Deep Learning Optimizations

Intel® AI Analytics Toolkit

Accelerate end-to-end AI and data analytics pipelines with libraries optimized for Intel® architectures

Who needs this product?

Data scientists, AI researchers, ML and DL developers, AI application developers

Top Features/Benefits

- Deep learning performance for training and inference with Intel optimized DL frameworks and tools
- Drop-in acceleration for data analytics and machine learning workflows with compute-intensive Python packages

Intel® AI Analytics Toolkit

Deep Learning
- Intel® Optimization for TensorFlow
- Intel® Optimization for PyTorch
- Intel® Neural Compressor
- Model Zoo for Intel® Architecture

Machine Learning
- Intel® Extension for Scikit-learn
- Intel-optimized XGBoost

Data Analytics
- Intel® Distribution of Modin
- OmniSci Backend

Intel-optimized Python
- NumPy
- SciPy
- Numba
- Pandas
- Data Parallel Python

CPU GPU

Hardware support varies by individual tool. Architecture support will be expanded over time.

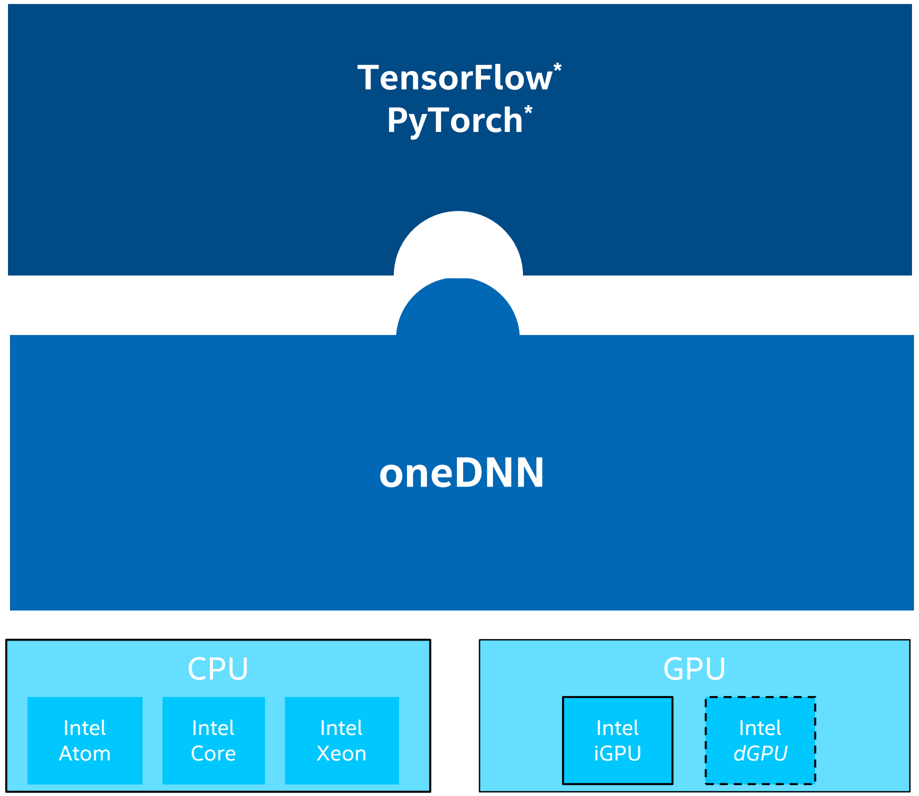
Get the Toolkit HERE or via these locations

Intel Installer | Docker | Apt, Yum | Conda | Intel® DevCloud

Back to Domain-specific Toolkits for Specialized Workloads

Intel® oneAPI Deep Neural Network Library (oneDNN)

Deliver High Performance Deep Learning



Deep learning and AI ecosystem includes edge and datacenter applications.

- **Open source frameworks** (TensorFlow*, PyTorch*, ONNX Runtime*)
- OEM applications (Matlab*, DL4J*)
- Cloud service providers internal workloads
- **Intel deep learning products** (OpenVINO™, BigDL)

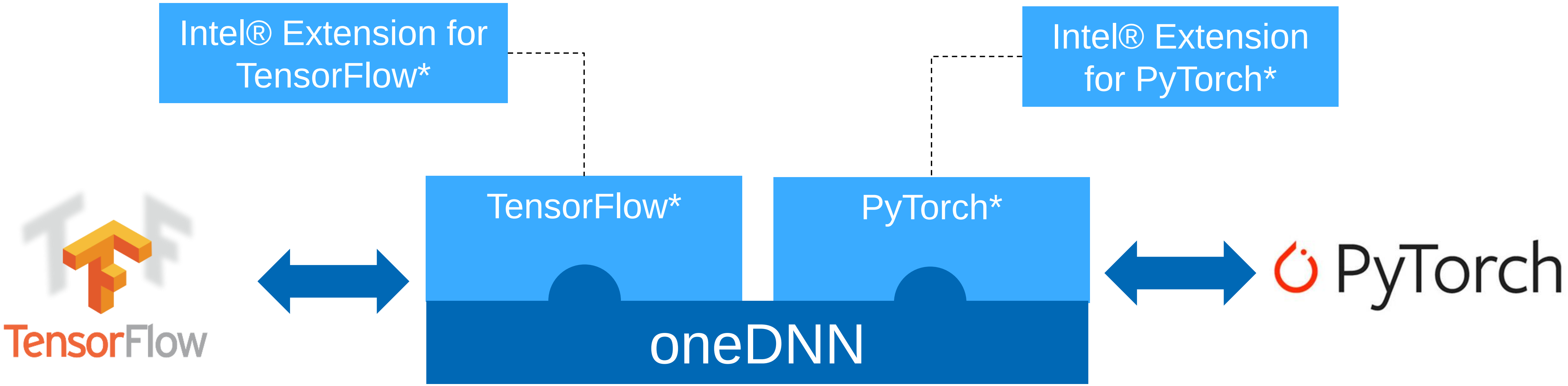
oneDNN is an open source performance library for deep learning applications

