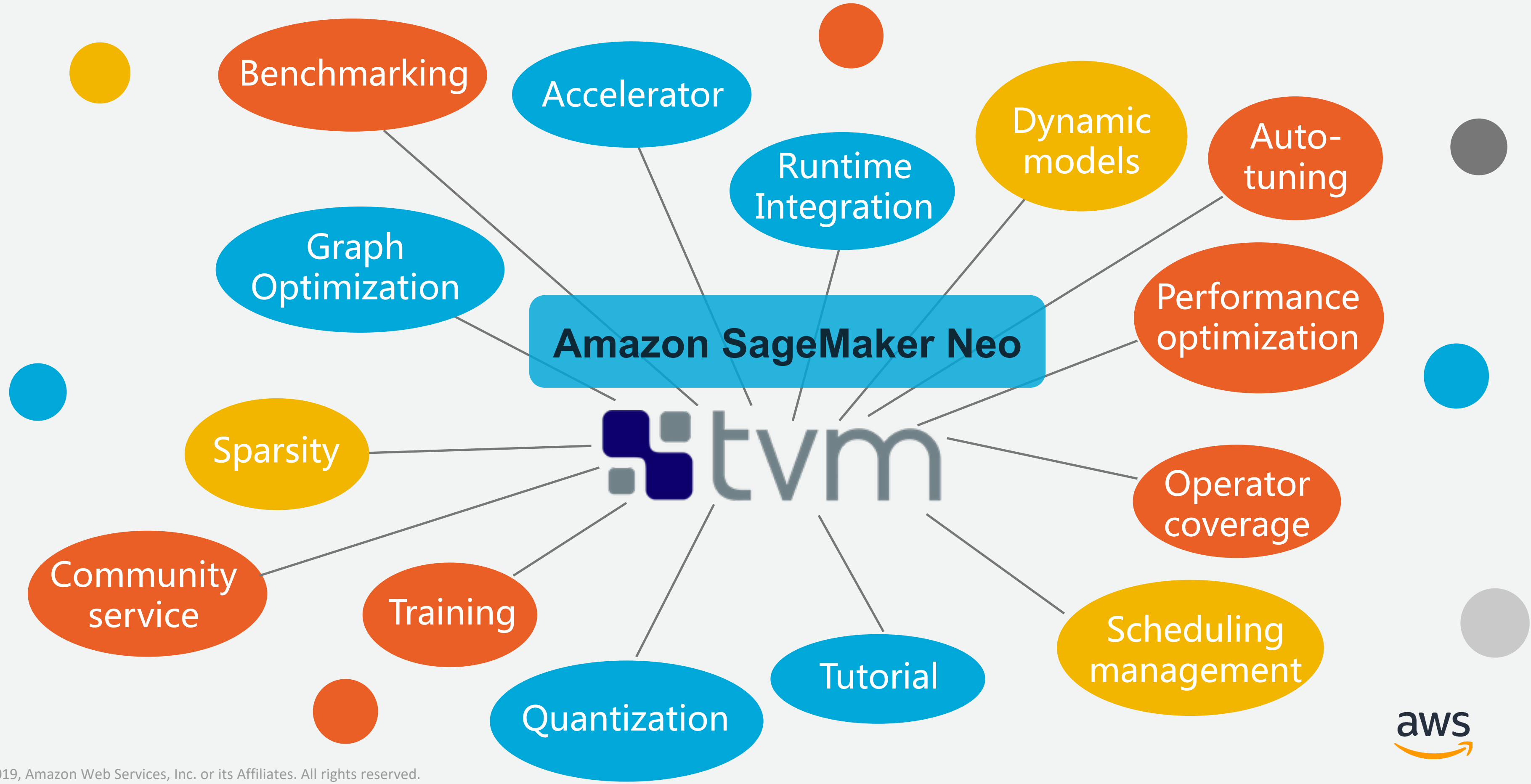
# Deep Learning Compiler

Yida Wang and Zhi Chen
AWS AI

# A reduced snapshot of AWS AI

| | VISION | SPEECH | | TEXT | | |
|---|---|---|---|---|---|---|
| AI SERVICES | Amazon Rekonition | Amazon Polly | Amazon Transcribe | Amazon Translate | Amazon Comprehend | … |
| AMAZON SAGEMAKER | ML Marketplace | Model training | Model tuning | SageMaker Autopilot | SageMaker Neo | … |
| ML FRAMEWORKS & INFRASTRUCTURE | | GPUs and CPUs | Elastic Inference | Inferentia | FPGA | … |

