TINYML in TmallGenie

见明2022.10

TINY ML ASIA
November 2 – 5, 2021

天猫精灵
TMALL GENIE

Catalog

Alibaba

Motivation

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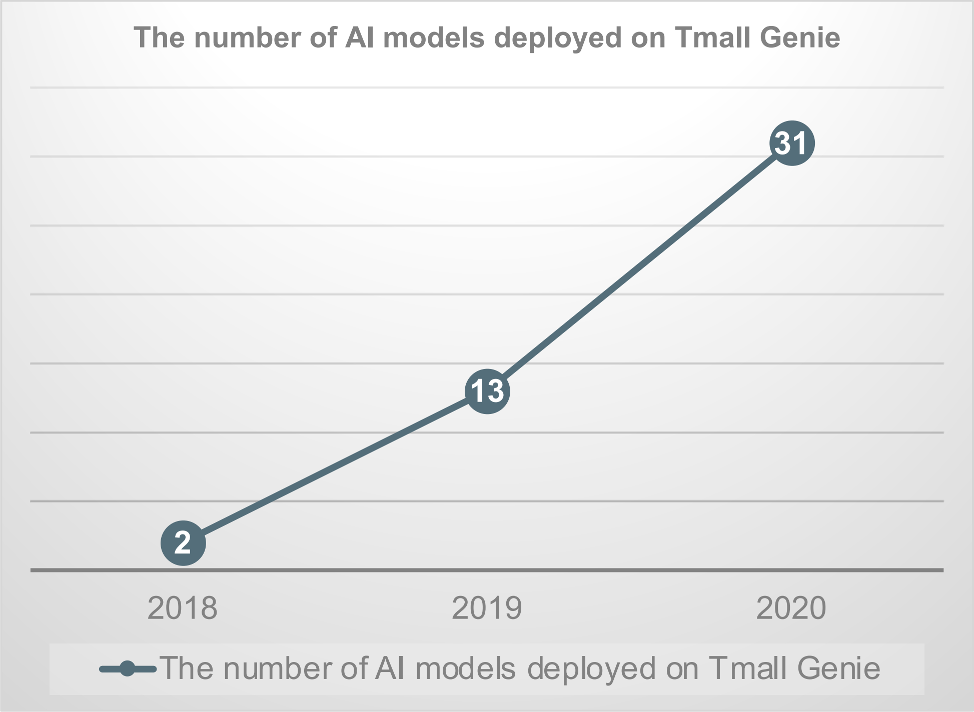

Gesture Recognition | People Recognition | Voiceprint Recognition | Age Recognition | Motion Recognition

ASR | TTS | OCR | NLU | ……

The number of AI models deployed on Tmall Genie and other AIoT devices is growing rapidly.

Situation

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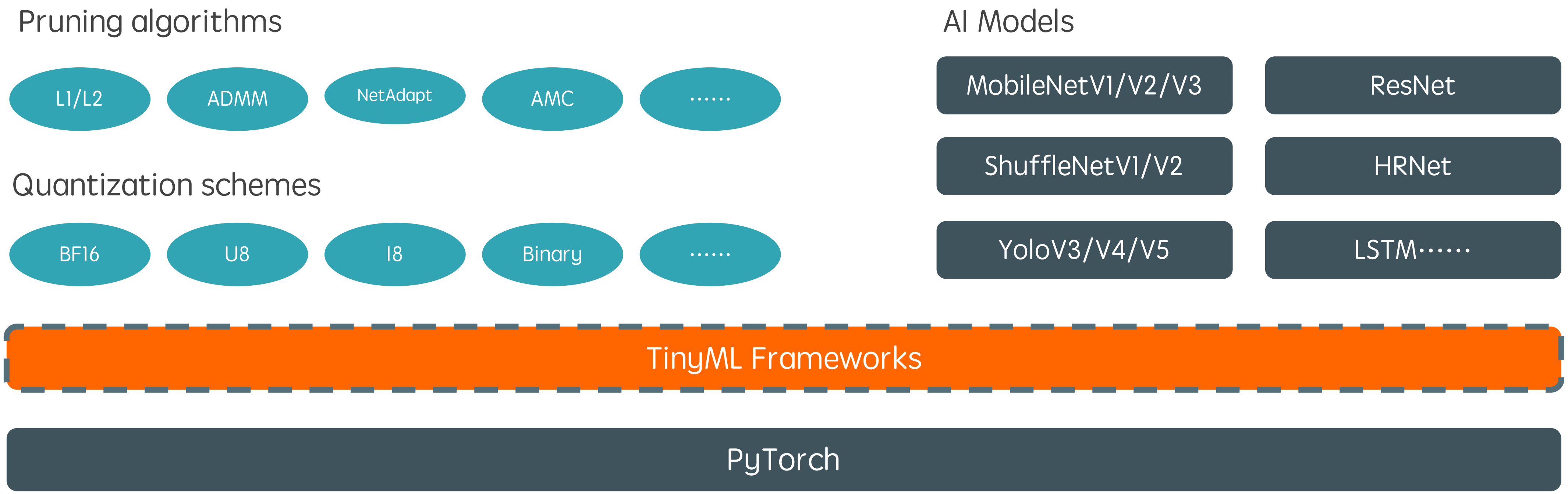

