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

- Apache
- Meta
- Microsoft
- tvm
- Glow
- NNFusion
- arXiv
- OSDI’18
- 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.

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

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.

![Diagram of BTD process]

- **x86 DNN Executable** → **BTD** → **Full DNN Model Specification** (architecture + parameters)
Threat Model

- Binary access

With pre-trained parameters inside

Model

Can read the DNN executable image directly

Hardware Devices

Downstream Tasks

Watch

Speaker

Cleaner
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:

\[
\text{out}(N_i, C_{out_j}) = \text{bias}(C_{out_j}) + \sum_{k=0}^{C_{in}-1} \text{weight}(C_{out_j}, k) \times \text{input}(N_i, k)
\]

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.
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

(a) Symbolic Constraint of Glow

```
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)
```

(b) Symbolic Constraint of TVM –O0

```
output =
( 0 +
  load(0x284dcd8,4) * 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

| 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 (97835ec670bd2f), 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](https://github.com/onnx/models)

• Real-world image classification models trained on ImageNet
Results

• Step 1: 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)
Results

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

| 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](https://github.com/monkbai/DNN-decompiler)*