- Includes **optimized** versions of **key deep learning functions**
- **Abstracts out** instruction set and other complexities of performance optimizations
- Same API for both Intel CPU's and GPU's, use the best technology for the job
- **Open** for community contributions

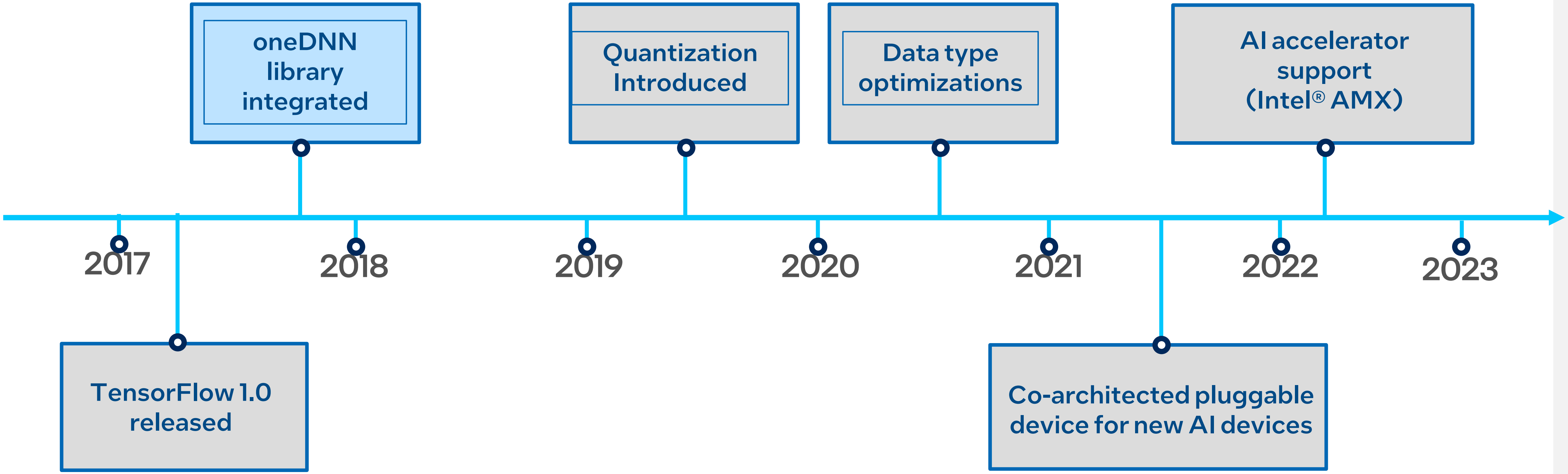
Optimization Notice: Intel's compilers may or may not optimize to the same degree for non-Intel microprocessors for optimizations that are not unique to Intel microprocessors. These optimizations include SSE2, SSE3, and SSSE3 instruction sets and other optimizations. Intel does not guarantee the availability, functionality, or effectiveness of any optimization on microprocessors not manufactured by Intel. Microprocessor-dependent optimizations in this product are intended for use with Intel microprocessors. Certain optimizations not specific to Intel microarchitecture are reserved for Intel microprocessors. Please refer to the applicable product User and Reference Guides for more information regarding the specific instruction sets covered by this notice.
Notice Revision #20110804

Intel-optimized Deep Learning Frameworks

- Intel-optimized DL frameworks are drop-in replacement
  - No front code change for the user
- Optimizations are upstreamed automatically
- Latest optimizations in extension libraries