Common problems to be tackled in PyTorch-based TinyML framework

1. The dynamic graph used by PyTorch makes operator dependency analysis difficult, which poses challenges for automatic pruning and quantization of complex models.
2. PyTorch models do not translate well to TFLite models, making them difficult to deploy on many AIoT devices
3. When the pruning rate is high (for example, more than 95% of the flop is compressed), the effectiveness of existing pruning methods will be severely deteriorated.
4. Other works only generate tiny models, but still have a lot of works to do to run the model in devices, this is hard to use, we need a end to end framework to make TinyML more easier to use.

The End to End TinyML Framework

Architecture

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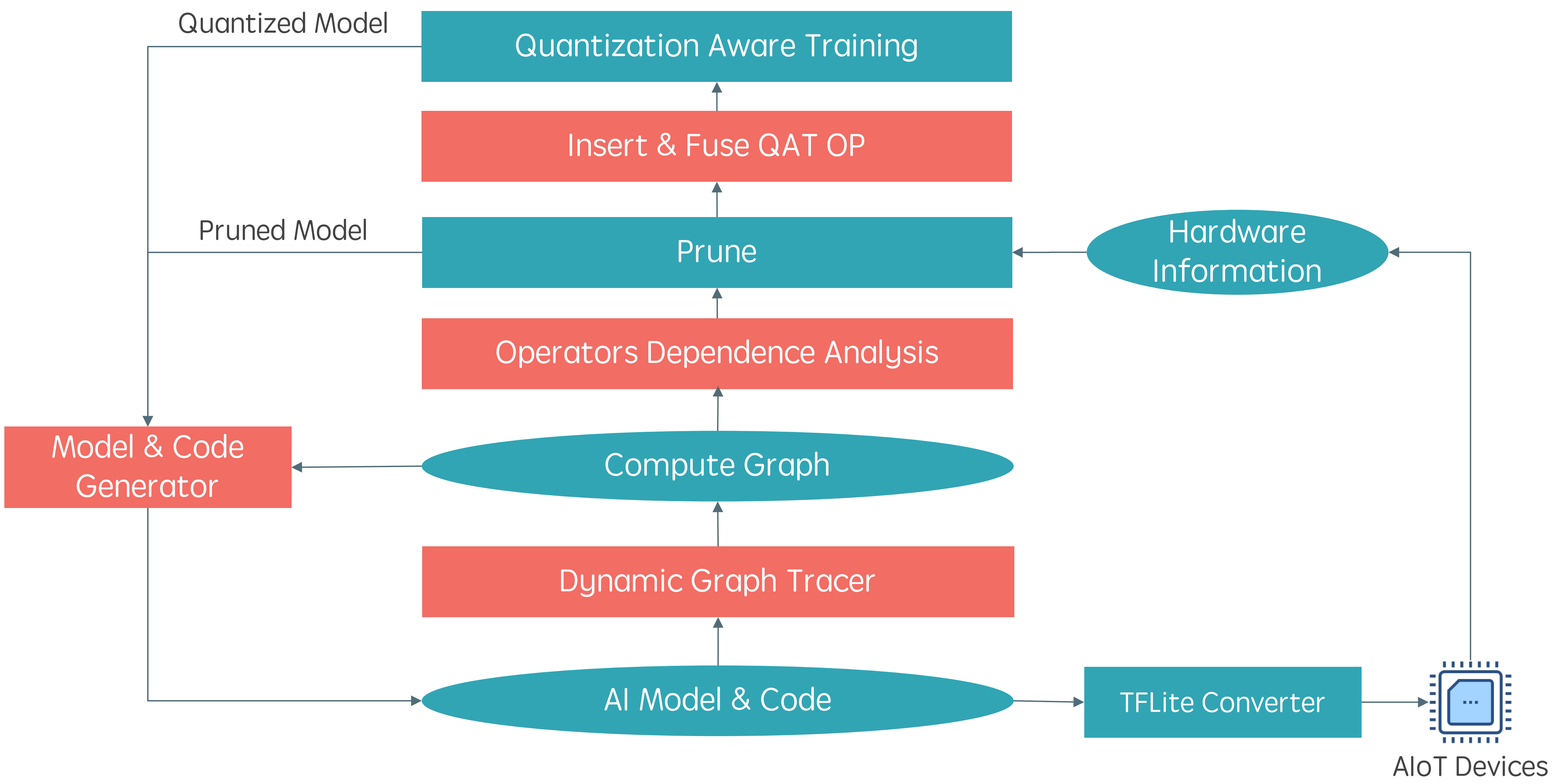
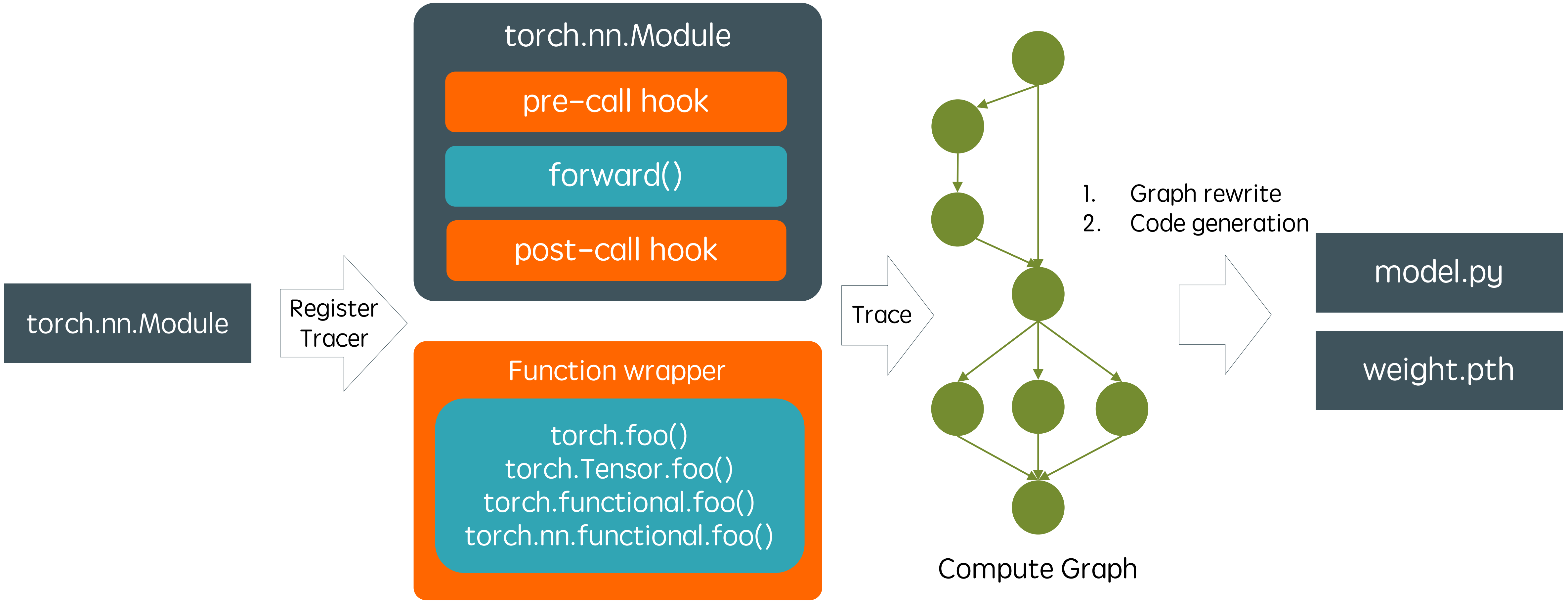


