v173 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v50), v55), v173);
v174 = _mm_add_ps(_mm_mul_ps(*(__m128 *)(v8 + 4 * v51), v55), v174);
v56 = (__m128)*(unsigned int *)(v7 + 4 * v29 + 2048);
v57 = _mm_shuffle_ps(v56, v56, 0);
```

Decompiled with IDA

Challenges

- Hardware-aware optimizations during compilation.
  - memory layout optimization
  - → better memory locality & compatible with SIMD

Weights of a Conv



Our Work

- The traditional software reverse engineering techniques are unable to tackle DNN executables.
- We propose BTD (Bin-To-DNN), the first DNN executable decompiler.

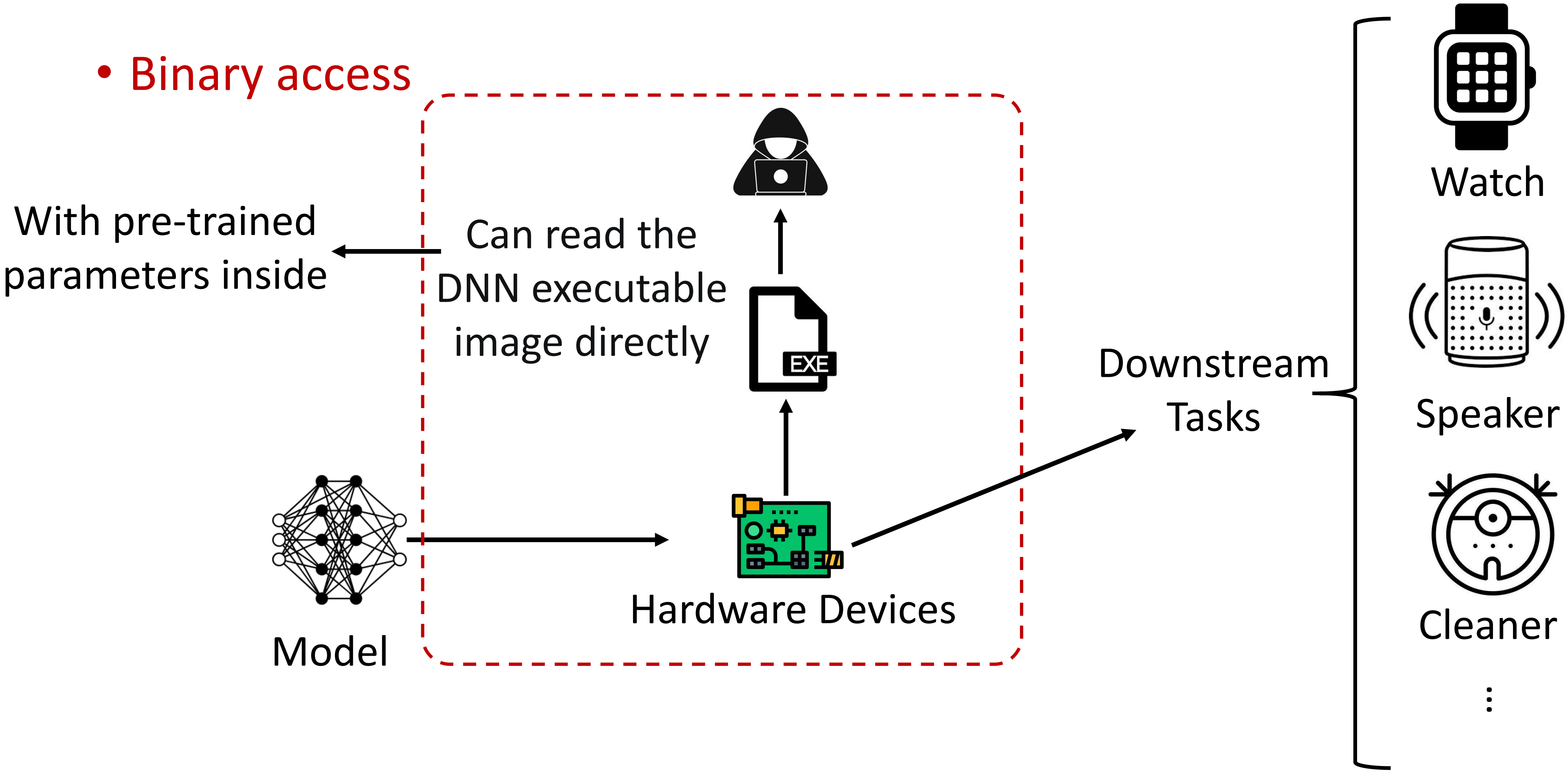
x86 DNN Executable

BTD

Full DNN Model Specification (architecture + parameters)

Threat Model

- Binary access



Observation

DL compilers generate distinct low-level code but retain operator high-level semantics, because DNN operators are generally defined in a clean and rigorous manner.