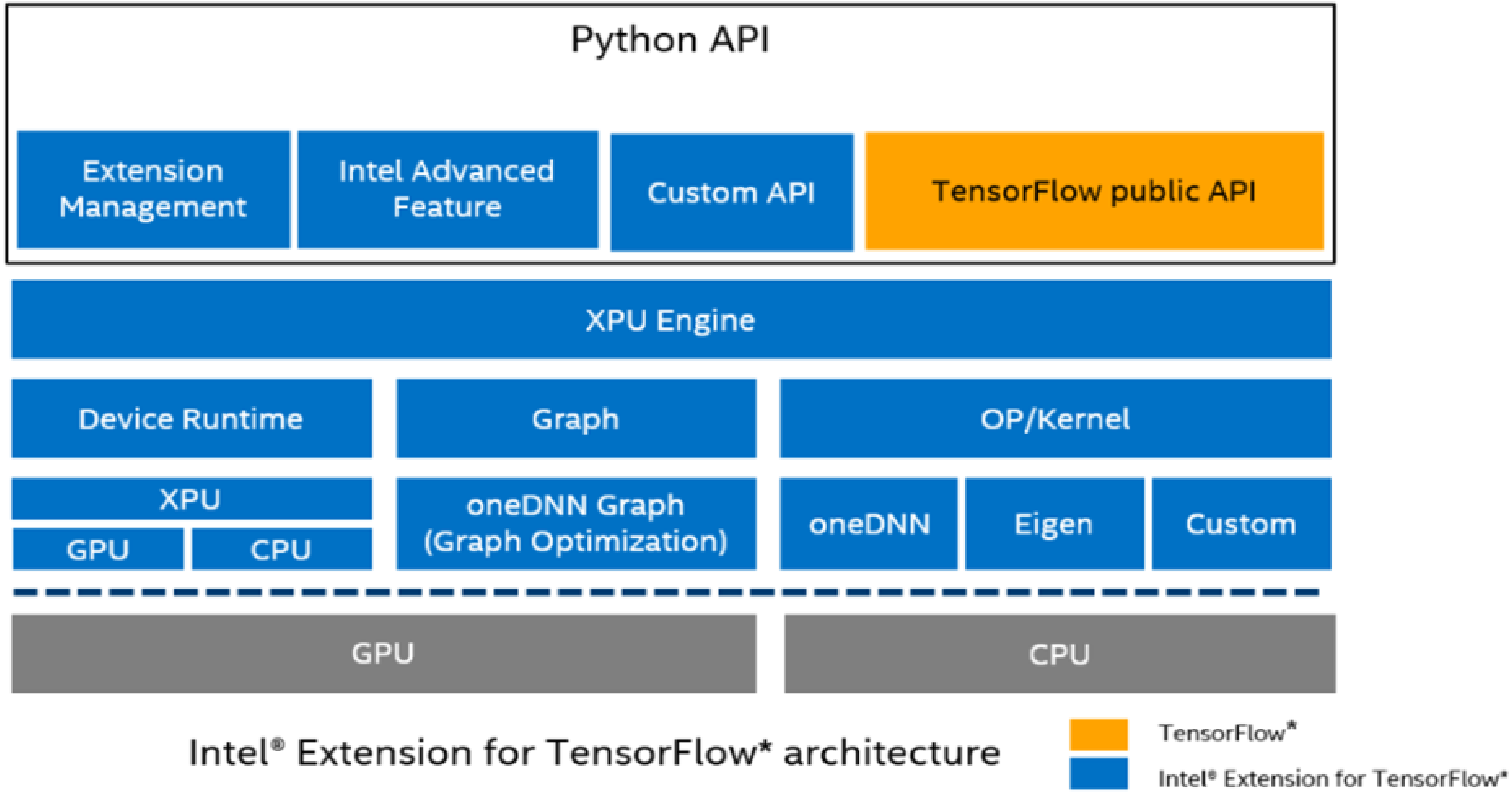


Intel Contributions in TensorFlow



~6 years of close collaboration between Intel and Google

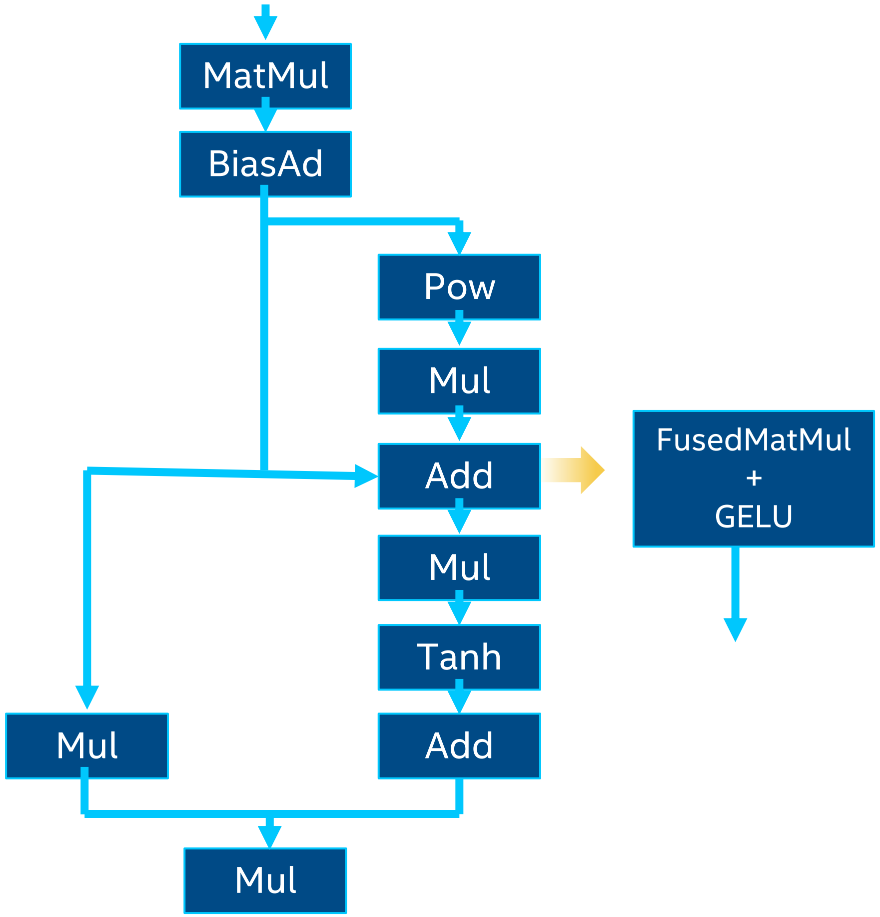
Intel® Extension for TensorFlow* Architecture



