Amanda: Unified Instrumentation Framework for Deep Neural Networks

ASPLOS’24

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Background

- Instrumentation in traditional programming analysis

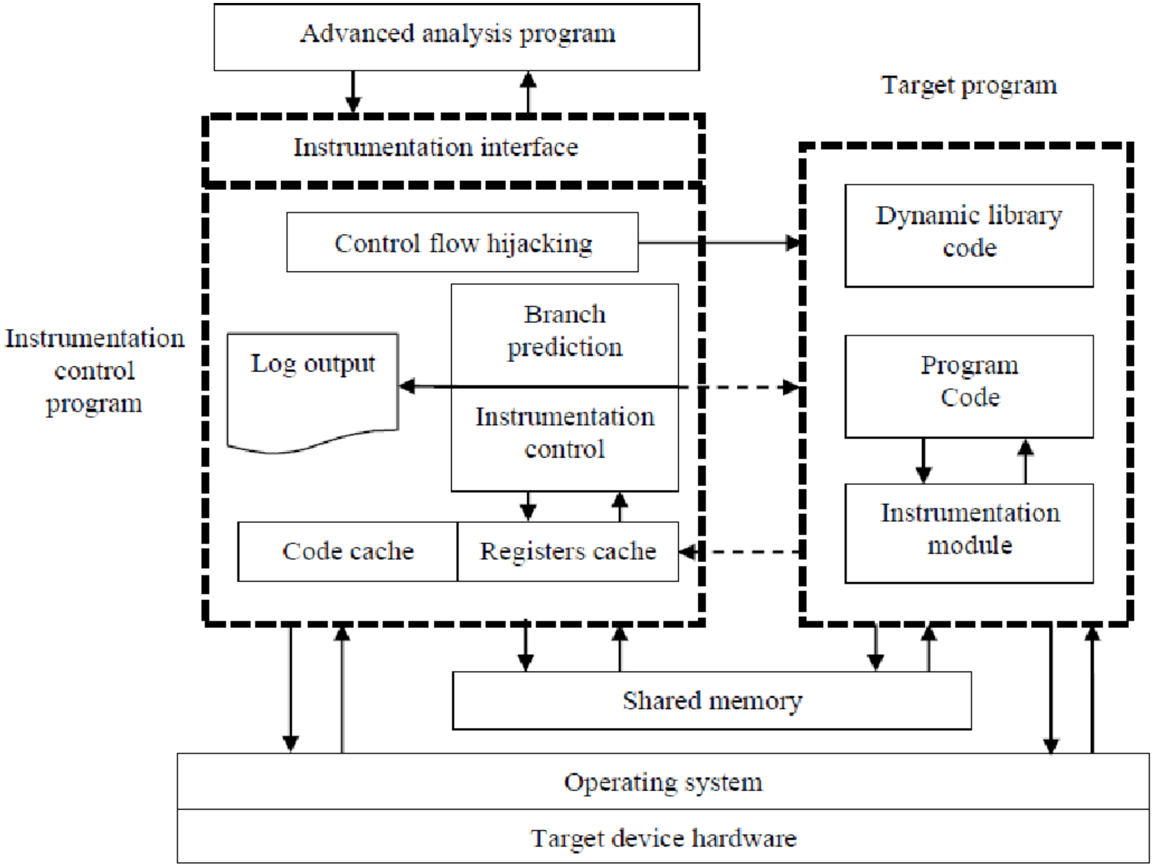
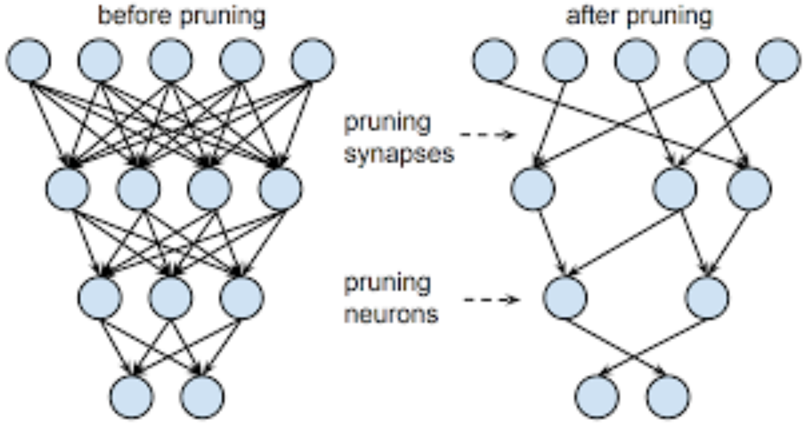
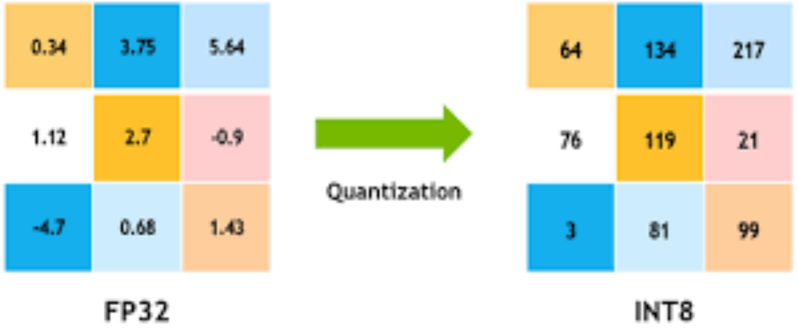


Figure 2. Dynamic binary instrumentation overall framework.

Background and Motivation

- Lots of works focus on analyzing or accelerating DNN inference or training





0.34	3.75	5.64
1.12	2.7	-0.9
-4.7	0.68	1.43

FP32

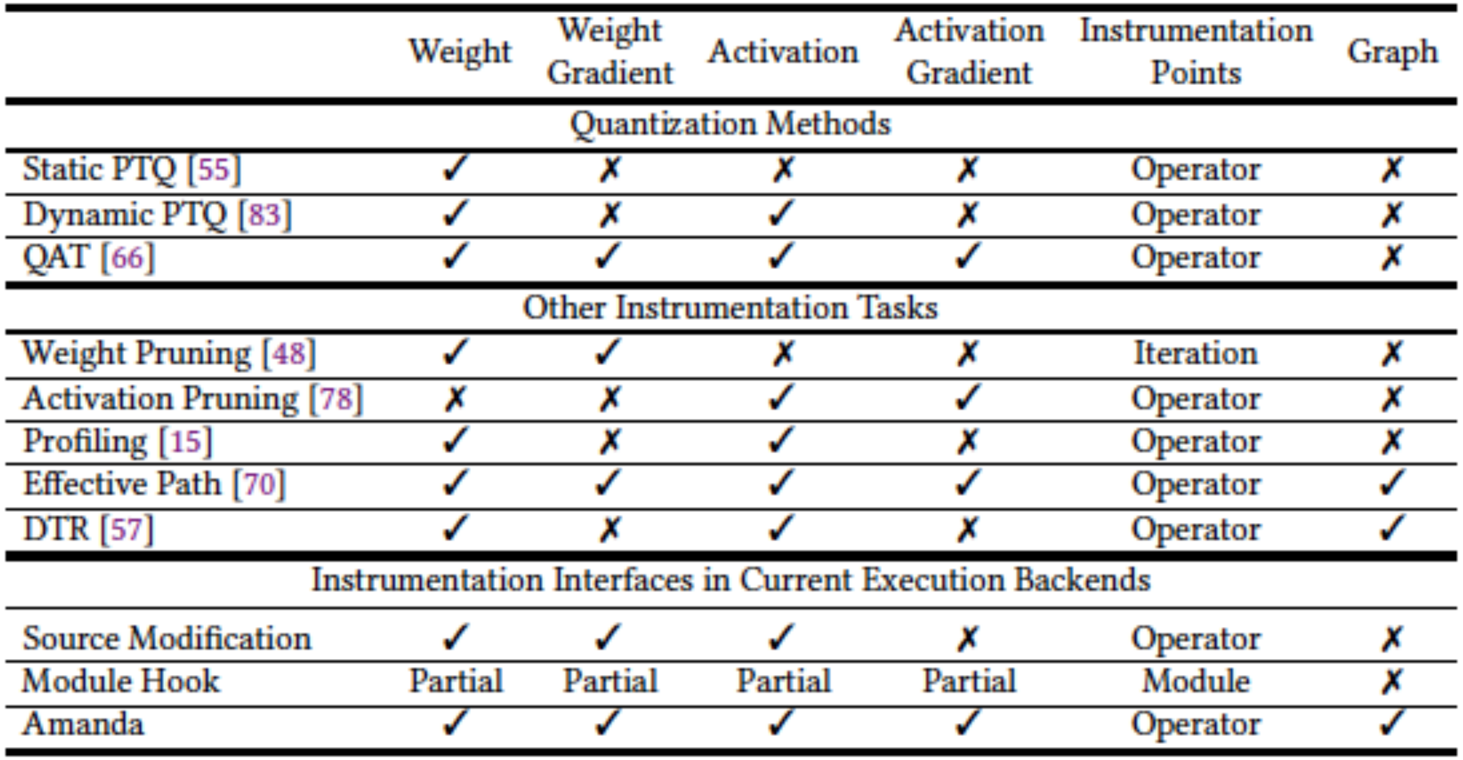
64	134	217
76	119	21
3	81	99

INT8

Alpa

Background and Motivation

- The common requirements of these tasks is to monitor and manipulate the computation process of DNN models.