E.g., mathematical definition of Conv:

$$\text{out}(N_i, C_{\text{out}_j}) = \text{bias}(C_{\text{out}_j}) + \sum_{k=0}^{C_{\text{in}}-1} \text{weight}(C_{\text{out}_j}, k) \star \text{input}(N_i, k)$$

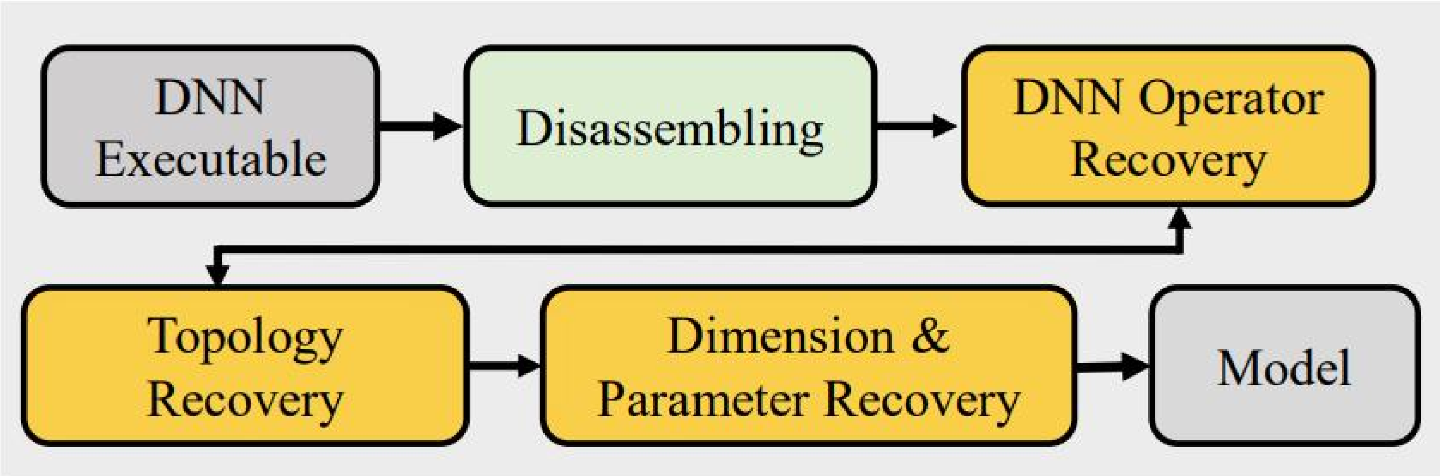
Semantics of different implementation should be consistent!

Observation

- Differences between DNN executables and general software
  - ➢overwhelming arithmetic operations
    - →hard to understand
  - ➢only one valid execution path!
    - →no path explosion problem
    - →get high-level semantics with symbolic execution!
- Give us an opportunity to summarize the semantics from low-level binary code

Workflow

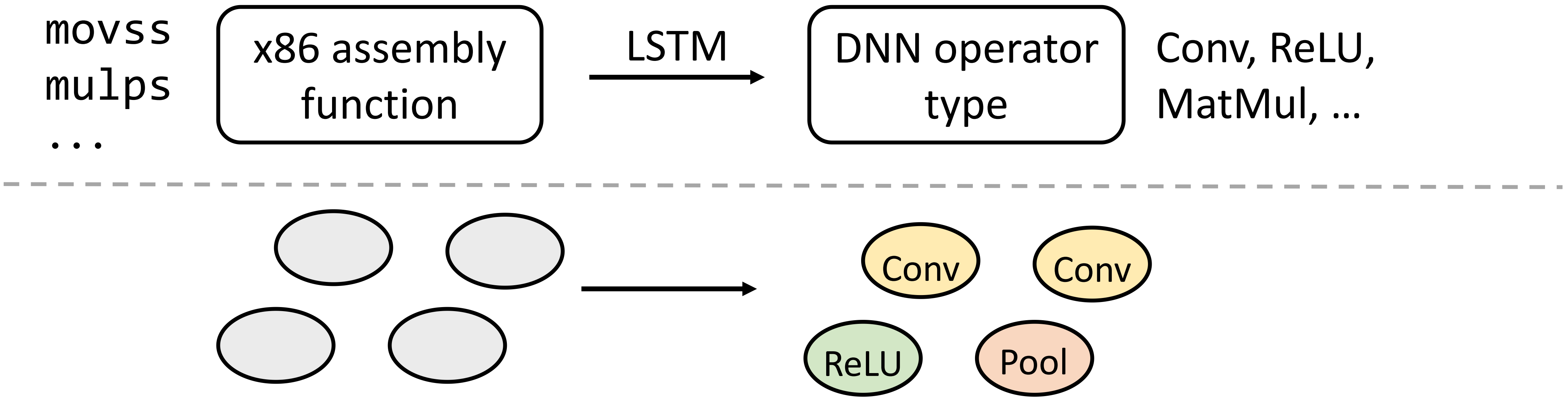
- BTD consists of 3 steps: operator recovery, topology recovery, dimension & parameter recovery.