Intel® Extension for TensorFlow* architecture

Major Optimization Methodologies

- oneDNN Integration with TensorFlow
  - Replaces compute-intensive standard TF ops with highly optimized custom oneDNN ops
  - Aggressive op fusions to improve performance of Convolutions and Matrix Multiplications
- bfloat16 and 8-bit low precision data types supported by SPR
  - New matrix-based instructions set, Intel AMX



BF16 API

1. Train with BF16 with AVX-512

```
# BF16 without AMX
os.environ["ONEDNN_MAX_CPU_ISA"] = "AVX512_BF16"
tf.config.optimizer.set_experimental_options({'auto_mixed_precision_onednn_bfloat16':True})

transformer_layer = transformers.TFDistilBertModel.from_pretrained('distilbert-base-uncased')
tokenizer = transformers.DistilBertTokenizer.from_pretrained('distilbert-base-uncased')
model = build_model(transformer_layer, max_len=160)

# fine tune model according to disaster tweets dataset
if is_tune_model:
    train_input = bert_encode(train.text.values, tokenizer, max_len=160)
    train_labels = train.target.values
    start_time = time.time()
    train_history = model.fit(train_input, train_labels, validation_split=0.2, epochs=1, batch_size=16)
    end_time = time.time()
  # save model weights so we don't have to fine tune it every time
    os.makedirs(save_weights_dir, exist_ok=True)
    model.save_weights(save_weights_dir + "/bf16_model_weights.h5")
```

Turned on by default after TF 2.11

2. Train with BF16 with AMX

```
# BF16 without AMX
os.environ["ONEDNN_MAX_CPU_ISA"] = "AVX512_BF16"
```

```
# BF16 with AMX
os.environ["ONEDNN_MAX_CPU_ISA"] = "AMX_BF16"
```

BF16 API (cont.)

3. Inference with BF16 without AMX

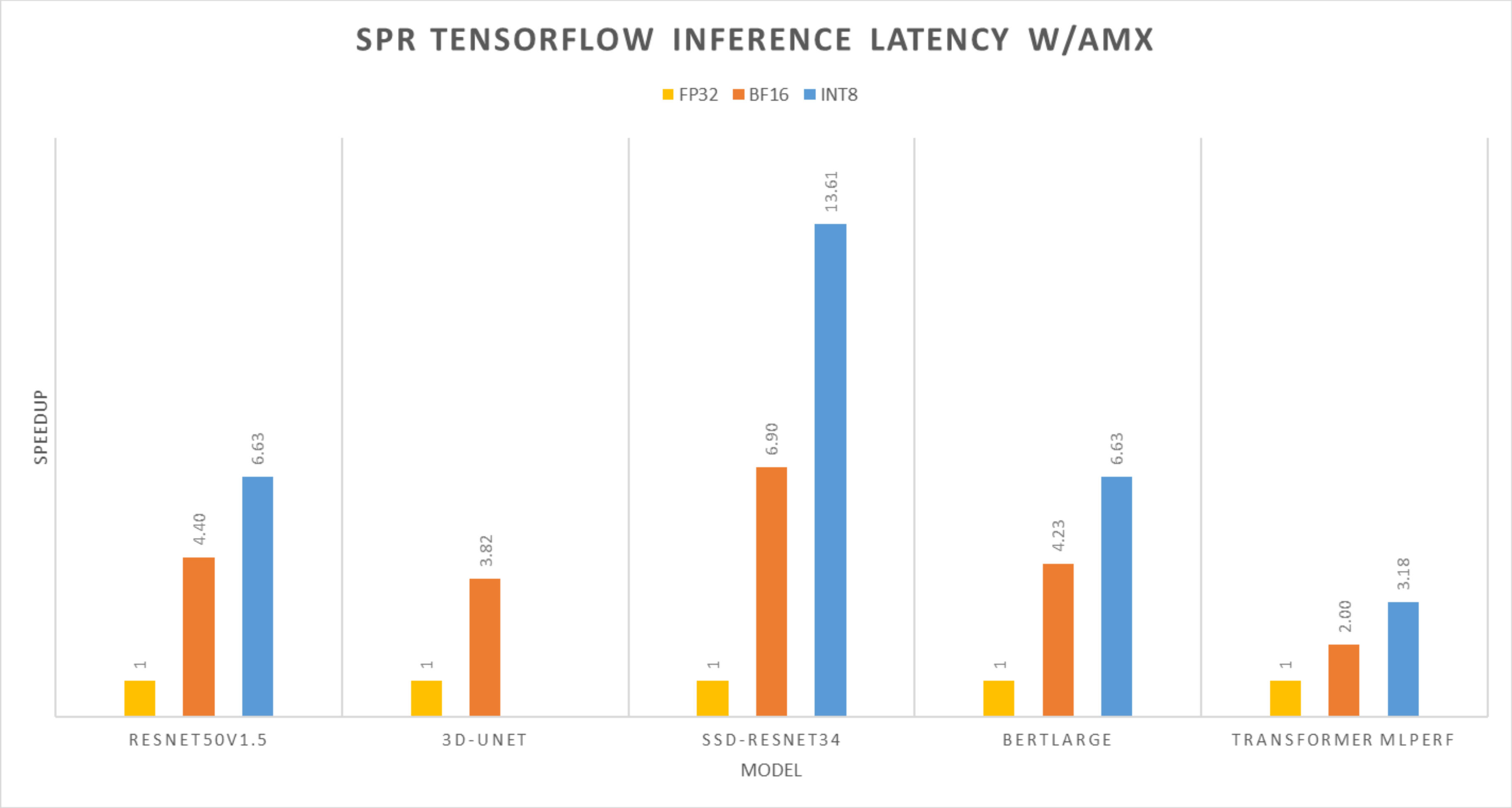
```
# Reload the model as the bf16 model with AVX512 to compare inference time
os.environ["ONEDNN_MAX_CPU_ISA"] = "AVX512_BF16"
tf.config.optimizer.set_experimental_options({'auto_mixed_precision_onednn_bfloat16':True})
bf16_model_noAmx = tf.keras.models.load_model('models/my_saved_model_fp32')

bf16_model_noAmx_export_path = "models/my_saved_model_bf16_noAmx"
bf16_model_noAmx.save(bf16_model_noAmx_export_path)
```