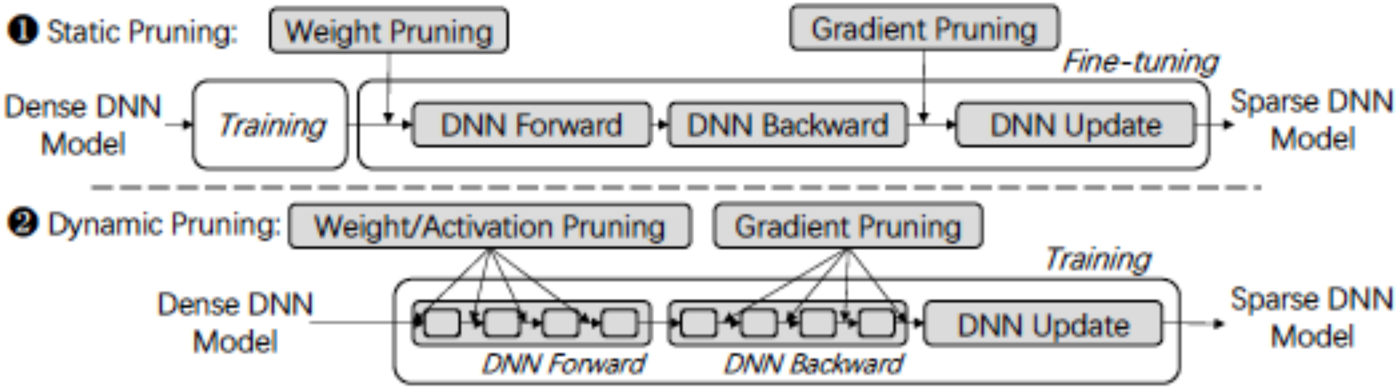


	Weight	Weight Gradient	Activation	Activation Gradient	Instrumentation Points	Graph
Quantization Methods						
Static PTQ [55]	✓	✗	✗	✗	Operator	✗
Dynamic PTQ [83]	✓	✗	✓	✗	Operator	✗
QAT [66]	✓	✓	✓	✓	Operator	✗
Other Instrumentation Tasks						
Weight Pruning [48]	✓	✓	✗	✗	Iteration	✗
Activation Pruning [78]	✗	✗	✓	✓	Operator	✗
Profiling [15]	✓	✗	✓	✗	Operator	✗
Effective Path [70]	✓	✓	✓	✓	Operator	✓
DTR [57]	✓	✗	✓	✗	Operator	✓
Instrumentation Interfaces in Current Execution Backends						
Source Modification	✓	✓	✓	✗	Operator	✗
Module Hook	Partial	Partial	Partial	Partial	Module	✗
Amanda	✓	✓	✓	✓	Operator	✓

Various requirements for implementation

Background and Motivation

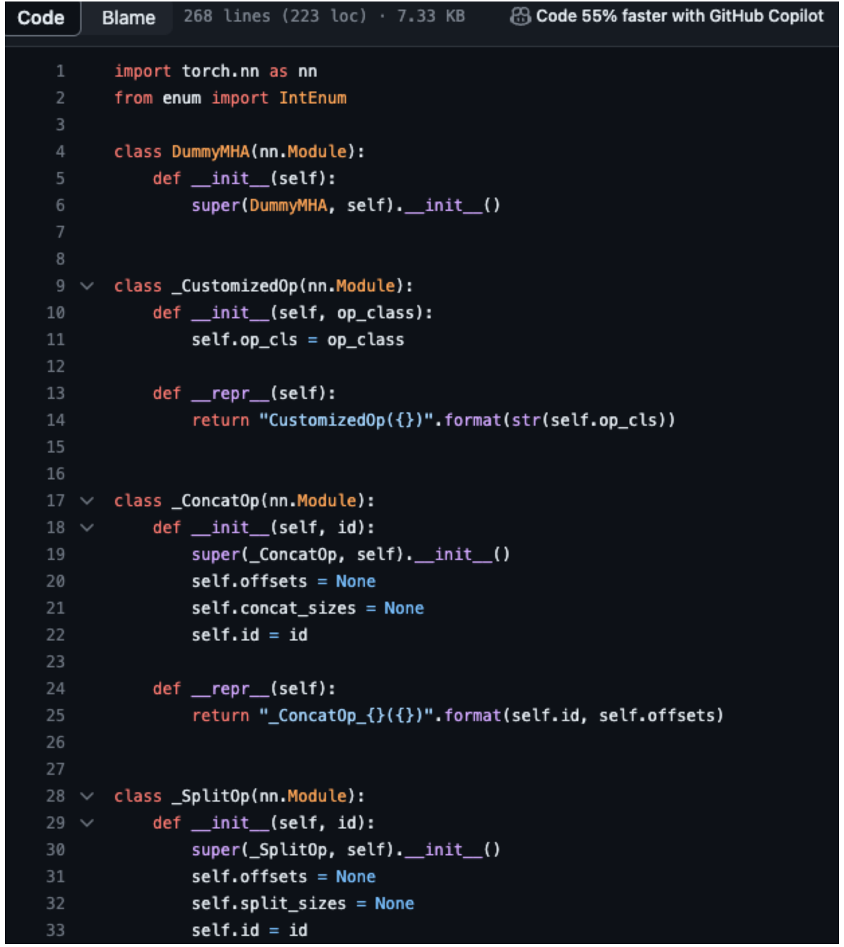
- Problems of existed implementation and backend support
  - Ad-hoc instrumentation points



Background and Motivation

- Problems of existed implementation and backend support
  - Fragmented state representations

Developers often manually wrap every PyTorch module with additional operators.


Code
Blame
268 lines (223 loc) · 7.33 KB
Code 55% faster with GitHub Copilot

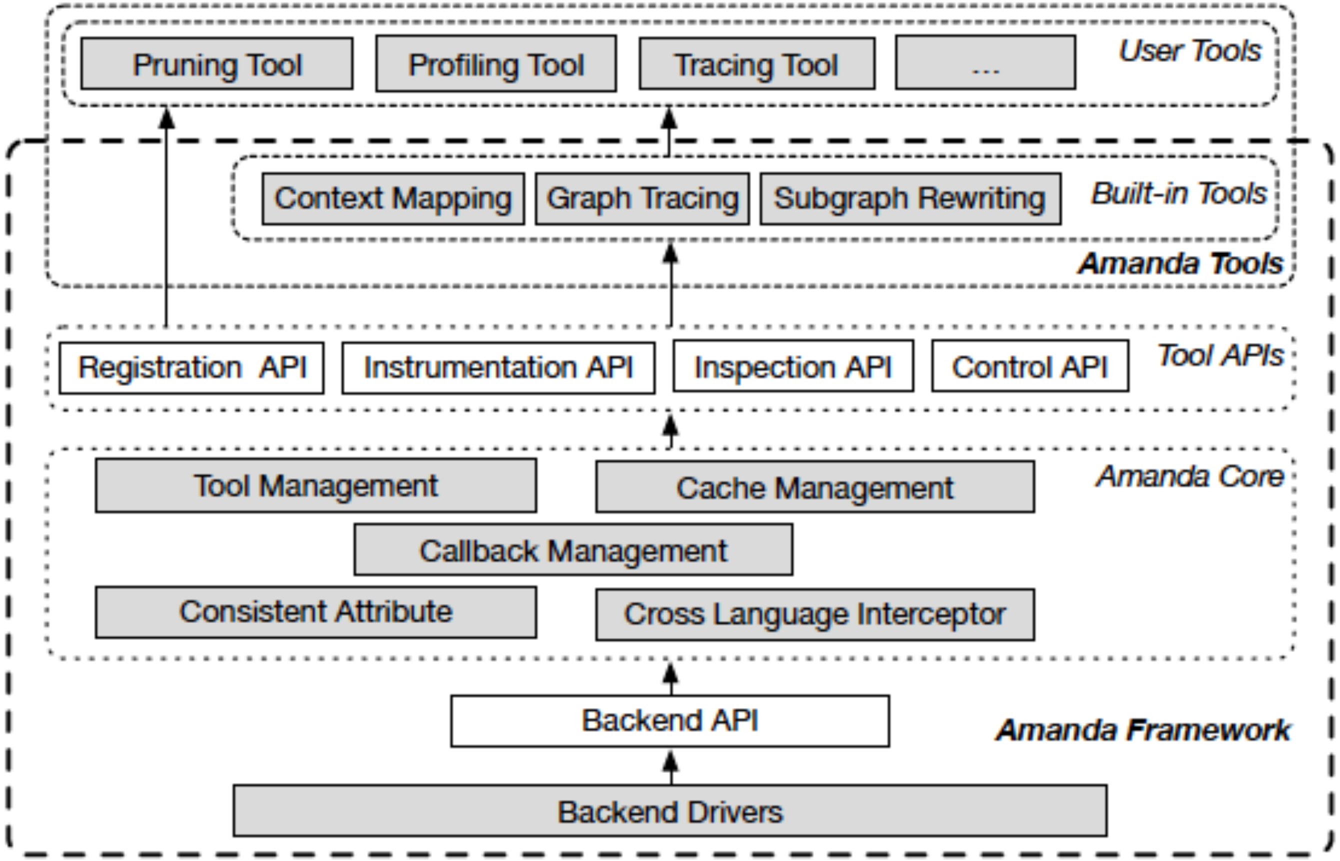
```python
import torch.nn as nn
from enum import IntEnum

class DummyMHA(nn.Module):
    def __init__(self):
        super(DummyMHA, self).__init__()


class _CustomizedOp(nn.Module):
    def __init__(self, op_class):
        self.op_cls = op_class

    def __repr__(self):
        return "CustomizedOp({})".format(str(self.op_cls))


class _ConcatOp(nn.Module):
    def __init__(self, id):
        super(_ConcatOp, self).__init__()
        self.offsets = None
        self.concat_sizes = None
        self.id = id

    def __repr__(self):
        return "_ConcatOp_{}({})".format(self.id, self.offsets)


class _SplitOp(nn.Module):
    def __init__(self, id):
        super(_SplitOp, self).__init__()
        self.offsets = None
        self.split_sizes = None
        self.id = id
```

Background and Motivation

- Problems of existed implementation and backend support
  - Execution modes
    - Graph mode: Cook all, eat one by one.
    - Eager mode: Cook one, eat one.