- BTD is able to recover full model specification (including operators, topologies, dimensions, and parameters) from DNN executable.

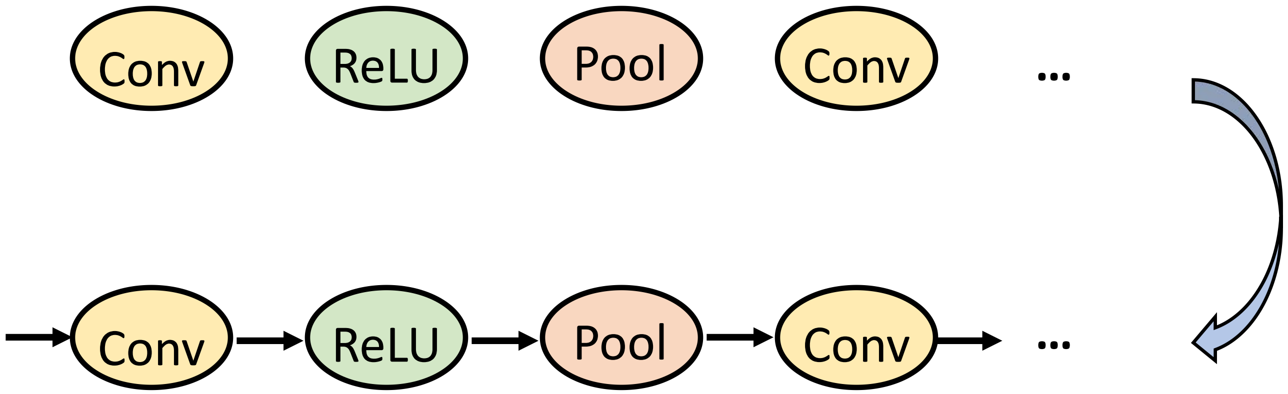
Step 1: DNN Operator Recovery

- We train an LSTM model to map assembly functions to DNN operators.
  - Treat x86 opcodes as language tokens.
  - Segment x86 opcodes using Byte Pair Encoding (BPE).
  - Multiclass classification task



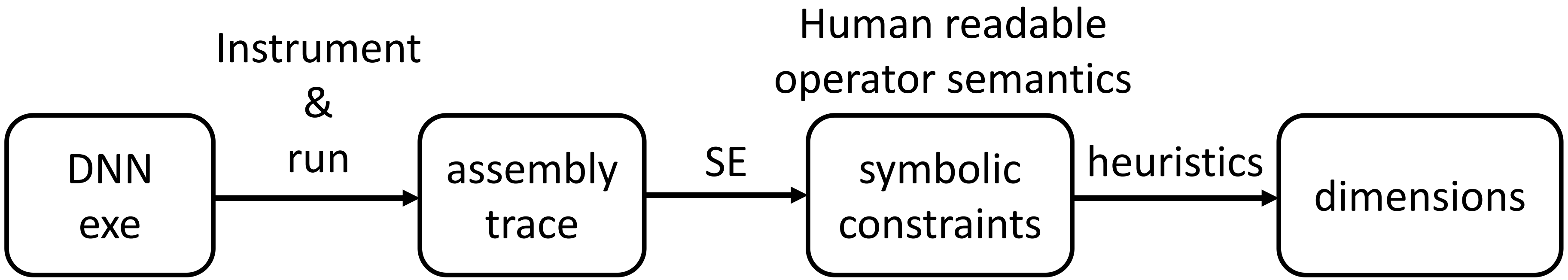
Step 2: Topology Recovery

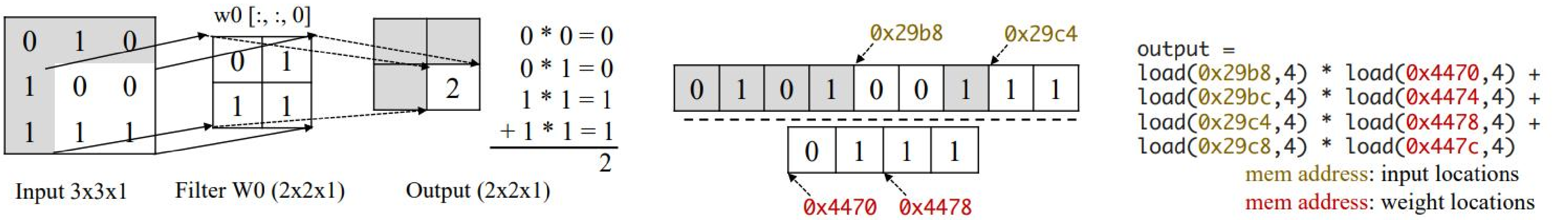
- DL compilers compile DNN operators into assembly functions and pass inputs and outputs as memory pointers through function arguments.