4. Inference with BF16 with AMX

```
# Reload the model as the bf16 model with AMX to compare inference time
os.environ["ONEDNN_MAX_CPU_ISA"] = "AMX_BF16"
tf.config.optimizer.set_experimental_options({'auto_mixed_precision_onednn_bfloat16':True})
bf16_model_withAmx = tf.keras.models.load_model('models/my_saved_model_fp32')

bf16_model_withAmx_export_path = "models/my_saved_model_bf16_with_amx"
bf16_model_withAmx.save(bf16_model_withAmx_export_path)
```

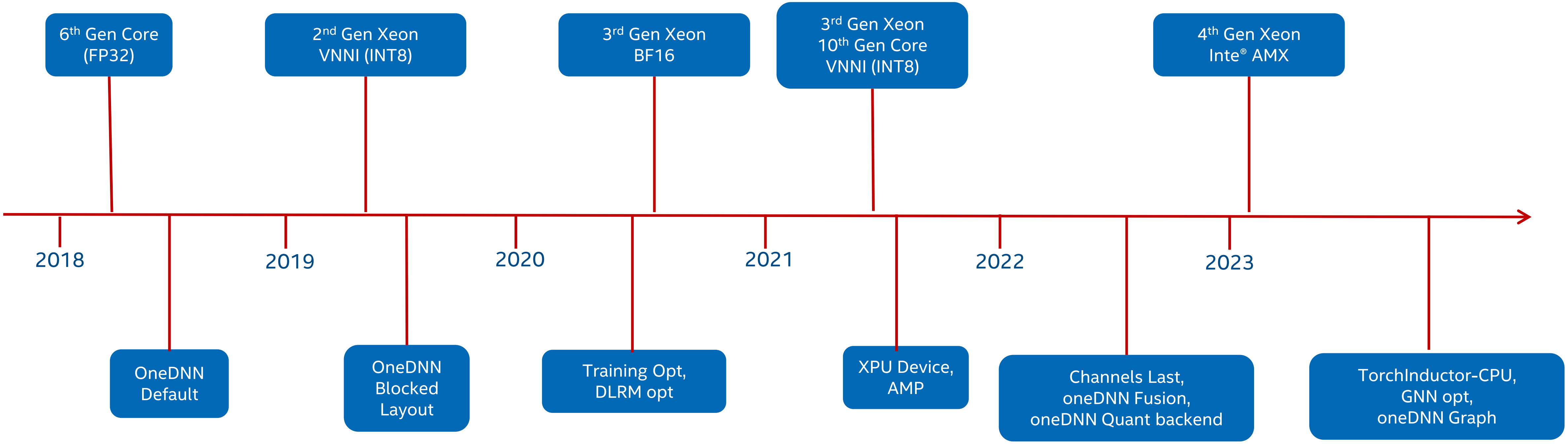
TensorFlow Benchmark: SPR Inference (Batch Size = 1)