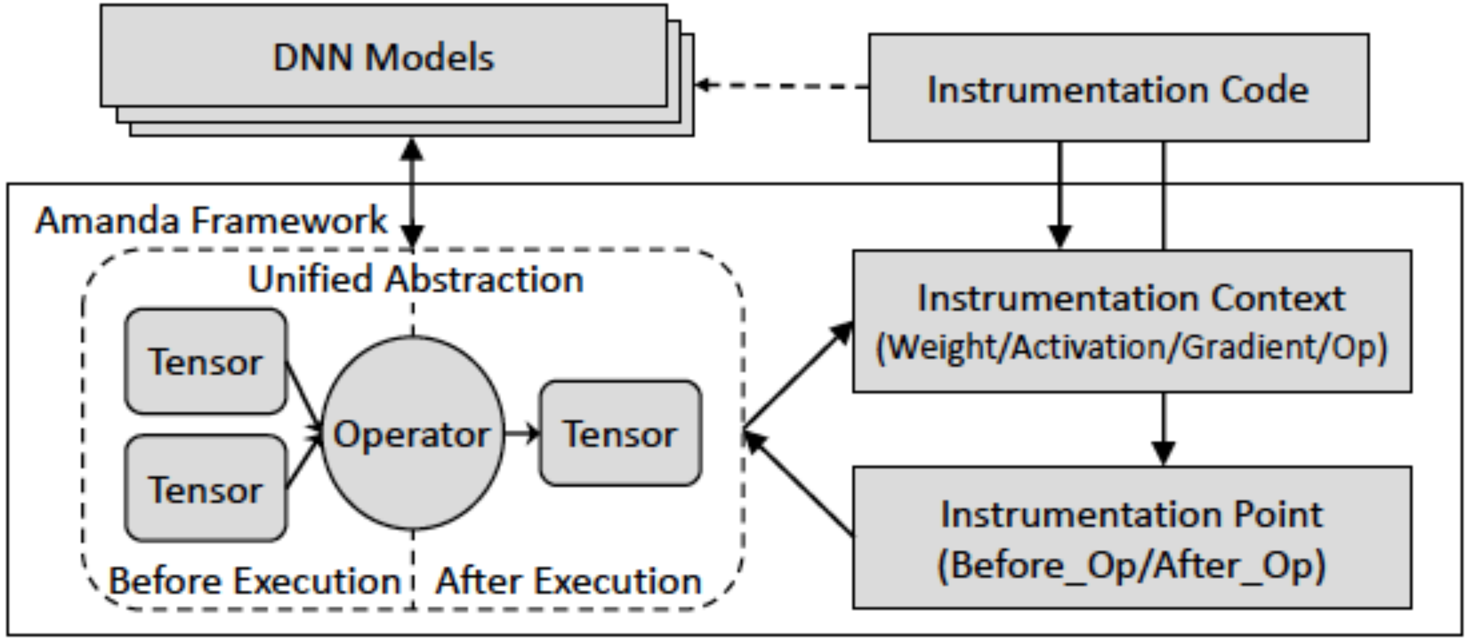
Some tasks need to use graph mode to analyze the DNN which add the extra complexity dimension in implementation.

System Overview



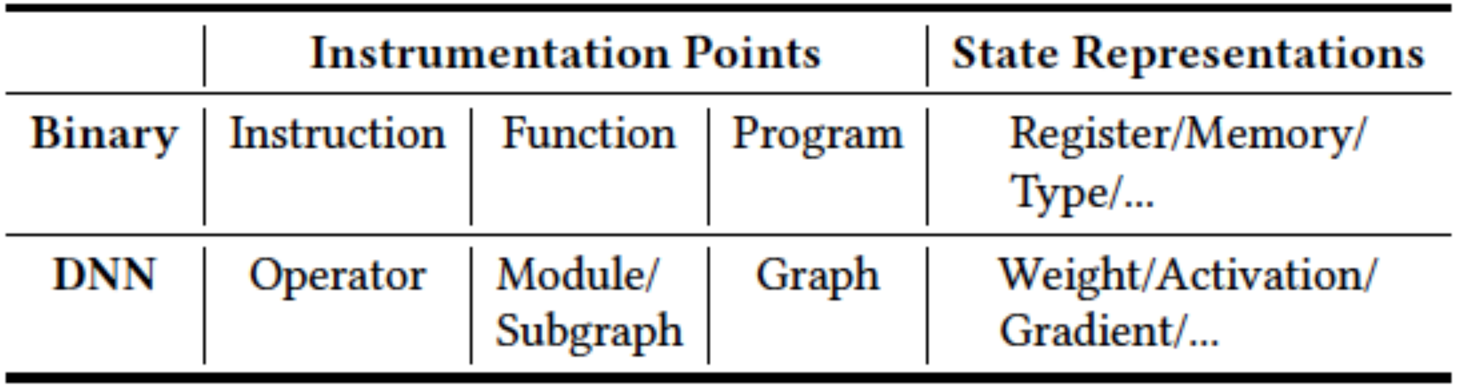
Instrumentation

- Points



Instrumentation

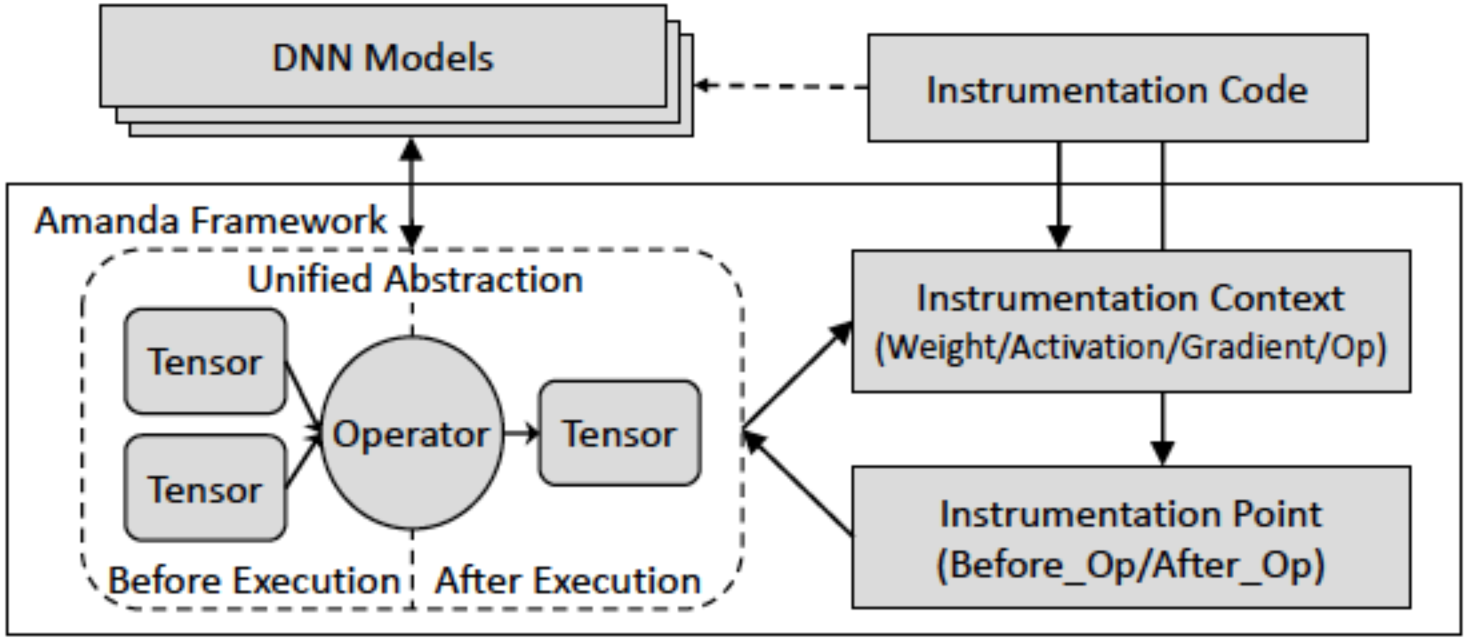
- Compare with traditional concept



	Instrumentation Points			State Representations
Binary	Instruction	Function	Program	Register/Memory/ Type/...
DNN	Operator	Module/ Subgraph	Graph	Weight/Activation/ Gradient/...

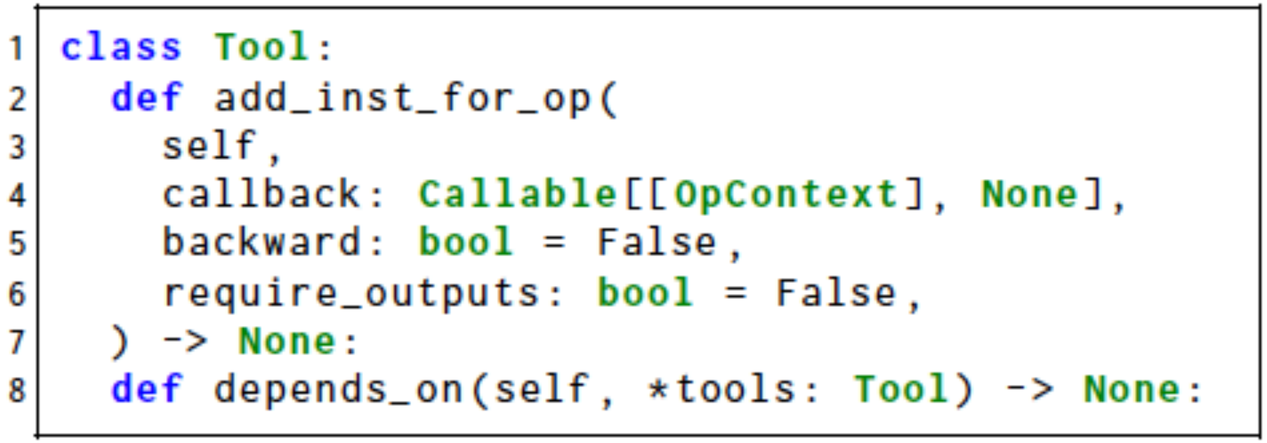
Instrumentation

- Analysis routines and instrumentation routines
  - Analysis routines: Init, check status, locate point and register instrumentations.
  - Instrumentation routines: Modify operators. Execute in runtime states.