Graph Tracer



Application

1. Construct the compute graph from the model via tracing.
2. Generate the corresponding model definition code from the compute graph.

Network Pruning

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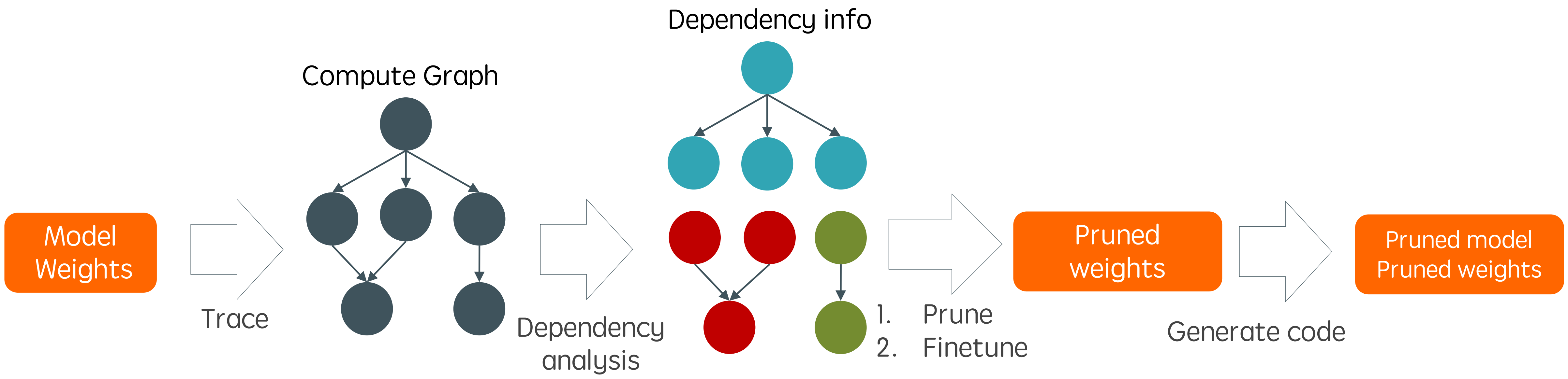