- We hook every call site to record the memory address, and chain operators into computation graph.



Step 3: Dimension & Parameter Recovery

- Idea: we launch trace-based symbolic execution (SE) to infer dimensions and localize parameters for DNN operators





(a) One Convolution Operation (b) Memory Layout and Addresses (c) Corresponding Symbolic Formula

Step 3: Dimension & Parameter Recovery

- Symbolic constraints extracted from vastly different binaries are mostly consistent.
  - Our (symbolic constraint-based) heuristics are general and cross-compilers

```
output =
max(
 (load(0x22a5a84,4) * load(0x7e1f54,4) +
  load(0x22a5a7c,4) * load(0x7e1f4c,4) +
  load(0x22a5a80,4) * load(0x7e1f50,4) +
  load(0x22a5a78,4) * load(0x7e1f48,4) +
  ...),
0)
```

(a) Symbolic Constraint of Glow

```
output =
( 0 +
 load(0x29cfe98,4) * load(0x293cd60,16) +
 load(0x29cfe9c,4) * load(0x293cde0,16) +
 load(0x29cfea0,4) * load(0x293ce60,16) +
 load(0x29cfea4,4) * load(0x293cee0,16) +
...)
```

(b) Symbolic Constraint of TVM –O0

```
output =
( 0 +
 load(0x284dcc8,4) * load(0x7a9180,16) +
 load(0x284dccc,4) * load(0x7a9200,16) +
 load(0x284dcd0,4) * load(0x7a9280,16) +
 load(0x284dcd4,4) * load(0x7a9300,16) +
...)
```

(c) Symbolic Constraint of TVM –O3

mem address: input locations
mem address: weight locations

Step 3: Dimension & Parameter Recovery

- We infer operator dimensions (e.g., kernel size, #input channels, #output channels, stride) from extracted symbolic constraints with a set of heuristics.

- Then instrument the DNN executable to dump parameters (e.g., weights, biases) during execution.

- With all extracted information (i.e., operator types, topologies, dimensions, and parameters) we can rebuild a new model showing identical behavior with the original model.

Evaluation

- 8 version of 3 state-of-the-art, production level DL compilers

Table 1: Compilers evaluated in our study.

Tool Name	Publication	Developer	Version (git commit)
TVM [20]	OSDI '18	Amazon	v0.7.0 v0.8.0 v0.9.dev
Glow [77]	arXiv	Facebook	2020 (07a82bd9fe97dfd) 2021 (97835cec670bd2f) 2022 (793fec7fb0269db)
NNFusion [58]	OSDI '20	Microsoft	v0.2 v0.3

Evaluation

- 7 models cover all operators used in the CV models from ONNX Zoo https://github.com/onnx/models
- Real-world image classification models trained on ImageNet

Table 2: Statistics of DNN models and their compiled executables evaluated in our study.

Model	#Parameters	#Operators	TVM -O0		TVM -O3		Glow -O3	
			Avg. #Inst.	Avg. #Func.	Avg. #Inst.	Avg. #Func.	Avg. #Inst.	Avg. #Func.