Instrumentation

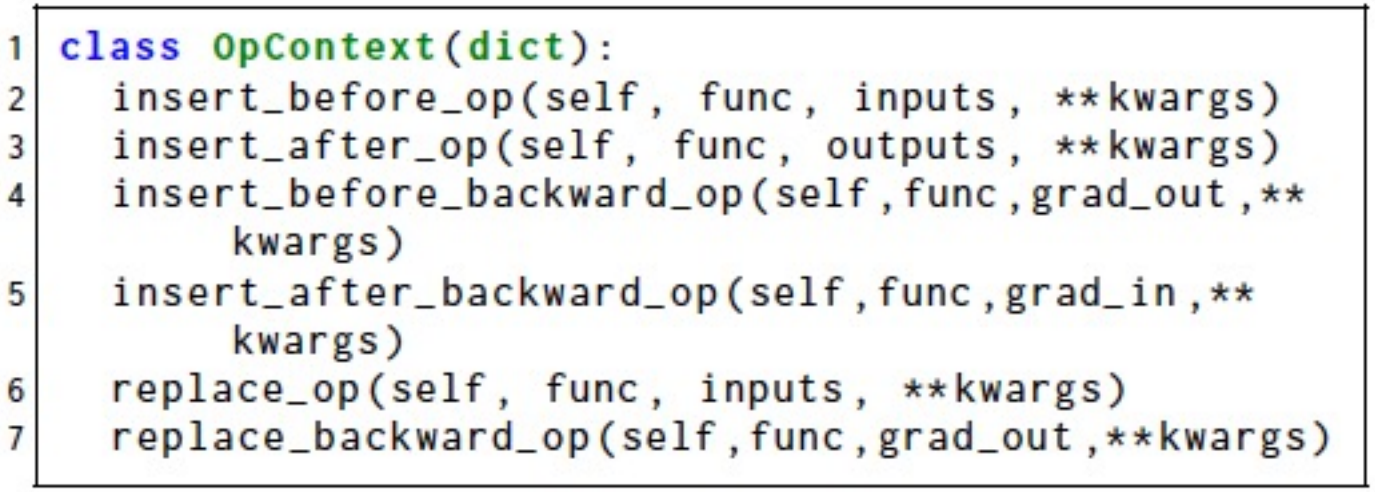
- Tool APIs
  - Registration APIs



```
class Tool:
  def add_inst_for_op(
    self,
    callback: Callable[[OpContext], None],
    backward: bool = False,
    require_outputs: bool = False,
  ) -> None:
  def depends_on(self, *tools: Tool) -> None:
```

Instrumentation

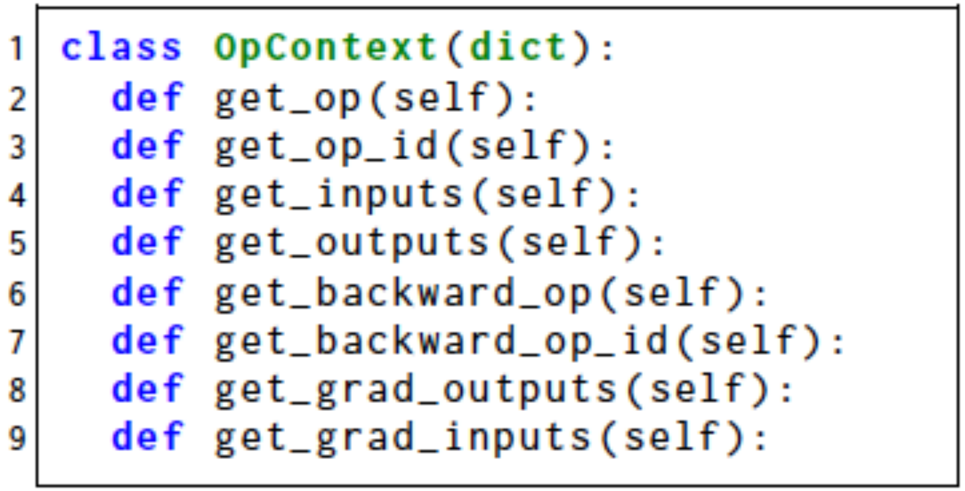
- Tool APIs
  - Instrumentation APIs



```
class OpContext(dict):
  insert_before_op(self, func, inputs, **kwargs)
  insert_after_op(self, func, outputs, **kwargs)
  insert_before_backward_op(self,func,grad_out,**
       kwargs)
  insert_after_backward_op(self,func,grad_in,**
       kwargs)
  replace_op(self, func, inputs, **kwargs)
  replace_backward_op(self,func,grad_out,**kwargs)
```

Instrumentation

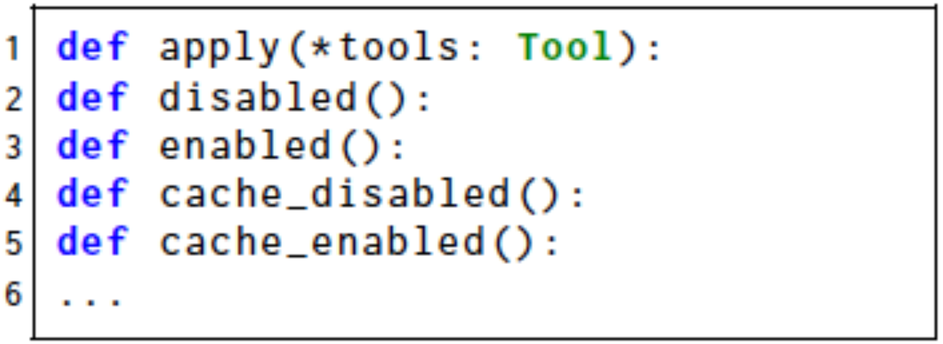
- Tool APIs
    - Inspection APIs



```python
class OpContext(dict):
  def get_op(self):
  def get_op_id(self):
  def get_inputs(self):
  def get_outputs(self):
  def get_backward_op(self):
  def get_backward_op_id(self):
  def get_grad_outputs(self):
  def get_grad_inputs(self):
```

Instrumentation

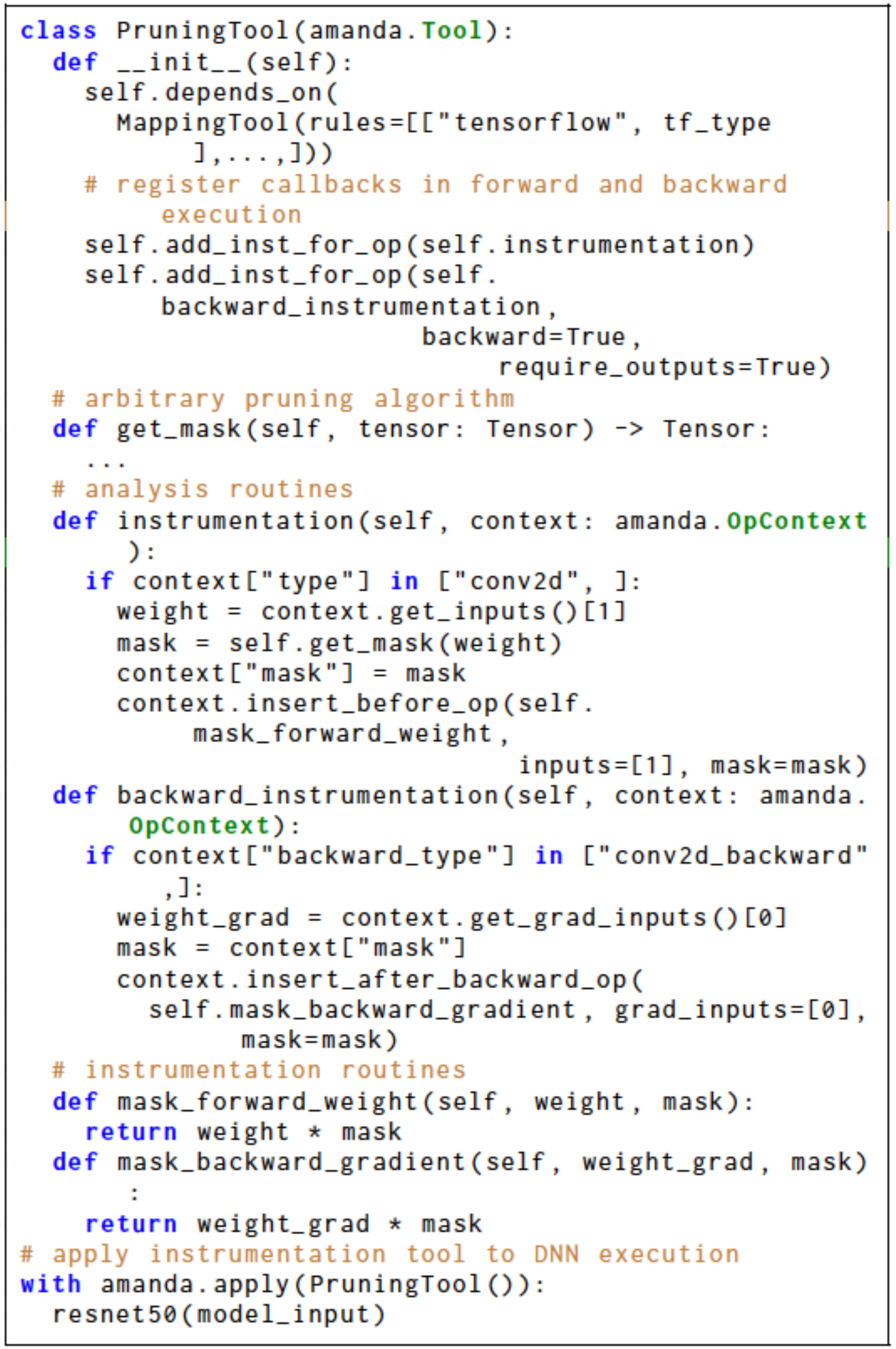
- Tool APIs
  - Control APIs



```
def apply(*tools: Tool):
def disabled():
def enabled():
def cache_disabled():
def cache_enabled():
...
```