# Deep learning compiler projects at AWS AI

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# QNN Dialect

*-- Animesh Jain*

# How to consume a pre-quantized model via TVM?

## Option 1 – Completely add new ops from scratch

- New Relay passes and TVM schedules required
  - AlterOpLayout, Graph Fusion etc require work/operator
- No reuse of existing Relay and TVM infrastructure

## Option 2 – Lower to a sequence of existing Relay operators

- We introduced a new Relay dialect – QNN to encapsulate this work
- Complete reuse of Relay pass infrastructure
- Possible reuse of TVM schedules (only to some extent)

# QNN Dialect

- Design operators that satisfy many framework operators
    - qnn.quantize, qnn.dequantize, qnn.requantize
    - qnn.conv2d, qnn.dense
    - qnn.concatenate
    - qnn.add, qnn.mul

- QNN operators will be lowered to Relay operators

- QNN Optimization passes
    - Some optimizations are easier at QNN level
    - Intel x86 VNNI requires conv input dtypes to uint8 x int8

# Lowering of Qnn.Quantize

```
fn (%input_data: Tensor[(2, 5), float32]) {
  qnn.quantize(%input_data, out_dtype="uint8", output_zero_point=127, output_scale=0.5f)
}
```

```
def @main(%input_data: Tensor[(2, 5), float32]) -> Tensor[(2, 5), uint8] {
  %0 = divide(%input_data, 0.5f /* ty=float32 */) /* ty=Tensor[(2, 5), float32] */;
  %1 = round(%0) /* ty=Tensor[(2, 5), float32] */;
  %2 = cast(%1, dtype="int32") /* ty=Tensor[(2, 5), int32] */;
  %3 = add(%2, 127 /* ty=int32 */) /* ty=Tensor[(2, 5), int32] */;
  %4 = clip(%3, a_min=0f, a_max=255f) /* ty=Tensor[(2, 5), int32] */;
  cast(%4, dtype="uint8") /* ty=Tensor[(2, 5), uint8] */
}
```

# Lowering of Qnn.Conv2D

```
fn (%data: Tensor[(1, 3, 2, 3), uint8], %weight: Tensor[(3, 3, 2, 2), uint8]) {
  qnn.conv2d(%data, %weight, ... , out_dtype="int32", input_zero_point=1, kernel_zero_point=1)}
```

```
def @main(%data: Tensor[(1, 3, 2, 3), uint8], %weight: Tensor[(3, 3, 2, 2), uint8]) -> Tensor[(1, 3, 1, 2), int32] {
  %0 = nn.conv2d(%data, %weight, ... , out_dtype="int32") /* ty=Tensor[(1, 3, 1, 2), int32] */;
  %1 = cast(%data, dtype="int32") /* ty=Tensor[(1, 3, 2, 3), int32] */;
  %2 = multiply(%1, 4 /* ty=int32 */) /* ty=Tensor[(1, 3, 2, 3), int32] */;
  %3 = nn.avg_pool2d(%2, pool_size=[2, 2]) /* ty=Tensor[(1, 3, 1, 2), int32] */;
  %4 = sum(%3, axis=[1], keepdims=True) /* ty=Tensor[(1, 1, 1, 2), int32] */;
  %5 = multiply(1 /* ty=int32 */, %4) /* ty=Tensor[(1, 1, 1, 2), int32] */;
  %6 = subtract(%0, %5) /* ty=Tensor[(1, 3, 1, 2), int32] */;
  %7 = cast(%weight, dtype="int32") /* ty=Tensor[(3, 3, 2, 2), int32] */;
  %8 = sum(%7, axis=[1, 2, 3]) /* ty=Tensor[(3), int32] */;
  %9 = reshape(%8, newshape=[1, 3, 1, 1]) /* ty=Tensor[(1, 3, 1, 1), int32] */;
  %10 = multiply(1 /* ty=int32 */, %9) /* ty=Tensor[(1, 3, 1, 1), int32] */;
  %11 = subtract(12 /* ty=int32 */, %10) /* ty=Tensor[(1, 3, 1, 1), int32] */;
  add(%6, %11) /* ty=Tensor[(1, 3, 1, 2), int32] */}
```