Inference latency speedup: the higher the better

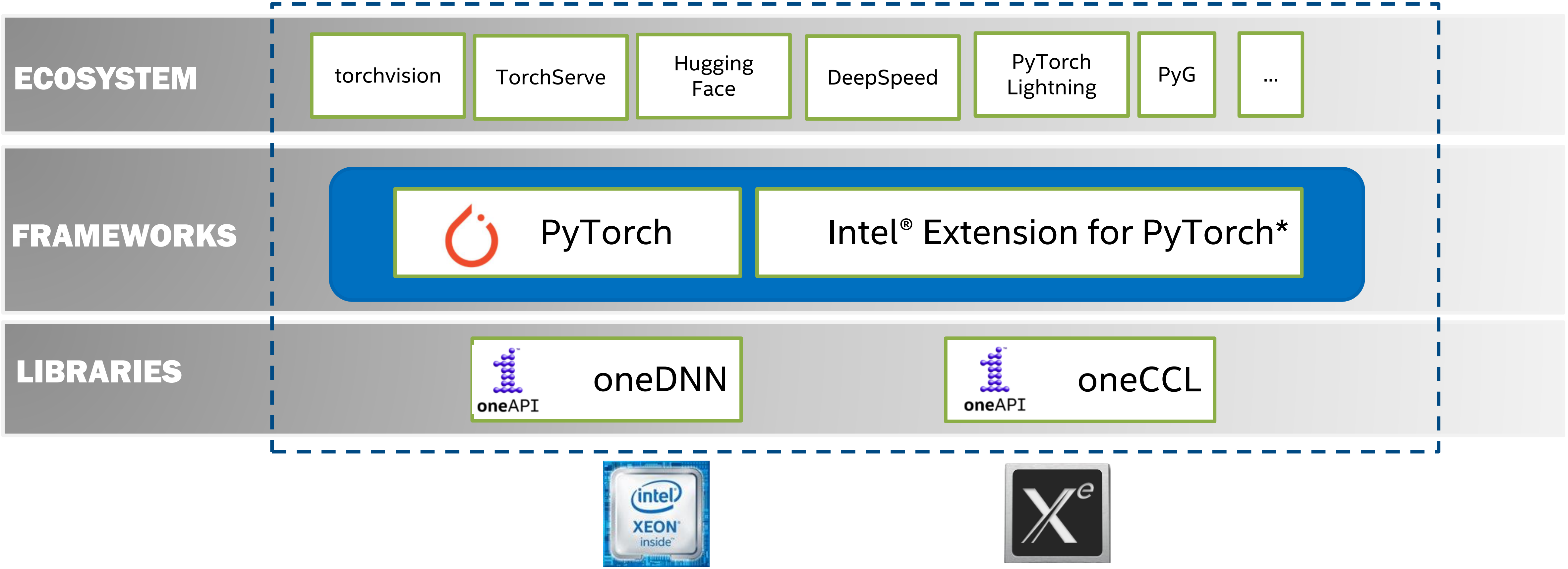


BF16: 2.00-6.90X
INT8: 3.18-13.61X

Intel® Optimization for PyTorch* upstream

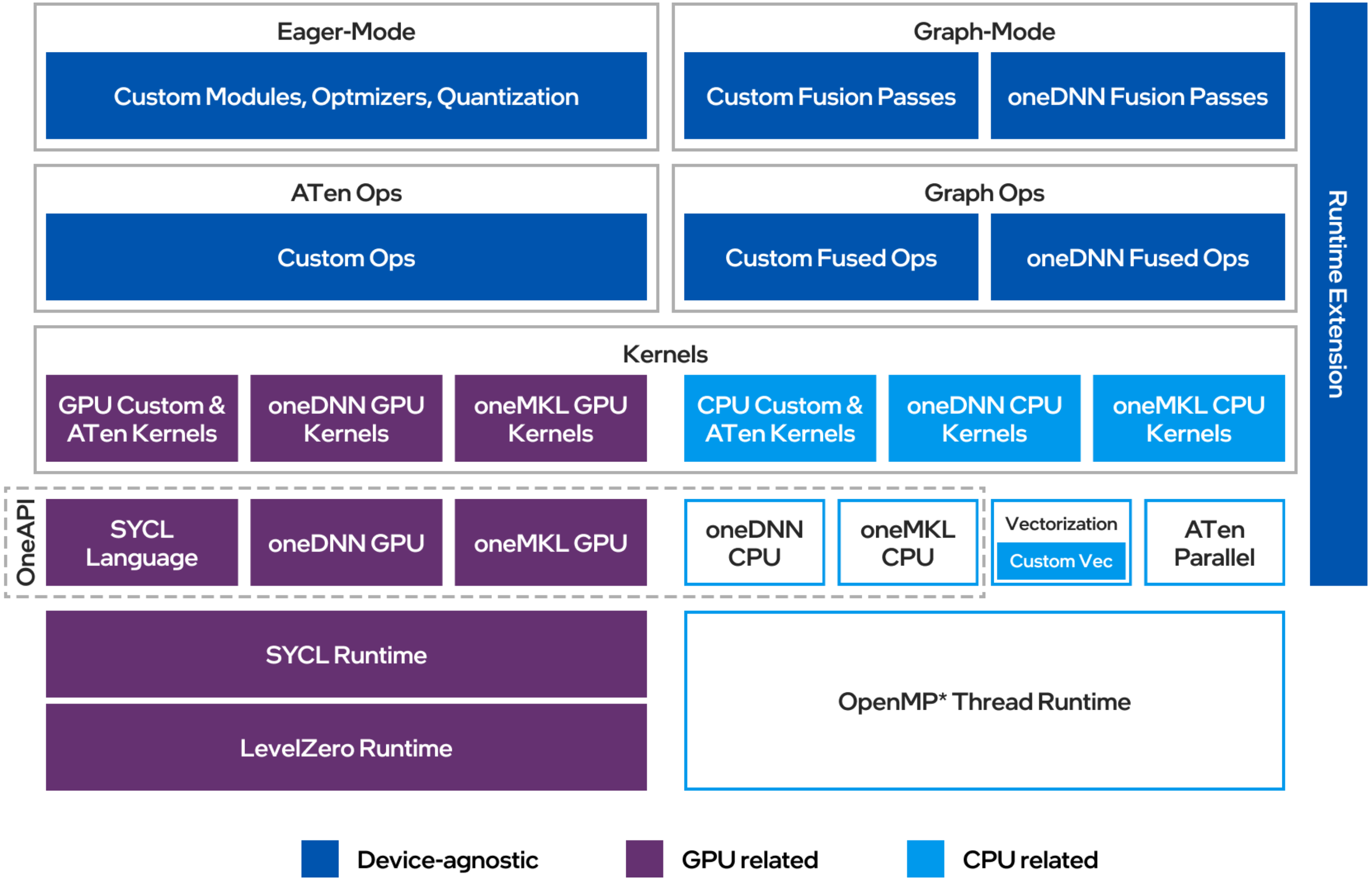


Intel® Optimization for PyTorch*



Other names and brands may be claimed as the property of others

Intel® Extension for PyTorch* Architecture



Major Optimization Methodologies

- General performance optimization and Intel new feature enabling in PyTorch upstream
- Additional performance boost and early adoption of aggressive optimizations through Intel® Extension for PyTorch*