Instrumentation

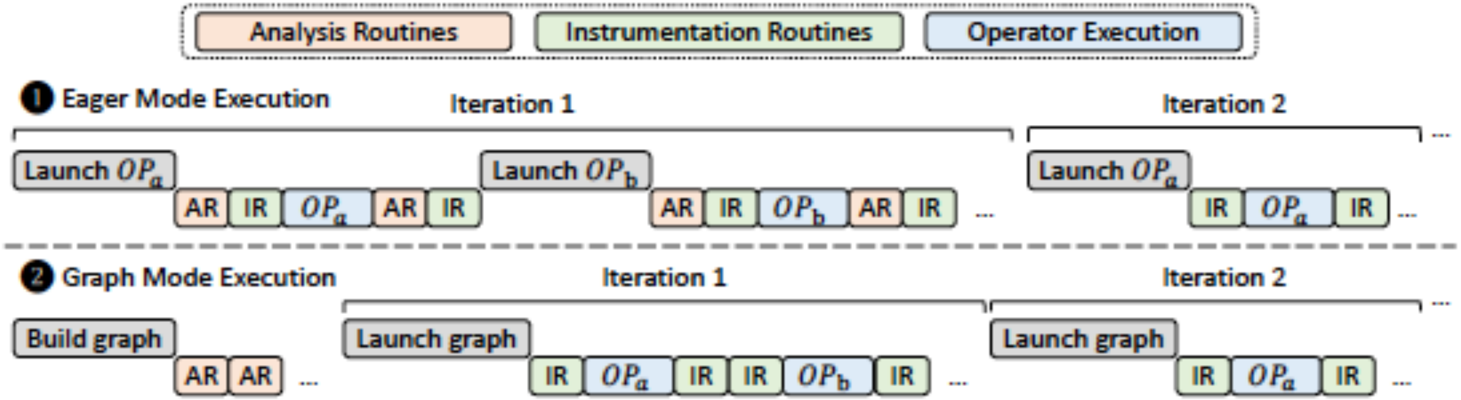
- Pruning case study



```
class PruningTool(amanda.Tool):
  def __init__(self):
    self.depends_on(
      MappingTool(rules=[["tensorflow", tf_type],...,]))
    # register callbacks in forward and backward execution
    self.add_inst_for_op(self.instrumentation)
    self.add_inst_for_op(self.backward_instrumentation,
                         backward=True,
                              require_outputs=True)
  # arbitrary pruning algorithm
  def get_mask(self, tensor: Tensor) -> Tensor:
    ...
  # analysis routines
  def instrumentation(self, context: amanda.OpContext):
    if context["type"] in ["conv2d", ]:
      weight = context.get_inputs()[1]
      mask = self.get_mask(weight)
      context["mask"] = mask
      context.insert_before_op(self.mask_forward_weight,
                               inputs=[1], mask=mask)
  def backward_instrumentation(self, context: amanda.OpContext):
    if context["backward_type"] in ["conv2d_backward",]:
      weight_grad = context.get_grad_inputs()[0]
      mask = context["mask"]
      context.insert_after_backward_op(
        self.mask_backward_gradient, grad_inputs=[0], mask=mask)
  # instrumentation routines
  def mask_forward_weight(self, weight, mask):
    return weight * mask
  def mask_backward_gradient(self, weight_grad, mask):
    return weight_grad * mask
# apply instrumentation tool to DNN execution
with amanda.apply(PruningTool()):
  resnet50(model_input)
```