Asymmetric

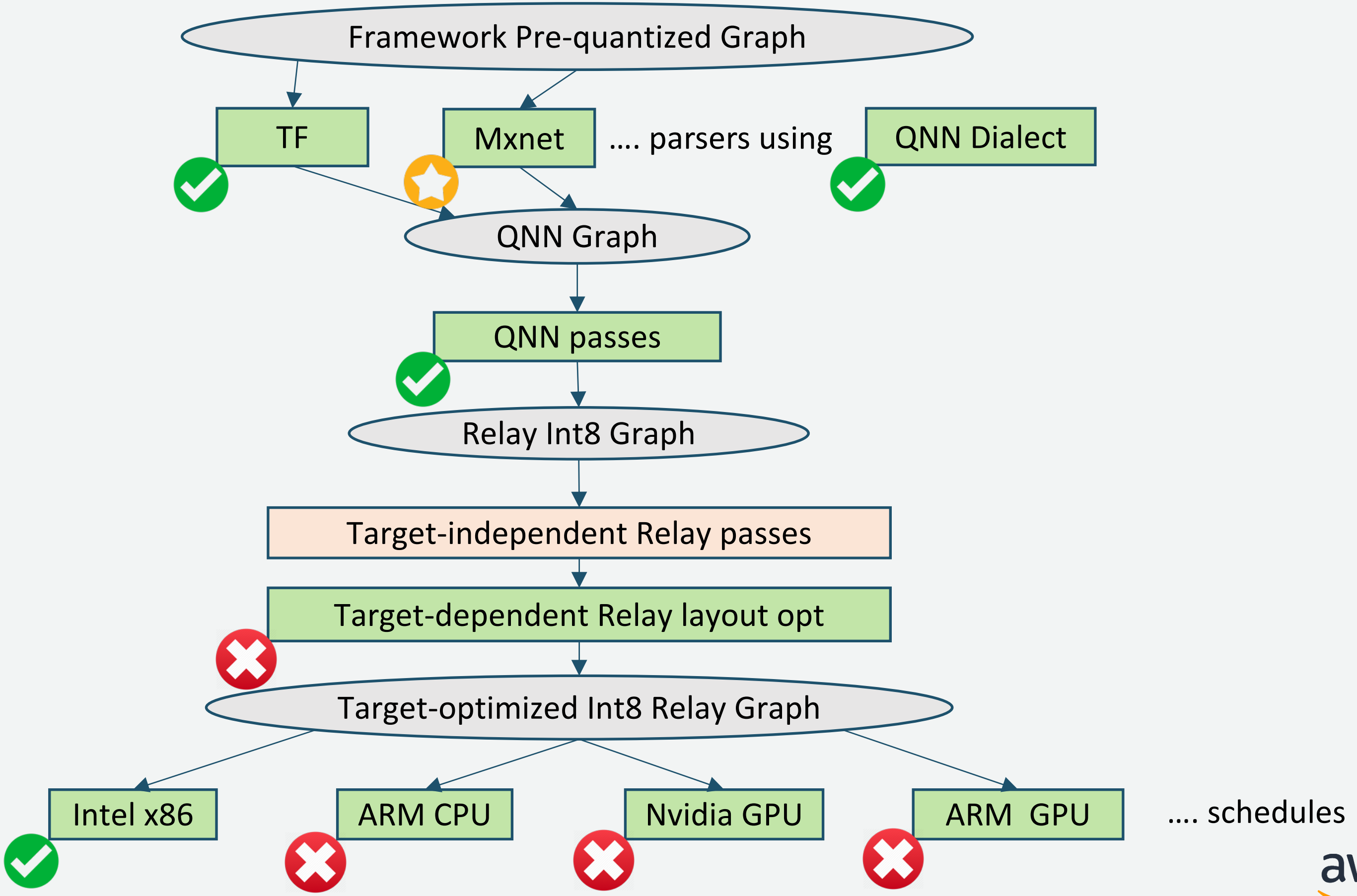
For zero-centered zero point, the lowering will have just nn.conv2d

# Proof of Concept on TFLite models

| Unit: ms | Float32 | Quantized | Speedup |
|---|---|---|---|
| Inception V1 | NA | 2.143 | NA |
| Inception V2 | NA | 8.919 | NA |
| Inception V3 | 10.373 | 6.115 | 1.7 |
| Inception V4 | 21.233 | 12.315 | 1.72 |

- Metric – Latency in ms for batch size = 1
- Comparable accuracies
- 1.7x speedup on Inception **asymmetric** quantized model
- **Symmetric** model improves the speedup to 2.8x

# How Can We Make It Better?



# New Amazon EC2 instances

*-- Hongbin Zheng, Yizhi Liu, Haichen Shen,*
*and many people in Annapurna Labs*

# Amazon EC2 Inf1 instances

- Powered by AWS Inferentia
- Low latency, 3x higher throughput, up to 40% lower cost-per-inference compared to G4
- Up to 2,000 TOPS at sub-millisecond latency
- Integrated with popular ML frameworks TensorFlow, PyTorch and MXNet

# AWS Inferentia Chip

- Four NeuroCores per chip → customized tensor-level optimization
- Two-stage memory hierarchy: large on-chip cache and commodity DRAM → Proactive data movement management
- Fast chip-to-chip interconnect via specialized communication protocol → Model parallelism in pipeline