Resnet18 [36]	11,703,912	69	49,762	281	61,002	204	11,108	39
VGG16 [81]	138,357,544	41	40,205	215	41,750	185	5,729	33
FastText [18]	2,500,101	3	9,867	142	7,477	131	405	14
Inception [83]	6,998,552	105	121,481	615	74,992	356	30,452	112
Shufflenet [99]	2,294,784	152	56,147	407	34,637	228	33,537	59
Mobilenet [41]	3,487,816	89	69,903	363	46,214	228	37,331	52
Efficientnet [84]	12,966,032	216	89,772	546	49,285	244	13,749	67

Results

- Step 1: DNN operator inference

Table 3: Average accuracy of DNN operator inference.

Model	Glow			TVM -O0			TVM -O3		
	2020	2021	2022	v0.7	v0.8	v0.9.dev	v0.7	v0.8	v0.9.dev
ResNet18	100%	100%	100%	99.79%	99.84%	100%	98.15%	99.06%	99.69%
VGG16	100%	100%	100%	99.95%	99.79%	99.57%	99.75%	100%	100%
Inception	100%	100%	100%	99.98%	99.88%	99.98%	100%	100%	100%
ShuffleNet	100%	100%	100%	99.96%	99.82%	100%	99.62%	99.71%	99.31%
MobileNet	100%	100%	100%	99.35%	99.46%	99.40%	99.80%	100%	100%
EfficientNet	100%	100%	100%	99.65%	99.68%	99.59%	99.81%	99.91%	100%

Results

- Step 3:
  - Parameter layout/dimension inference.

- BTD fails on two cases
  - Because of DL compiler optimizations
  - (details in our paper)

Table 10: Parameter/dimension inference. Lines 2–8 report each executable's total #dimensions, correctly-inferred dimensions, and accuracy rate for dimension inference. Lines 9–15 report total #parameters and accuracy rate for parameter inference. Different versions of the same compiler produce the same results, therefore we merge their columns.

Model	Glow (2020, 2021, 2022)	TVM -O0 (v0.7, v0.8, v0.9.dev)	TVM -O3 (v0.7, v0.8, v0.9.dev)
ResNet18	65/65/100%	51/47/**92.15%**	78/78/100%
VGG16	54/54/100%	59/59/100%	52/52/100%
FastText	7/7/100%	7/7/100%	7/7/100%
Inception	235/235/100%	223/223/100%	222/222/100%
ShuffleNet	82/82/100%	71/71/100%	71/71/100%
MobileNet	124/124/100%	144/144/100%	125/125/100%
EfficientNet	133/133/100%	133/133/100%	132/132/100%
ResNet18	11,684,712/100%	11,703,912/**99.37%**	11,684,712/**99.37%**
VGG16	138,357,544/100%	138,357,544/100%	138,357,544/100%
FastText	2,500,101/100%	2,500,101/100%	2,500,101/100%
Inception	6,998,552/100%	6,998,552/100%	6,998,552/100%
ShuffleNet	2,270,514/100%	2,294,784/100%	2,270,514/100%
MobileNet	3,487,816/100%	3,487,816/100%	3,487,816/100%
EfficientNet	12,950,384/100%	12,966,032/100%	12,950,384/100%

Results

- BTD is able to extract functional models in most cases.

Table 11: Recompilation. "NA" means that some errors in DNN models are not fixed, and thus the rebuilt models manifest inconsistent behavior.

Model	Glow (2020, 2021, 2022)	TVM -O0 (v0.7, v0.8, v0.9.dev)	TVM -O3 (v0.7, v0.8, v0.9.dev)
ResNet18	100%	100% (with fixing)	NA → 100%
VGG16	100%	100%	100%
FastText	100%	100%	100%
Inception	100%	100%	100%
ShuffleNet	100%	100%	100%
MobileNet	100%	100%	100%
EfficientNet	100%	100%	100%

- Thus, we can enable white-box attacks (e.g., adversarial example) on a black-box, obscure DNN executable

Implement

- BTD is released at: https://github.com/monkbai/DNN-decompiler
  - With a demo docker image

- With badges Available, Functional, Reproduced

Takeaways

- It is hard to reverse DNN executables with existing techniques due to complex control/data flow.
- There is only one execution path, giving us an opportunity to summarize the semantics with symbolic execution.
- We propose BTD (Bin-To-DNN), the first DNN executable decompiler.

Thanks

Q&A

- BTD: https://github.com/monkbai/DNN-decompiler