Dependency analysis

1. Divide the computational graph into multiple independent subgraphs.
2. Resolve channel dependency in the subgraphs.

Pruning

1. Use L1, L2, FPGM, ADMM, NetAdapt and other algorithms to prune the neural networks.
2. We propose a new progressive pruning algorithm, which reduces the accuracy deterioration under high pruning rate. (*ICLR Reviewing*)

Generating code

1. Generate the corresponding model definition code so that the pruned weights could be loaded.

Quantization-aware Training

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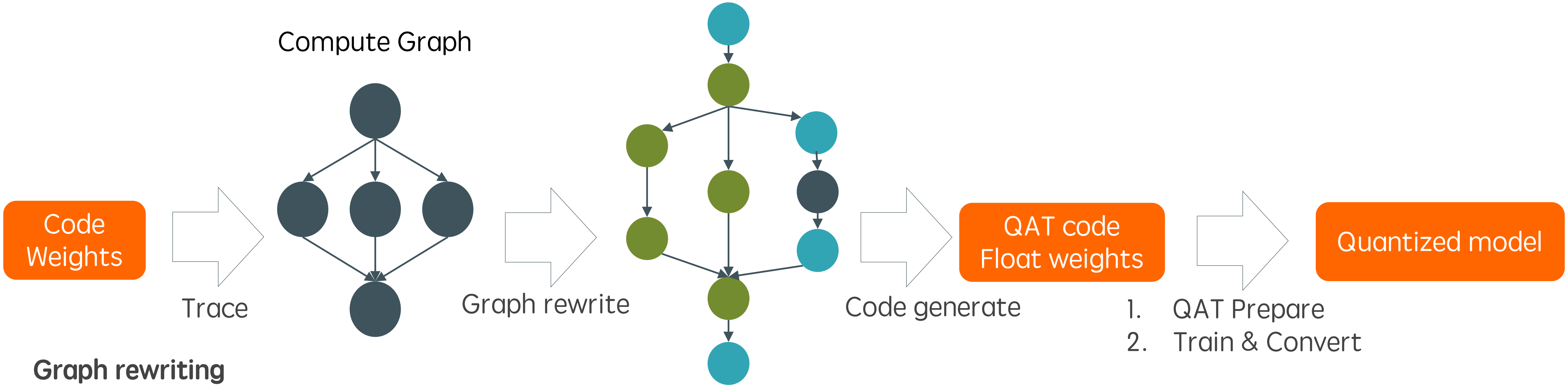

Graph rewriting

1. Insert FakeQuant nodes.
2. Replace the nodes that cannot be quantized with their quantizable equivalents.

Code generation

1. Generate the corresponding model definition code according to the rewritten compute graph.
2. The FakeQuant nodes may be removed or added in the generated model definition code to achieve mixed precision. (By default, we try to quantize as much as we can in the entire model).

QAT Preparation & Training

1. Operator fusion and preparation for quantization-aware training.
2. We proposed a new quantization-aware training algorithm that achieves substantial acceleration on AIoT devices (*IJCAI 2020, https://arxiv.org/abs/2005.13297*)

TFLite Converter

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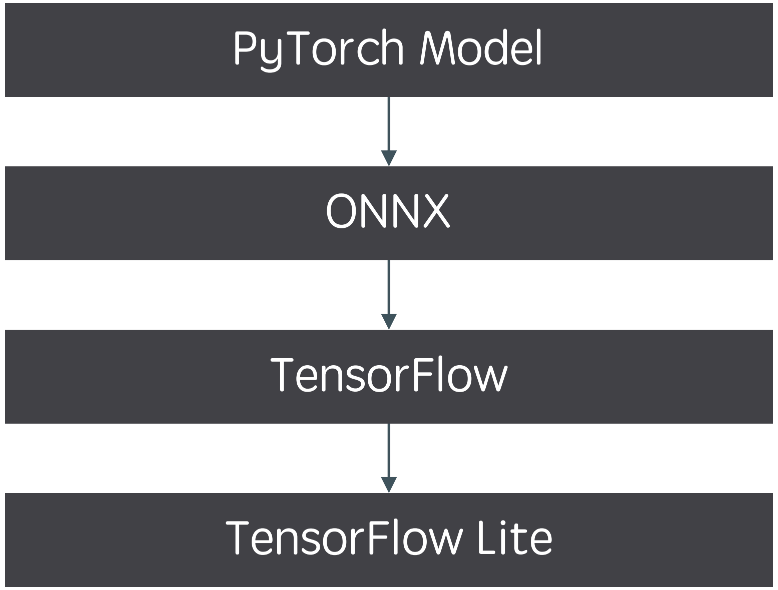