# Amazon EC2 M6g, R6g, C6g instances

- Powered by ARM-based AWS Graviton2 processors
- 4x more compute cores, 5x faster memory, and 7x the performance of initial Graviton offering
- 40% price/performance advantage over current x86-based instances

# ML inference on Graviton2

- General-purposed CPU is capable of doing machine learning/deep learning inference
  - Check out our paper *Optimizing CNN Model Inference on CPUs* at USENIX ATC '19
- Compared to M5, M6g does faster model inference with lower price

# Dive into Deep Learning Compiler

*-- Mu Li and Yida Wang*

# A typical conversation

## Customer/user/new hire/…

## Us/and maybe you…

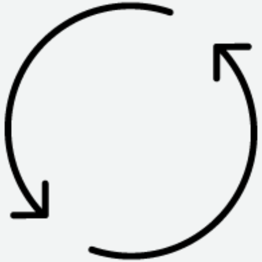
How to use TVM to do…

We can do the following steps…

Cool, is there any tutorial?

Yes, for this check this, for that check that…

I failed. TVM is REALLY REALLY hard to get started/use/deploy…



# From discuss.tvm.ai

**Any materials of Relay for beginners?**

Questions

**Confuse with module.get_out function**

Questions

r 26

**No speed increase when converting model to TVM**

Questions

ks

res

in

**How to save relay model for deploying to android?**

Questions

**Beginners Guide to Contributing**

Questions

madhavajay Oct '18

Hi,
I really want to be able to help out on this project and other DL edge frameworks, but I need some guidance on where to start.

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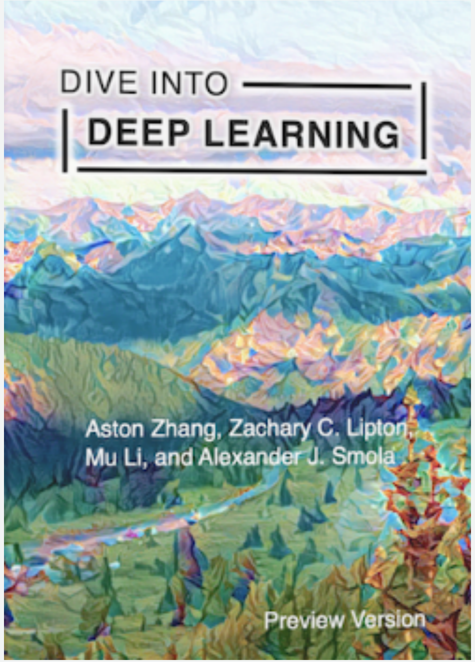
# Dive into Deep Learning (https://D2L.ai)

- An interactive deep learning book with code, math, and discussions
- GitHub: 18,000 stars, 200 contributors
- Presented in multiple languages: Chinese, English, Japanese, Korean
- The Chinese book is the No. 1 best seller at the largest Chinese online bookstore
- The English book is available in preview



# D2L adoption

- Adopted as a textbook by **40+** global universities and Amazon Machine Learning University
  - Carnegie Mellon University
  - Indian Institute of Technology Bombay
  - Massachusetts Institute of Technology
  - Peking University
  - Shanghai Jiao Tong University
  - University of California, Berkeley
  - University of Illinois at Urbana-Champaign
  - University of Science and Technology of China
  - Zhejiang University