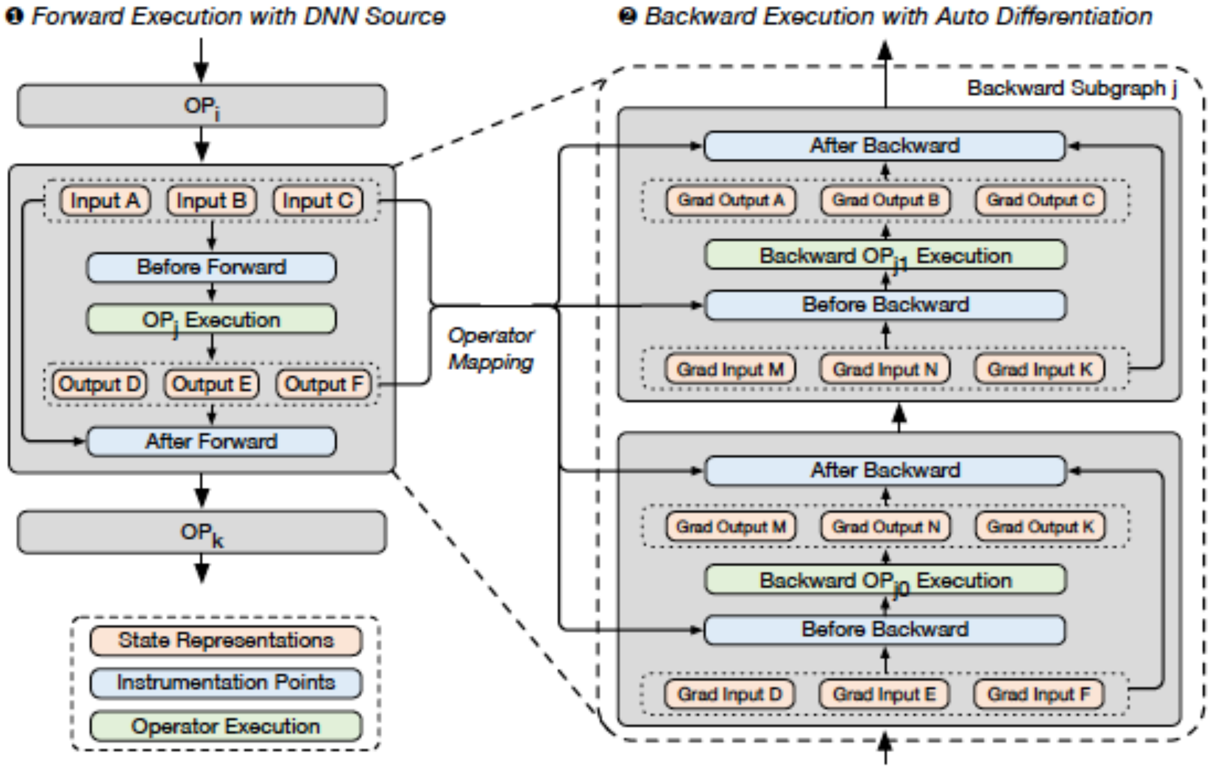
Amanda Core

- Harmonizing instrumentation semantics on different execution modes



Amanda Core

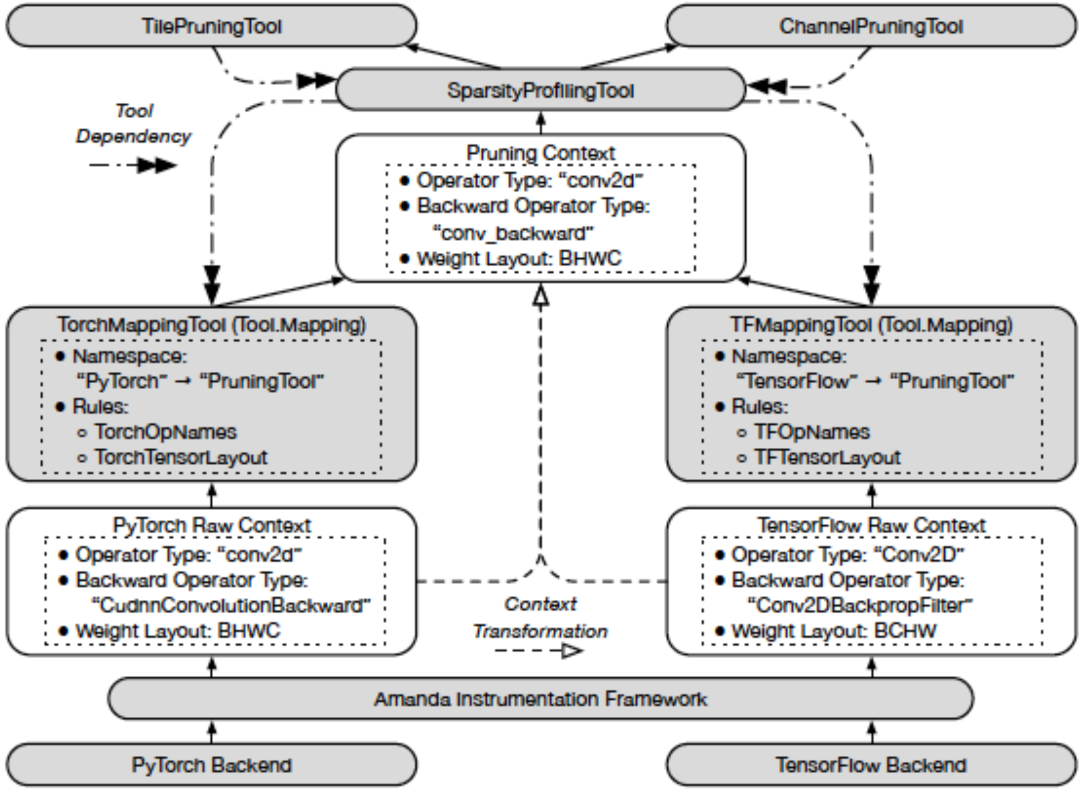
- Addressing AD mechanism



- Original + AD program
- Enable or disable control

Amanda Core

- Composable tools and context transformation

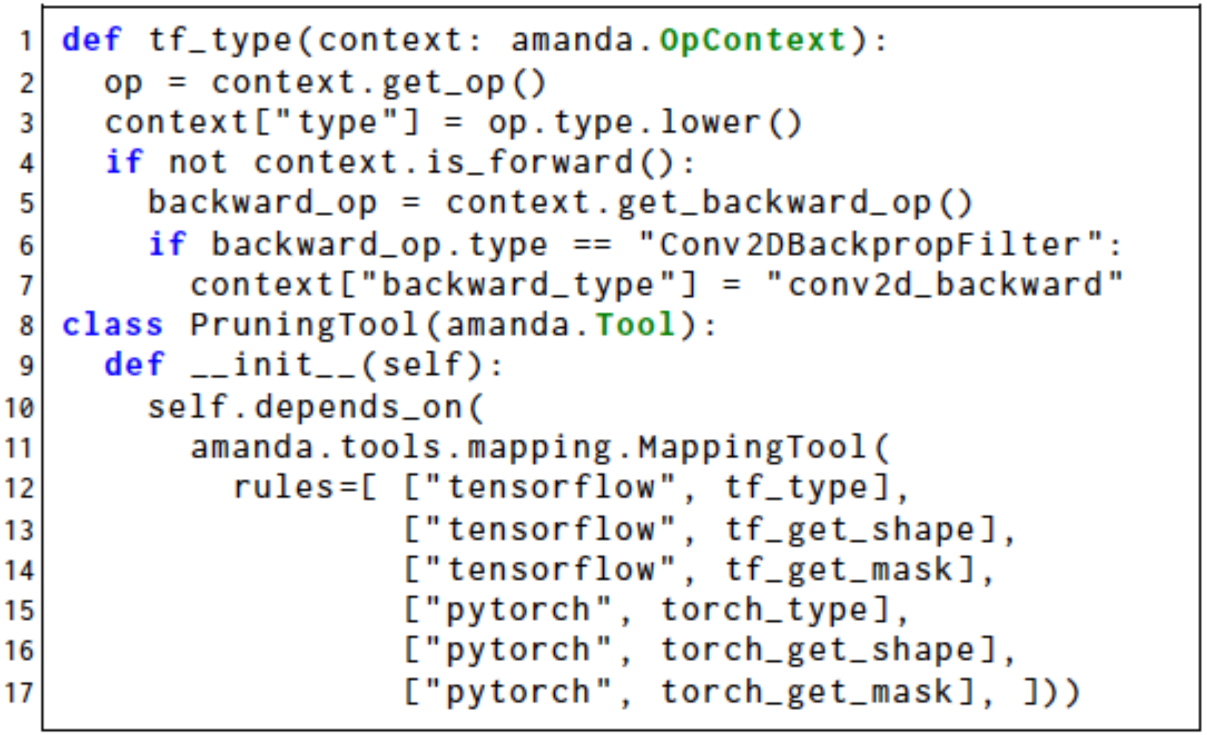


TilePruningTool
ChannelPruningTool
SparsityProfilingTool
Tool Dependency
Pruning Context
• Operator Type: "conv2d"
• Backward Operator Type: "conv_backward"
• Weight Layout: BHWC
TorchMappingTool (Tool.Mapping)
• Namespace: "PyTorch" → "PruningTool"
• Rules:
∘ TorchOpNames
∘ TorchTensorLayout
TFMappingTool (Tool.Mapping)
• Namespace: "TensorFlow" → "PruningTool"
• Rules:
∘ TFOpNames
∘ TFTensorLayout
PyTorch Raw Context
• Operator Type: "conv2d"
• Backward Operator Type: "CudnnConvolutionBackward"
• Weight Layout: BHWC
Context Transformation
TensorFlow Raw Context
• Operator Type: "Conv2D"
• Backward Operator Type: "Conv2DBackpropFilter"
• Weight Layout: BCHW
Amanda Instrumentation Framework
PyTorch Backend
TensorFlow Backend

- Dependency registration
- Resolving the dependency graph of instrumentation tools during initialization and detecting loop dependencies.

Amanda Core

- Composable tools and context transformation



```python
def tf_type(context: amanda.OpContext):
  op = context.get_op()
  context["type"] = op.type.lower()
  if not context.is_forward():
    backward_op = context.get_backward_op()
    if backward_op.type == "Conv2DBackpropFilter":
      context["backward_type"] = "conv2d_backward"
class PruningTool(amanda.Tool):
  def __init__(self):
    self.depends_on(
      amanda.tools.mapping.MappingTool(
        rules=[ ["tensorflow", tf_type],
                ["tensorflow", tf_get_shape],
                ["tensorflow", tf_get_mask],
                ["pytorch", torch_type],
                ["pytorch", torch_get_shape],
                ["pytorch", torch_get_mask], ]))
```

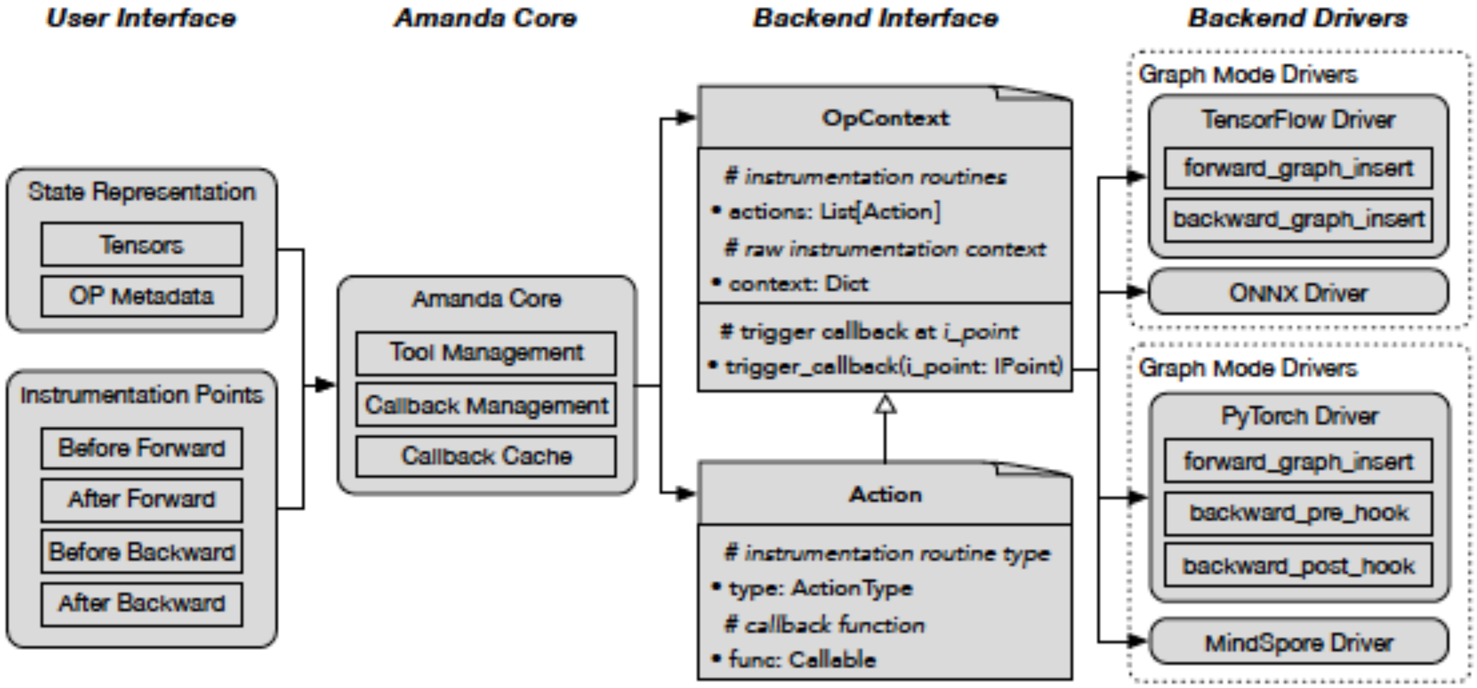
- Mapping tool makes tools are portable

Amanda Core

- Minimizing instrumentation overhead via caching
- Addressing the language disparity