Operator Optimization	Graph Optimization	Runtime Extension
• Vectorization • Parallelization • Memory Layout • Low Precision	• Operator fusion • Constant folding	• Thread affinity • Memory allocation

Training w/AMX BF16 on Intel Extension for PyTorch

```python
import torch
import torchvision
import intel_extension_for_pytorch as ipex

LR = 0.001
DOWNLOAD = True
DATA = 'datasets/cifar10/'

transform = torchvision.transforms.Compose([
  torchvision.transforms.Resize((224, 224)),
  torchvision.transforms.ToTensor(),
  torchvision.transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
])
train_dataset = torchvision.datasets.CIFAR10(
  root=DATA,
  train=True,
  transform=transform,
  download=DOWNLOAD,
)
train_loader = torch.utils.data.DataLoader(
  dataset=train_dataset,
  batch_size=128
)
```

```python
model = torchvision.models.resnet50()
criterion = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr = LR, momentum=0.9)
model.train()
model, optimizer = ipex.optimize(model, optimizer=optimizer, dtype=torch.bfloat16)

for batch_idx, (data, target) in enumerate(train_loader):
  optimizer.zero_grad()
  with torch.cpu.amp.autocast():
    output = model(data)
    loss = criterion(output, target)
    loss.backward()
  optimizer.step()
  print(batch_idx)
torch.save({
  'model_state_dict': model.state_dict(),
  'optimizer_state_dict': optimizer.state_dict(),
  }, 'checkpoint.pth')
```

Inference w/AMX BF16 on Intel Extension for PyTorch

```
import torch
import torchvision.models as models

model = models.resnet50(weights='ResNet50_Weights.DEFAULT')
model.eval()
data = torch.rand(1, 3, 224, 224)

#################### code changes ####################
import intel_extension_for_pytorch as ipex
model = ipex.optimize(model, dtype=torch.bfloat16)
######################################################

with torch.no_grad(), torch.cpu.amp.autocast():
  model = torch.jit.trace(model, torch.rand(1, 3, 224, 224))
  model = torch.jit.freeze(model)

  model(data)
```

BERT

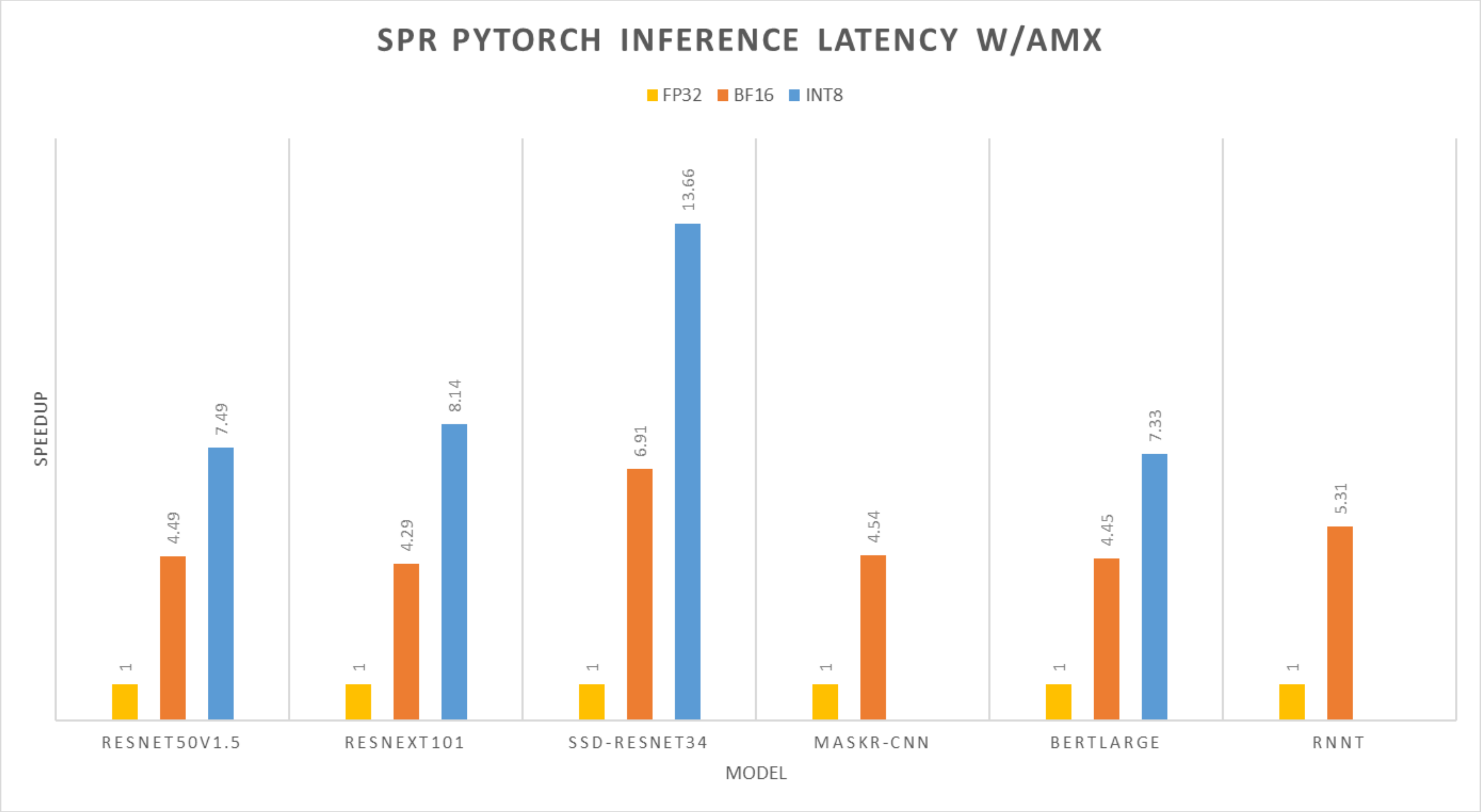
```
import torch
from transformers import BertModel

model = BertModel.from_pretrained("bert-base-uncased")
model.eval()

vocab_size = model.config.vocab_size
batch_size = 1
seq_length = 512
data = torch.randint(vocab_size, size=[batch_size, seq_length])

#################### code changes ####################
import intel_extension_for_pytorch as ipex
model = ipex.optimize(model, dtype=torch.bfloat16)
######################################################

with torch.no_grad(), torch.cpu.amp.autocast():
  d = torch.randint(vocab_size, size=[batch_size, seq_length])
  model = torch.jit.trace(model, (d,), check_trace=False, strict=False)
  model = torch.jit.freeze(model)

  model(data)
```