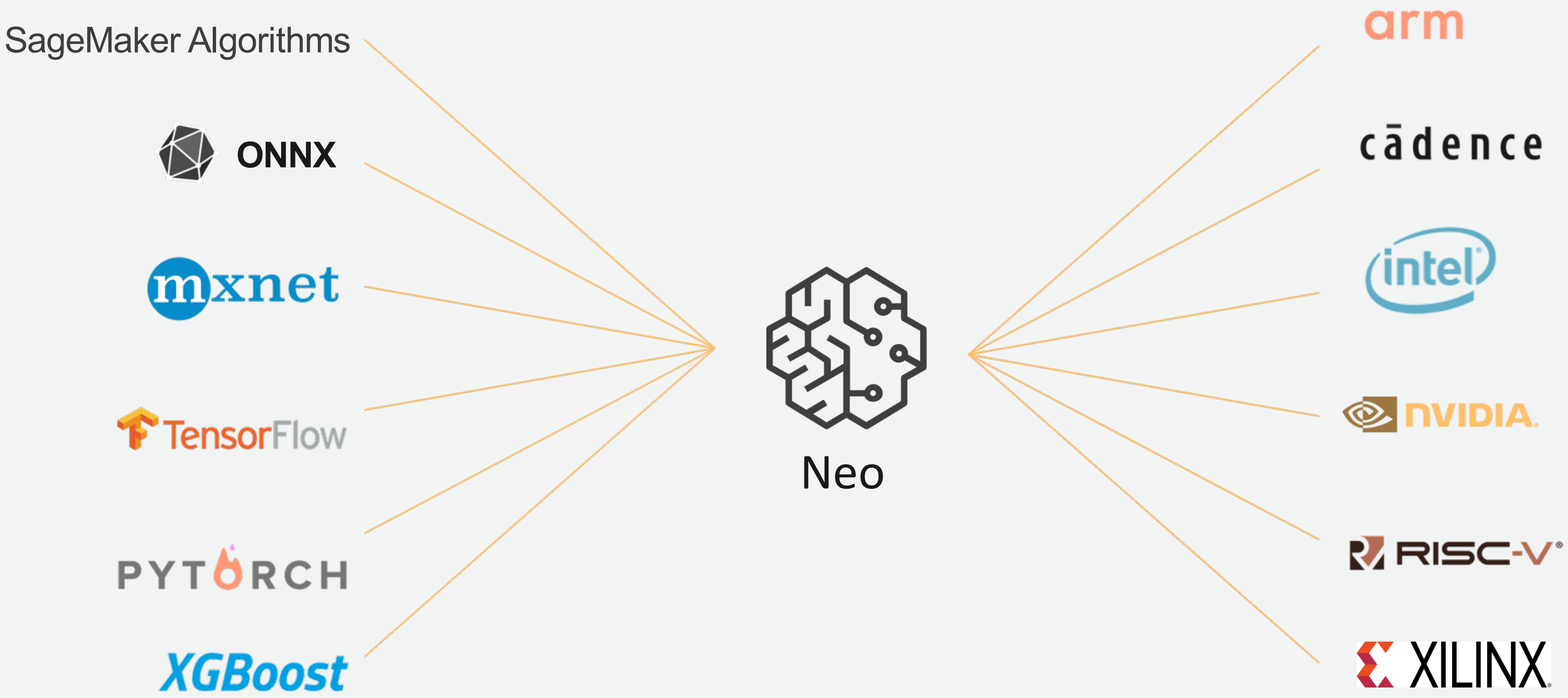
# D2L Compiler: http://tvm.d2l.ai

- A systematic tutorial to the beginners who want to ***USE*** TVM, and more broadly, who'd like to take DLC-101
- Python notebook based, runnable on Colab
- V0.1 released,  22 sections, covering getting started and basic operator-level optimization
- Call for contributors