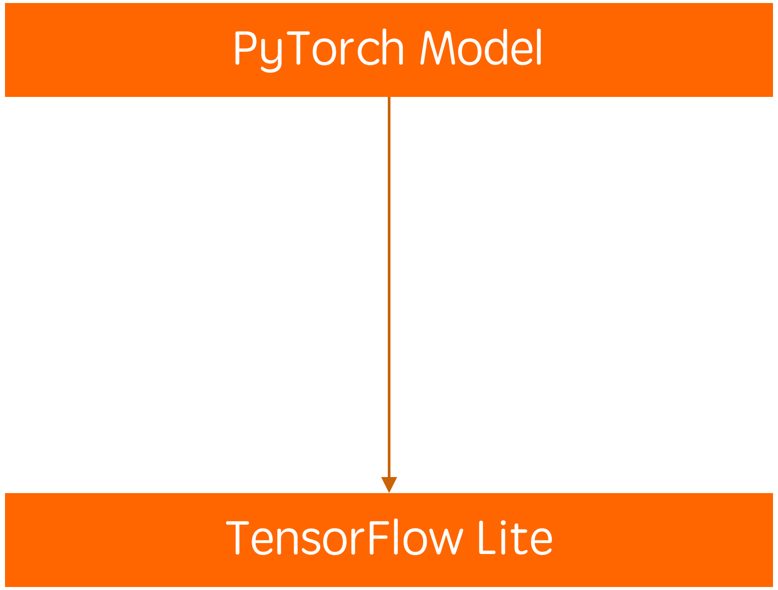

Current pipeline

1. Lengthy procedure leads to insufficient stability
2. Lack of support for quantized models
3. The converted model has a lot of redundant operators, thus leads to slow inference

Our converter

1. End-to-end conversion
2. Support quantized models
3. Support graph optimization (Transpose elimination, Slice fusion, BN and Activation fusion, etc.)

Model	ONNX->TF->TFLite	TinyML Converter
MobileNetV2	810 ms	384 ms
MobileNetV3	196 ms	106 ms

The experiment is performed on a Tmall Genie with MTK 8167

Example

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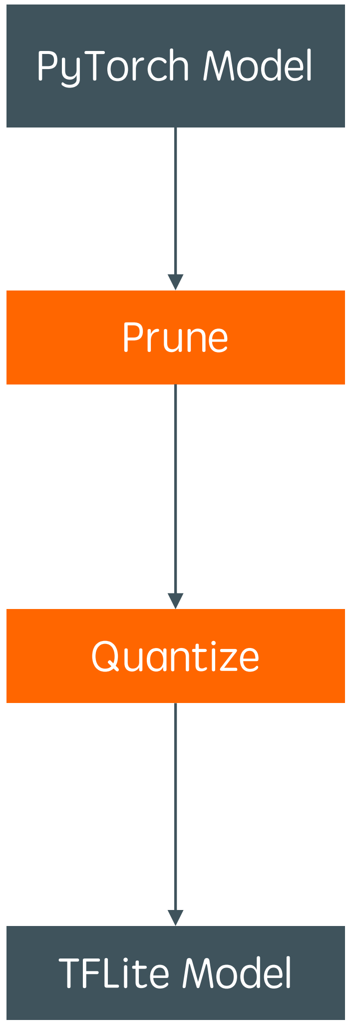
```
model = mobilenet.Mobilenet()
model.load_state_dict(torch.load(WEIGHT_PATH))

dummy_input = torch.ones(1, 3, 224, 224)

pruner = OneShotChannelPruner(model, dummy_input, config)
pruner.prune()

# Model finetune (custom code)
finetune(model)

quantizer = QATQuantizer(model, dummy_input, work_dir="./out")
qat_model = quantizer.quantize()

# Quantization aware training (custom code)
qat_finetune(qat_model)

converter = TFLiteConverter(qat_model, dummy_input, tflite_path="./out/mbv1_q.tflite")
converter.convert()
```