Amanda Backend

- Backend interface

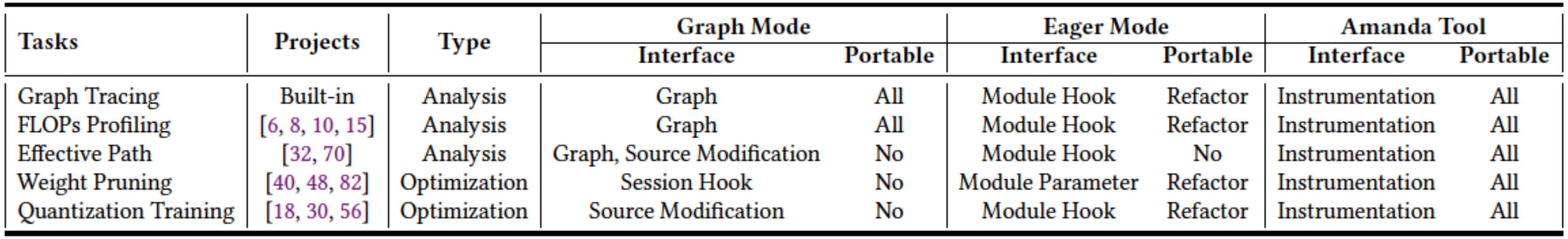


- Monkey-patching
- Traversing mapping

- Graph switching
- Store original and instrumented graphs

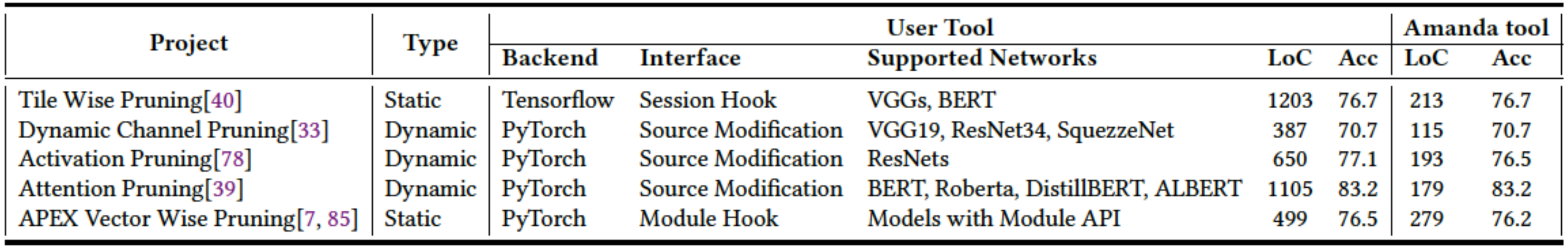
Results

- Tasks



Tasks	Projects	Type	Graph Mode		Eager Mode		Amanda Tool	
			Interface	Portable	Interface	Portable	Interface	Portable
Graph Tracing	Built-in	Analysis	Graph	All	Module Hook	Refactor	Instrumentation	All
FLOPs Profiling	[6, 8, 10, 15]	Analysis	Graph	All	Module Hook	Refactor	Instrumentation	All
Effective Path	[32, 70]	Analysis	Graph, Source Modification	No	Module Hook	No	Instrumentation	All
Weight Pruning	[40, 48, 82]	Optimization	Session Hook	No	Module Parameter	Refactor	Instrumentation	All
Quantization Training	[18, 30, 56]	Optimization	Source Modification	No	Module Hook	Refactor	Instrumentation	All

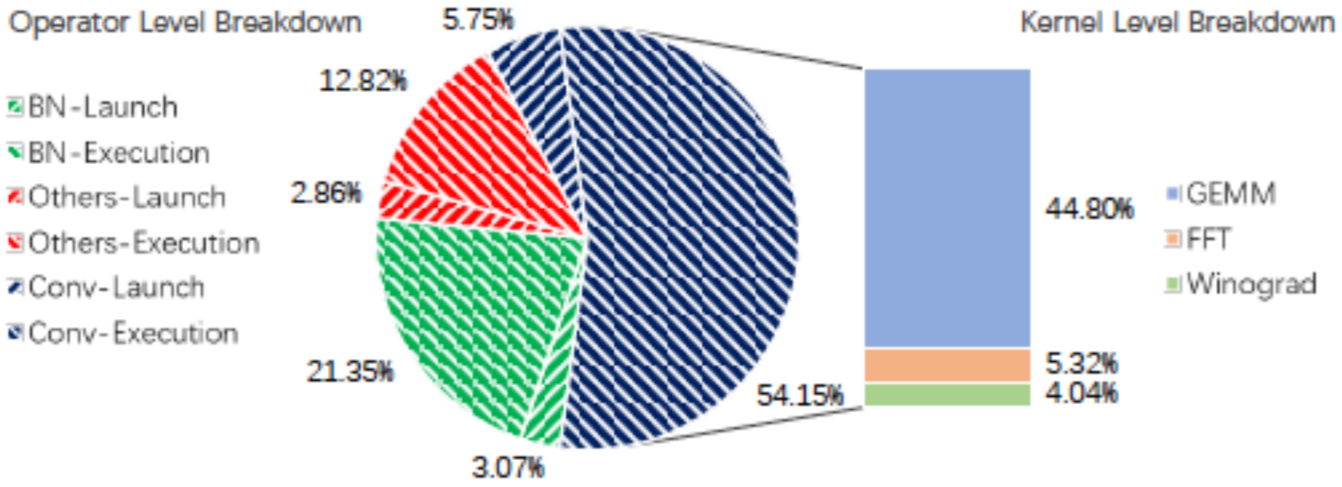
- Generality



Project	Type	User Tool					Amanda tool	
		Backend	Interface	Supported Networks	LoC	Acc	LoC	Acc
Tile Wise Pruning[40]	Static	Tensorflow	Session Hook	VGGs, BERT	1203	76.7	213	76.7
Dynamic Channel Pruning[33]	Dynamic	PyTorch	Source Modification	VGG19, ResNet34, SquzzeNet	387	70.7	115	70.7
Activation Pruning[78]	Dynamic	PyTorch	Source Modification	ResNets	650	77.1	193	76.5
Attention Pruning[39]	Dynamic	PyTorch	Source Modification	BERT, Roberta, DistillBERT, ALBERT	1105	83.2	179	83.2
APEX Vector Wise Pruning[7, 85]	Static	PyTorch	Module Hook	Models with Module API	499	76.5	279	76.2