# SageMaker Neo

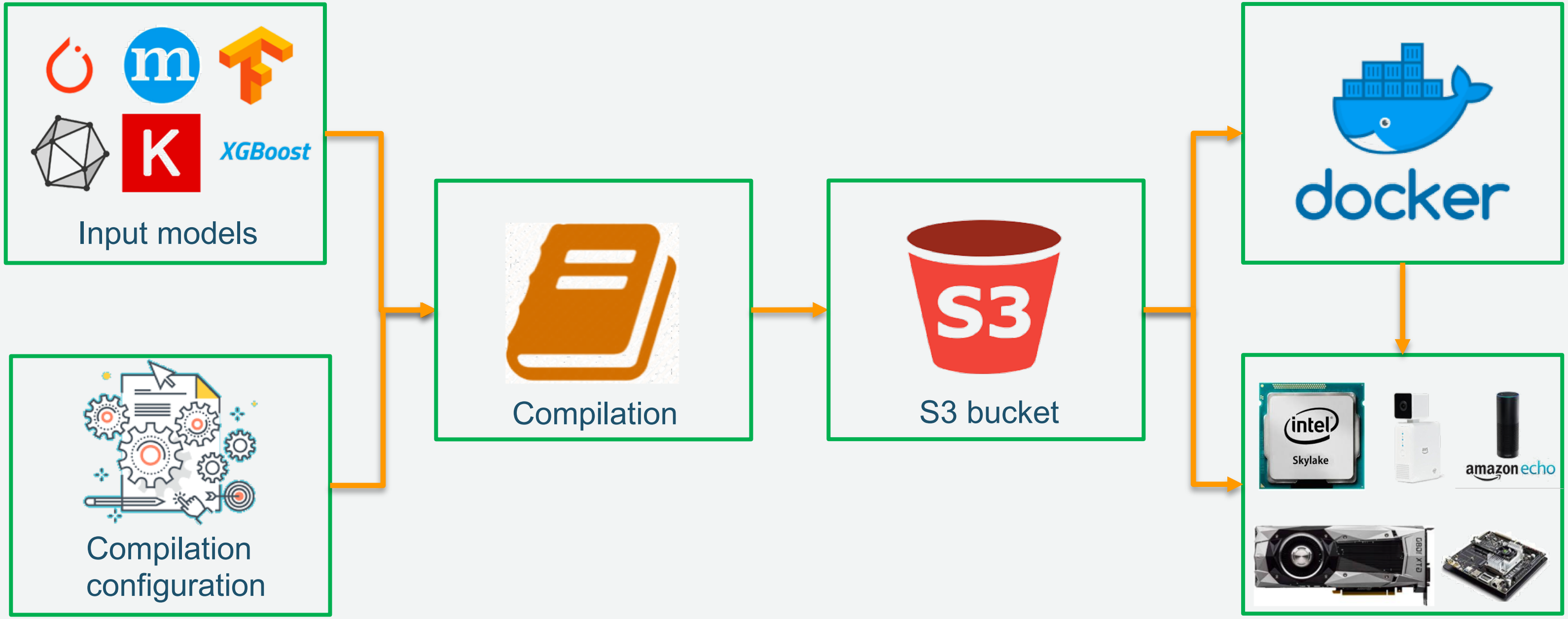
*-- Amazon [SageMaker Neo]() team*

# SageMaker Neo: Train once, Run anywhere

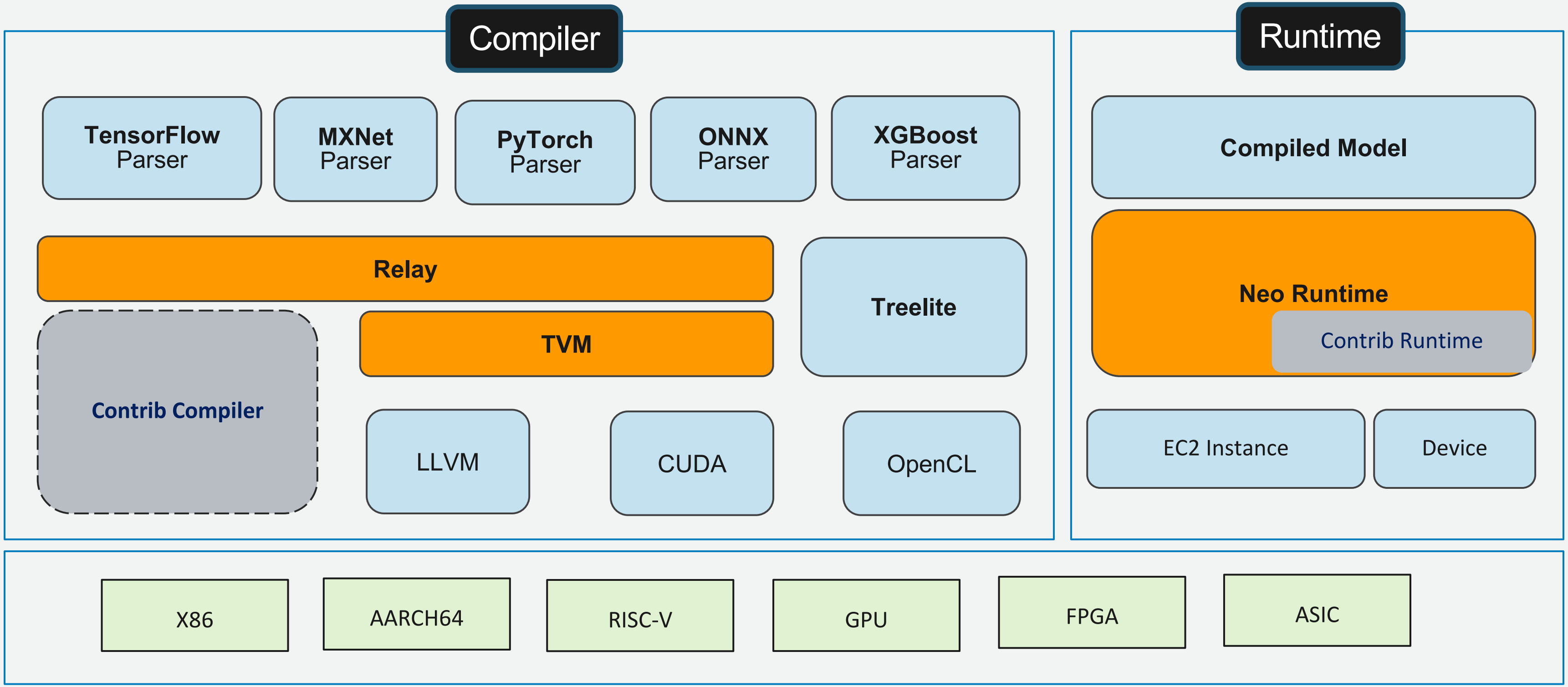



aws

# Amazon SageMaker Neo Pipeline



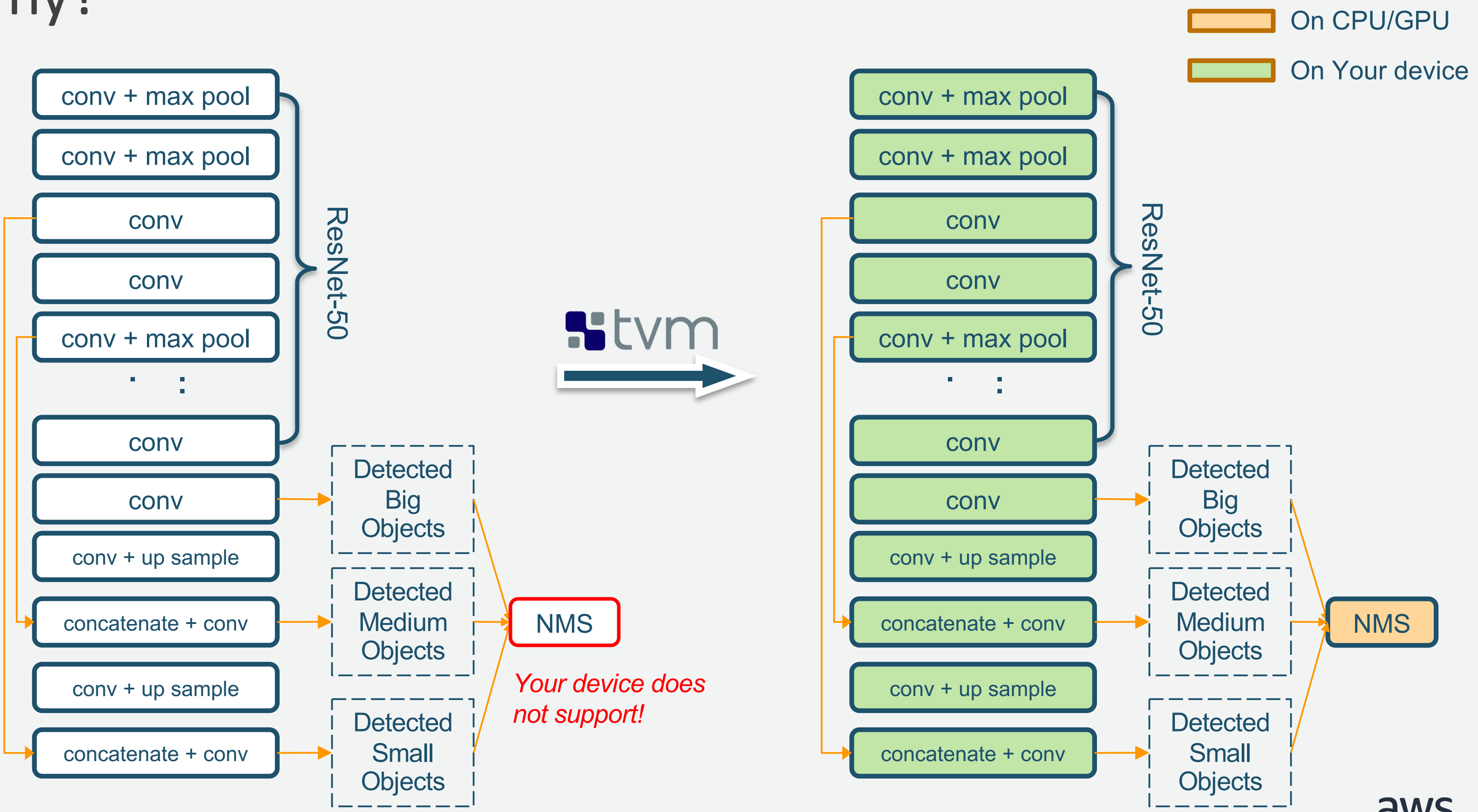
# Integration with SageMaker NEO



# Bring Your Own Codegen to TVM

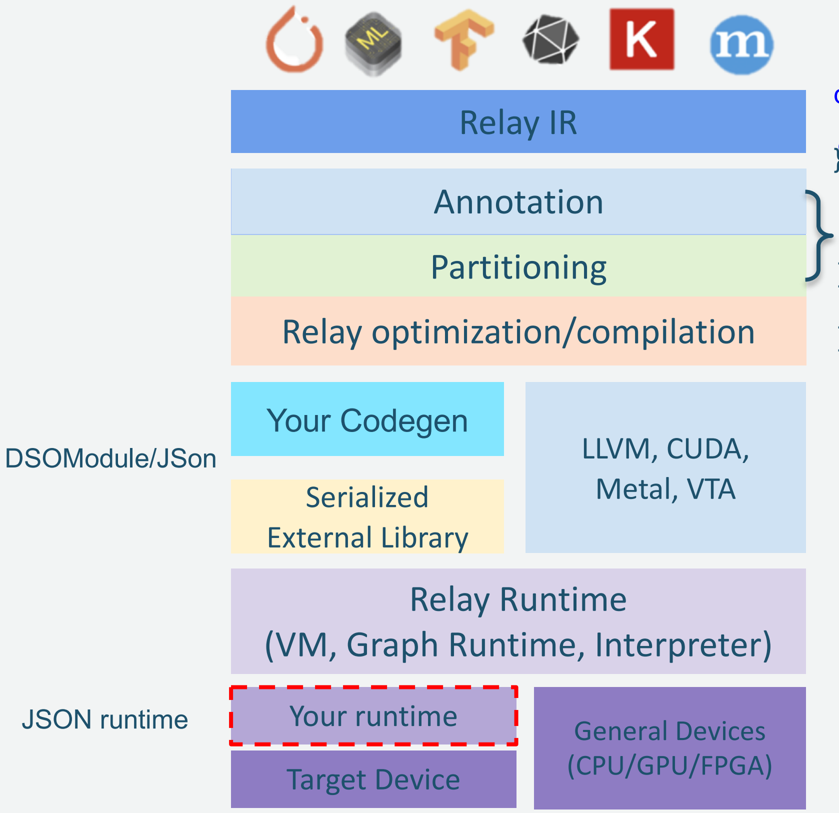
*-- Zhi Chen and Cody Yu*

# Why?



On CPU/GPU
On Your device
conv + max pool
conv + max pool
conv
conv
conv + max pool
conv
conv
conv + up sample
concatenate + conv
conv + up sample
concatenate + conv
ResNet-50
Detected Big Objects
Detected Medium Objects
Detected Small Objects
NMS
Your device does not support!
tvm
conv + max pool
conv + max pool
conv
conv
conv + max pool
conv
conv
conv + up sample
concatenate + conv
conv + up sample
concatenate + conv
ResNet-50
Detected Big Objects
Detected Medium Objects
Detected Small Objects
NMS

# How does it look like?




```
def @main(%x, %y) {
  add(%x, %y)
}
```

```
def @main(%x, %y) {
  %0 = fn (%gcc_input0, %gcc_input1,