Results

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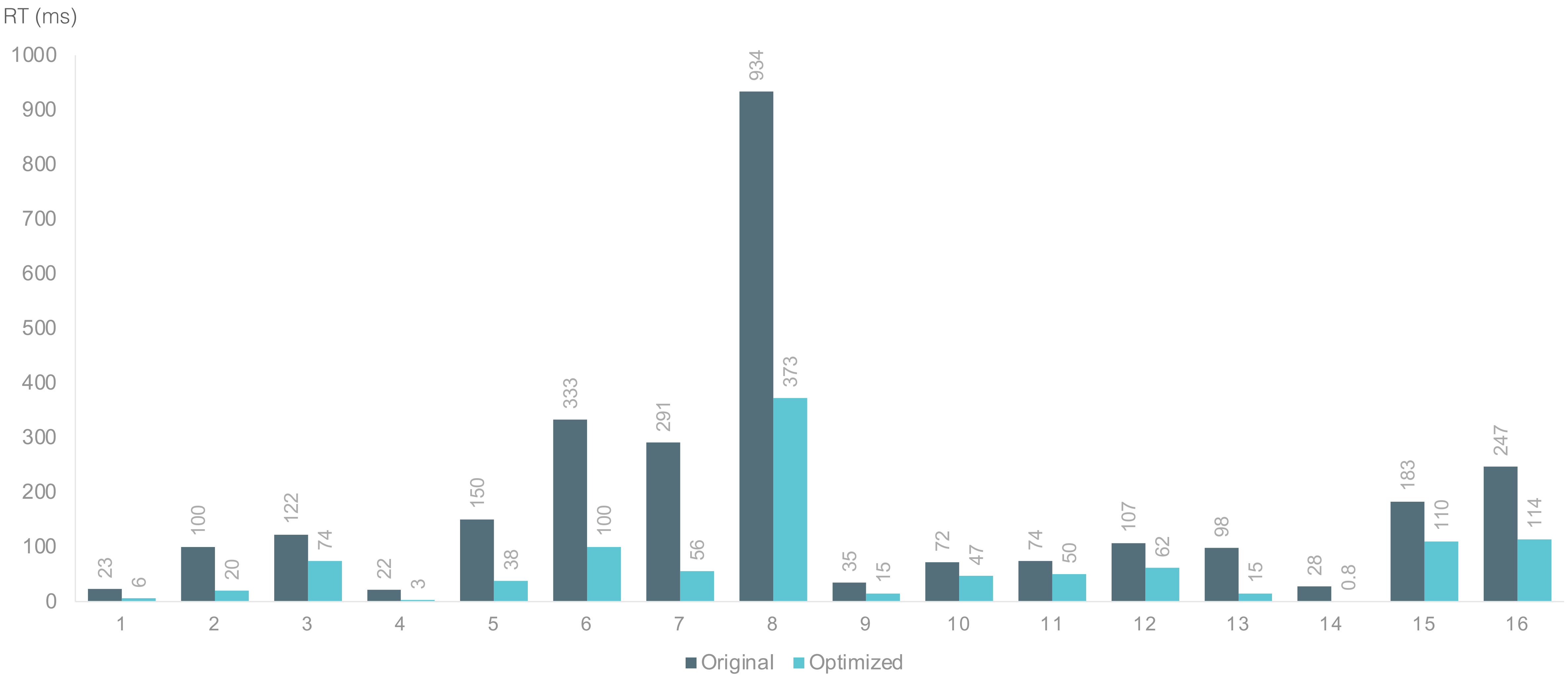