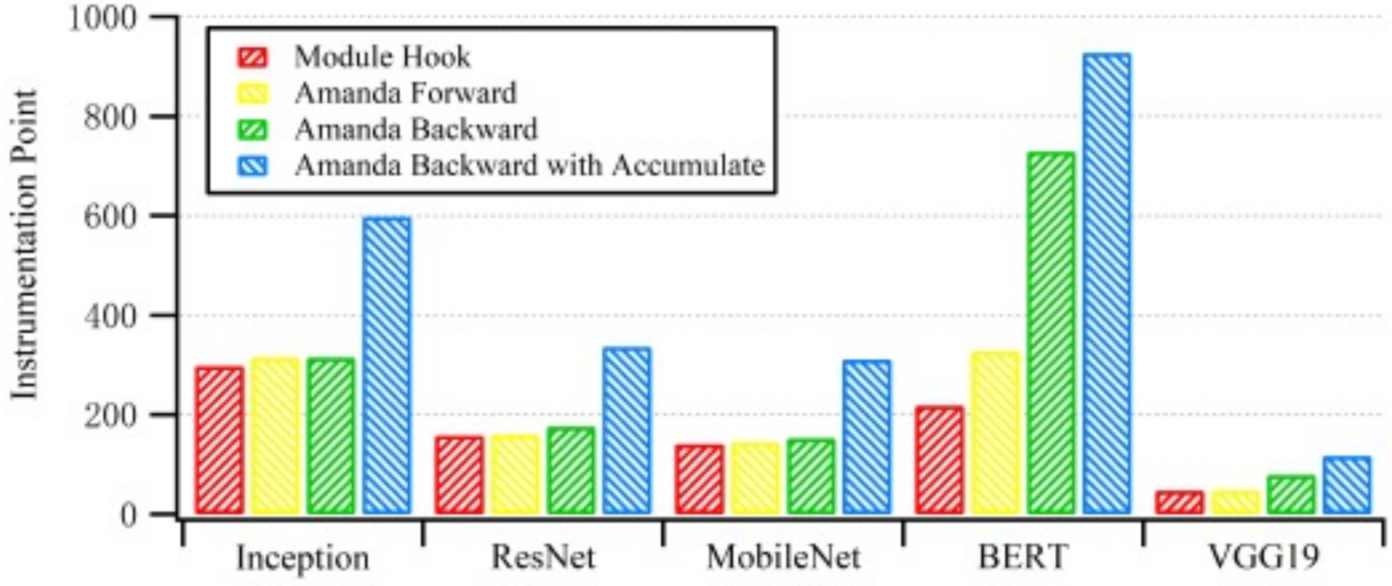
Results

- Integrated with GPU analysis API



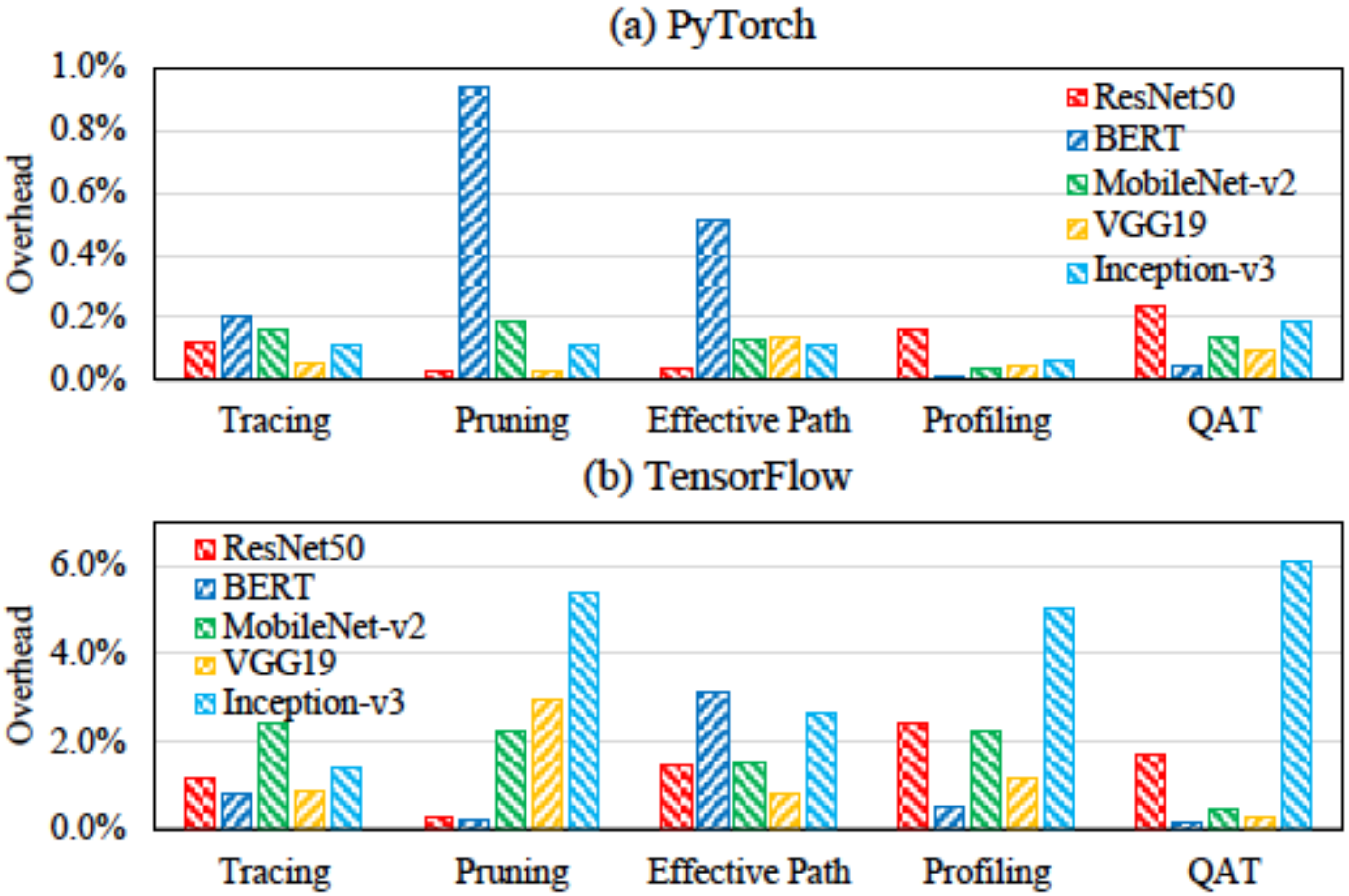
Results

- Instrumentation point coverage



Results

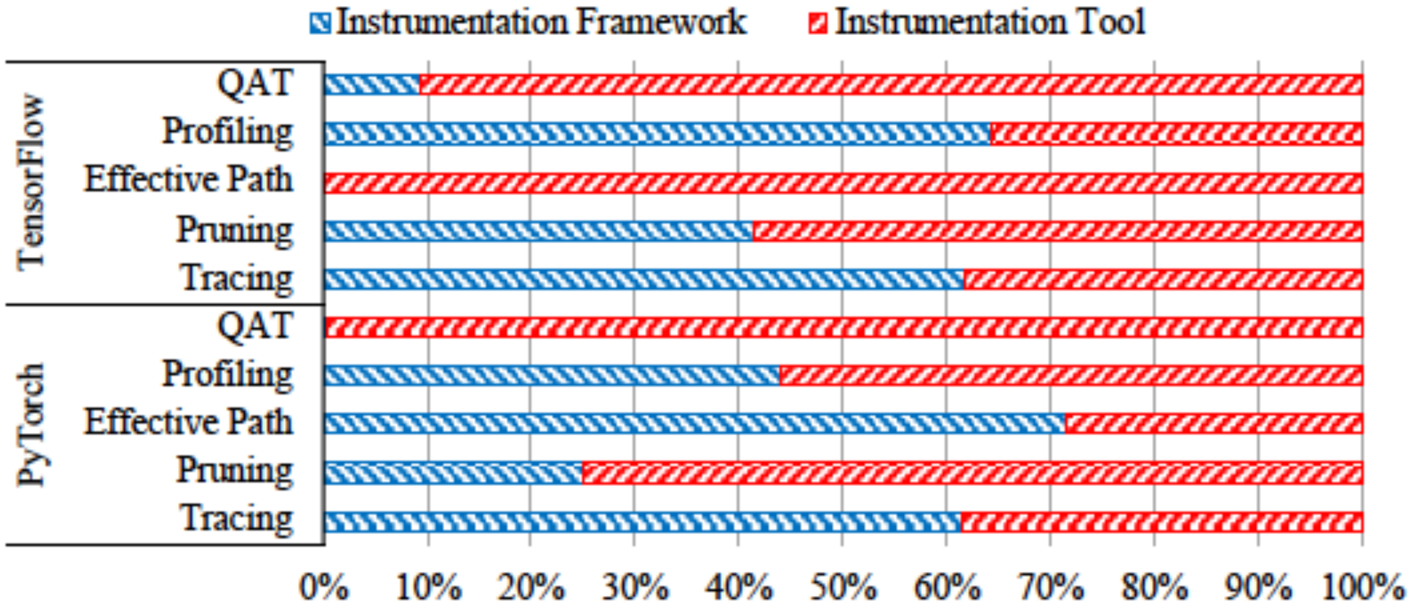
- Overhead


(a) PyTorch

(b) TensorFlow

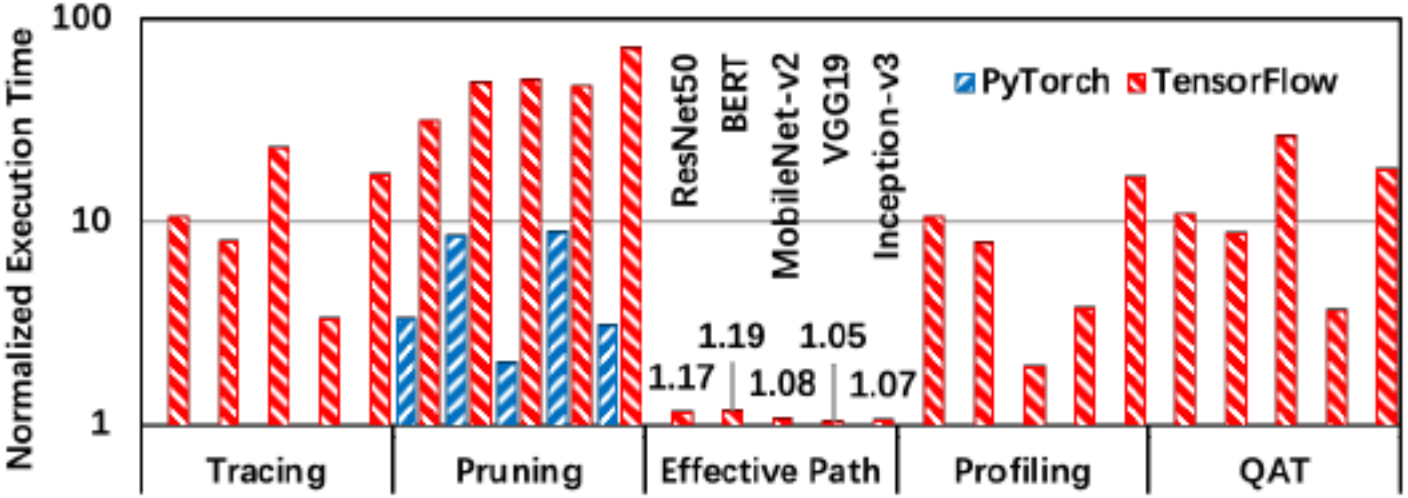
Results

- Execution time breakdown



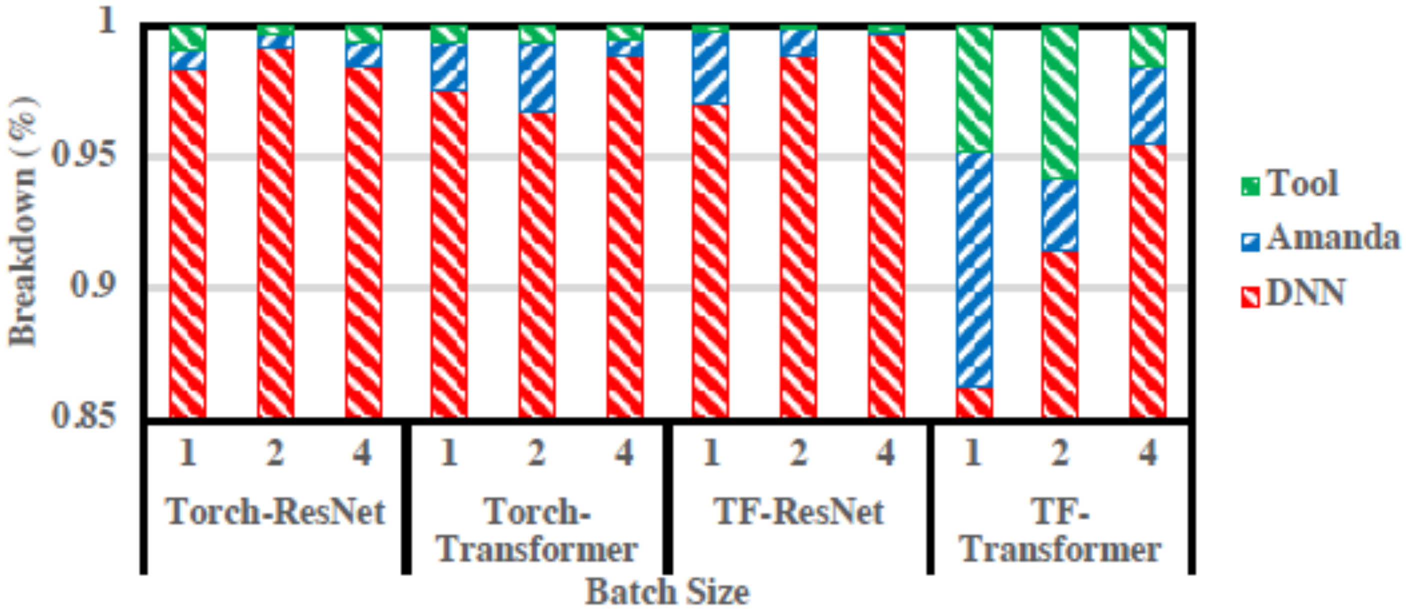
Results

- Memory footprint saved by cache mechanism



Results

- Memory footprint breakdown



Thoughts

- Expect the source code to be released.
- System work full of optimization.
- Driver may be hard to write.

Thank You!

Nov 13, 2023

Presented by Mengyang Liu