External="gcc", FuncName="gcc_0", Primitive=1) {
    add(%gcc_input0, %gcc_input1)
  };
  %0(%x, %y);
}
```

# How to Integrate?

- Codegen
  - With engine DNNL, TensorRT
    - Generate artifacts that can be loaded/saved through existing TVM runtime module, e.g. DSOModule
  - Without engine
    - Produce library wrappers that are compatible to TVM and generate DSOModule
- Runtime
  - Reuse existing TVM runtime
  - Custom runtime could be imported to TVM runtime
  - Invoke integrated runtime directly through PackedFunc

# Pass Manager

*-- Zhi Chen*

# What does it do?

- Traditional compiler
  - Make pass developers’ life easier
  - Maintain pass info, i.e. pass dependencies
  - Keep analysis info update to date
- Deep learning framework
  - PyTorch and Keras Sequential, Gluon Block
  - Allow flexible customized pipeline

# How does it work?

Relay IR

Compilation and Optimization (PM)

| Module Pass | Function Pass | Sequential Pass |
| --- | --- | --- |

- Apply a sequence of passes
- Help developers to customize optimization pipeline
- Fold scale axis, hardware dependent/independent passes

# How to Customize Your Optimization Pipeline?

```
seq1 = relay.transform.Sequential([a, b, c])
seq2 = relay.transform.Sequential([d, e, f])

with build_config(opt_level=2): # hardware independent
    mod1 = seq1(mod)

with build_config(opt_level=3, disabled_pass=[e]): # hardware dependent
    mod2 = seq2(mod1)
```

Tutorial: https://docs.tvm.ai/tutorials/dev/relay_pass_infra.html#sphx-glr-tutorials-dev-relay-pass-infra-py

# AWS in rest of today

- 12:10 Dynamic Execution and Virtual Machine
- 13:20 Dynamic Model - Graph Dispatching
- 17:30 Improving AutoTVM Efficiency by Schedule Sharing
- 17:40 Optimizing Sparse/Graph Kernels via TVM

# Takeaways

- Industry needs an open standard compiler for DL
  - AWS working on the TVM stack
- We are eager to collaborate with the community
  - Talk to us, we have 10+ people here today!
- We are hiring!
  - Write to Yida Wang (wangyida@amazon.com), Zhi Chen (chzhi@amazon.com), or Vin Sharma (vinarm@amazon.com)