Got an average speedup of 5.3x on 16 business models for Tmall Genie

HA NAS: TinyML for NPUS

HA NAS

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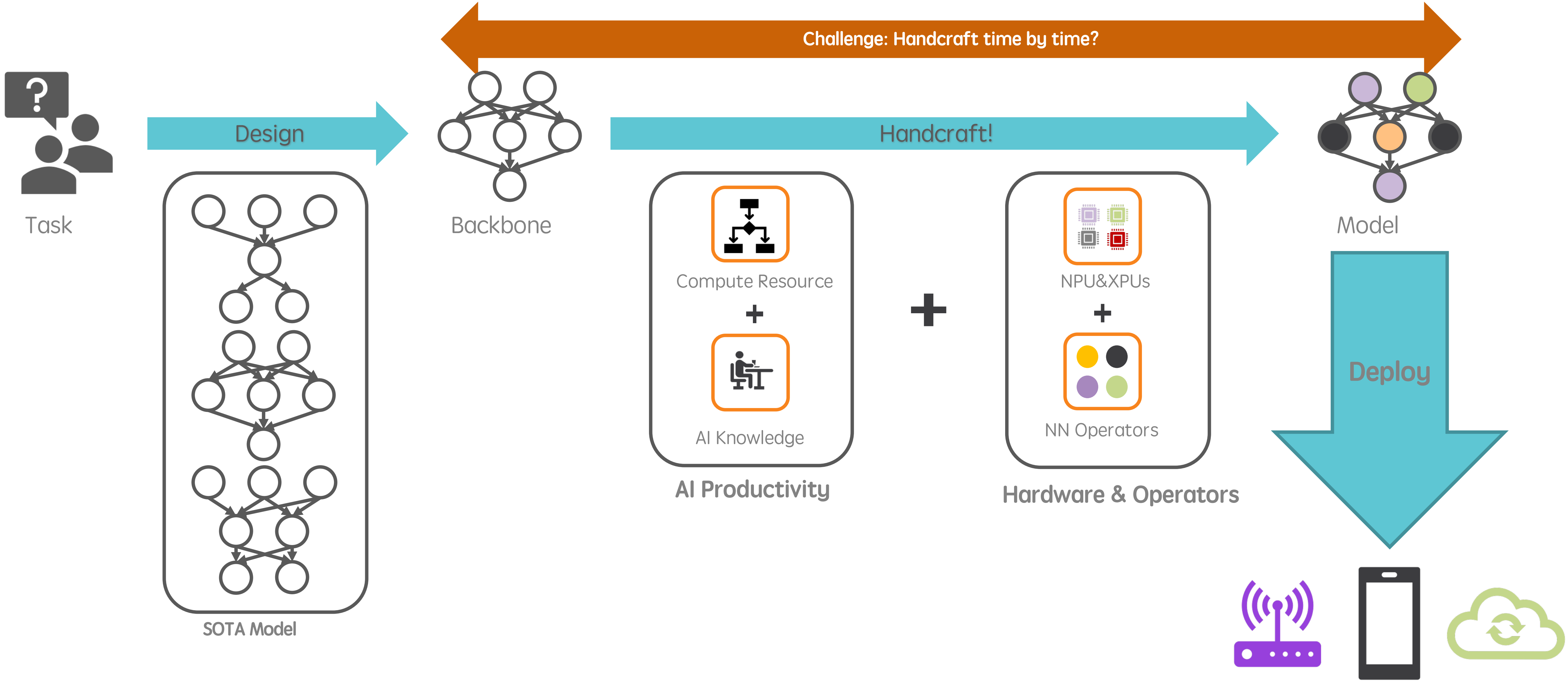
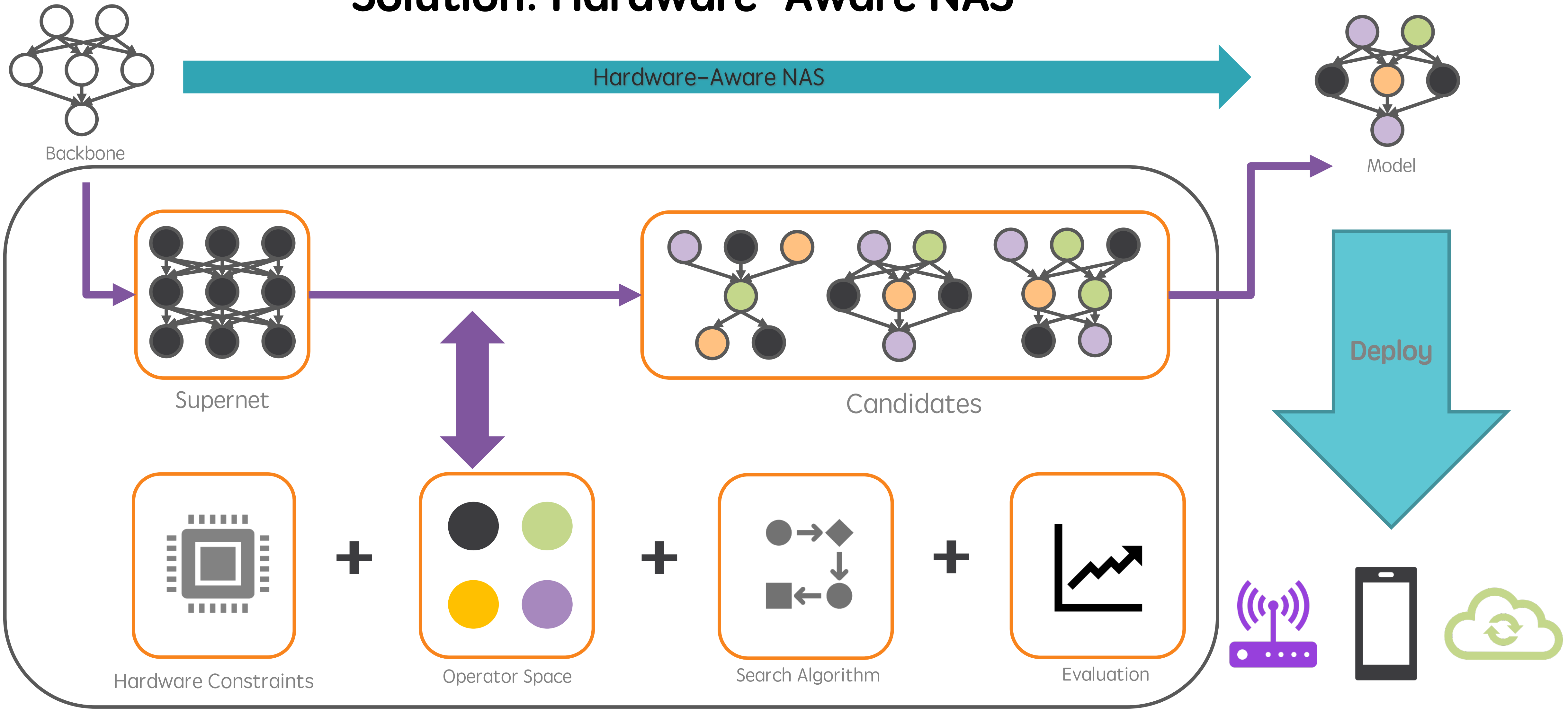
Challenge: Designing efficient & accurate models for NPUs



HA NAS

Solution: Hardware-Aware NAS



HA NAS

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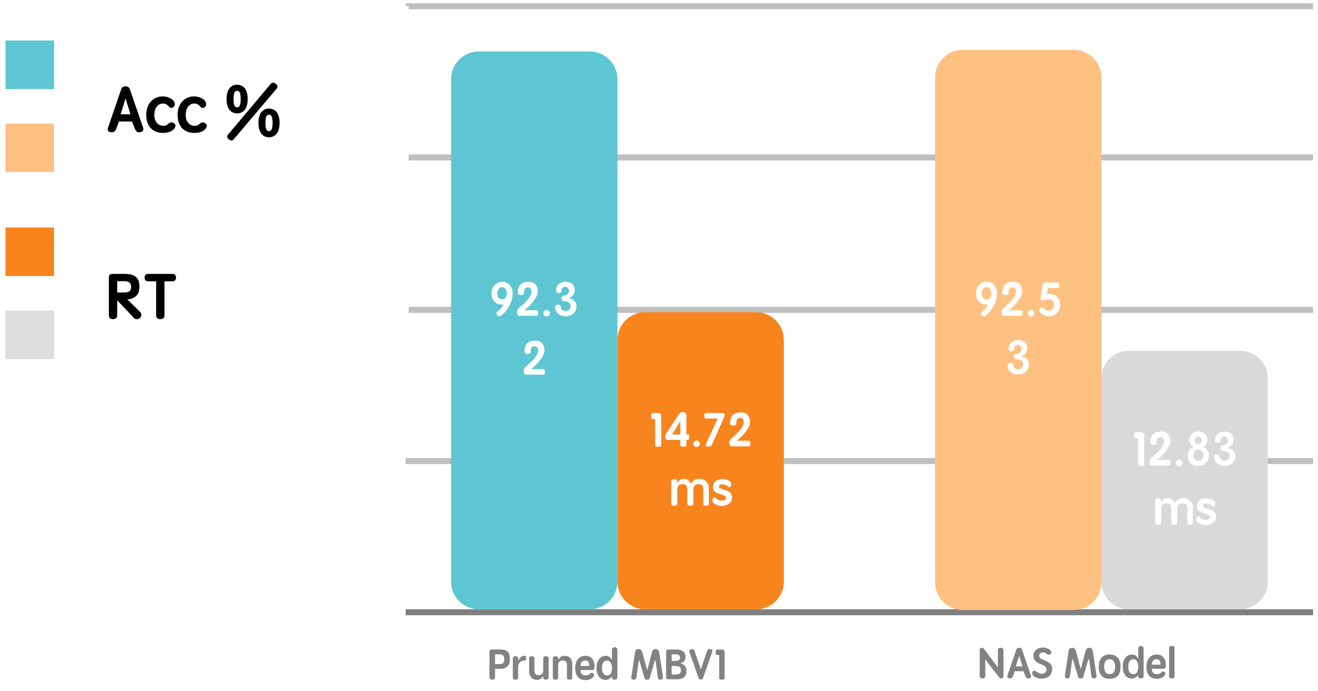

- RT measured on MTK 8175, evaluating validation accuracy using cifar-10
- Baseline: Model with 75% sparsity using one-shot L2 pruning

Future Works

Hardware aware NAS.
More automation makes for better results.
Develop new algorithms for better pruning, quantization and etc.
TF support and other features that made the framework easier to use.

We have made our framework open source in Github: alibaba/TinyNeuralNetwork
Look forward to see your contribution!
Let's make ML tinier together!

THANKS

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