Runtime Optimizations with Launch Script

- Automates configuration settings to optimize on topology
  - OpenMP library: Intel OpenMP library, GNU OpenMP library
  - Memory allocator: PyTorch default, Jemalloc, TCMalloc
  - Number of instances: single, multiple
  - Number of cores per instance
- Usage Guide with options and examples
- Sample Command
  - *ipexrun --ninstances 4 --ncore_per_instance 4 --enable_tcmalloc ${SCRIPT_PATH}*

PyTorch Benchmark: SPR Inference (Batch Size = 1)

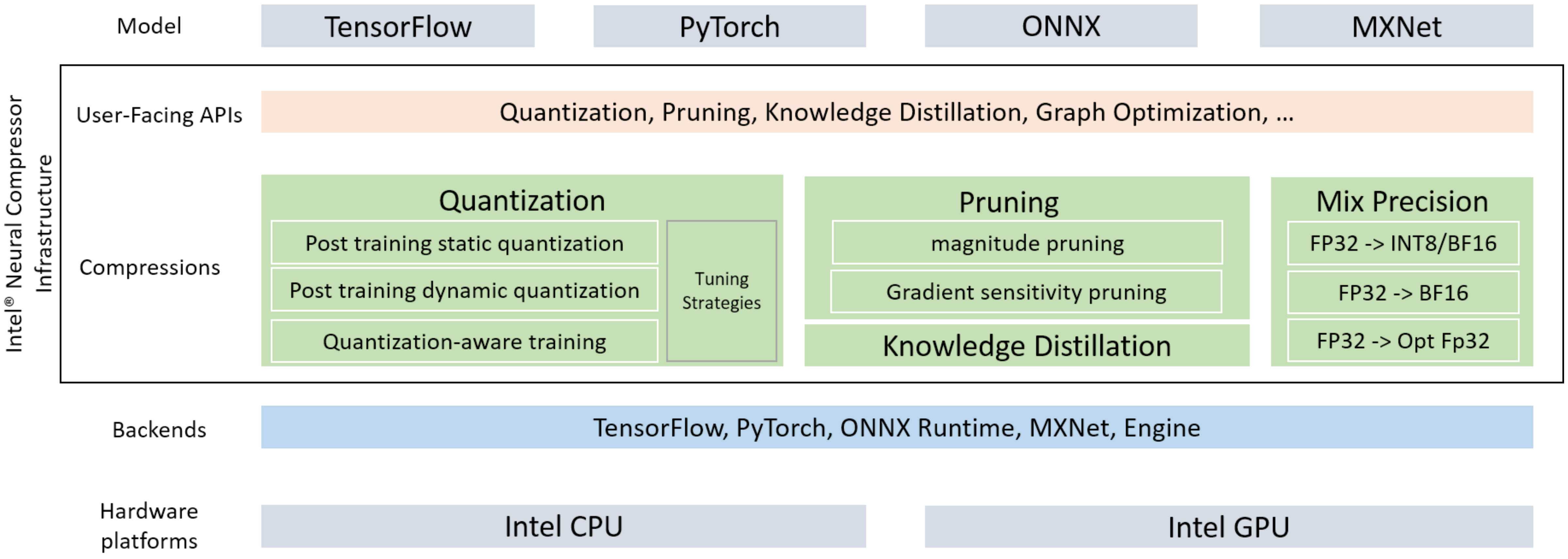
Inference latency speedup: the higher the better



BF16: 4.29-6.91X

INT8: 7.33-13.66X

Intel® Neural Compressor (INC)

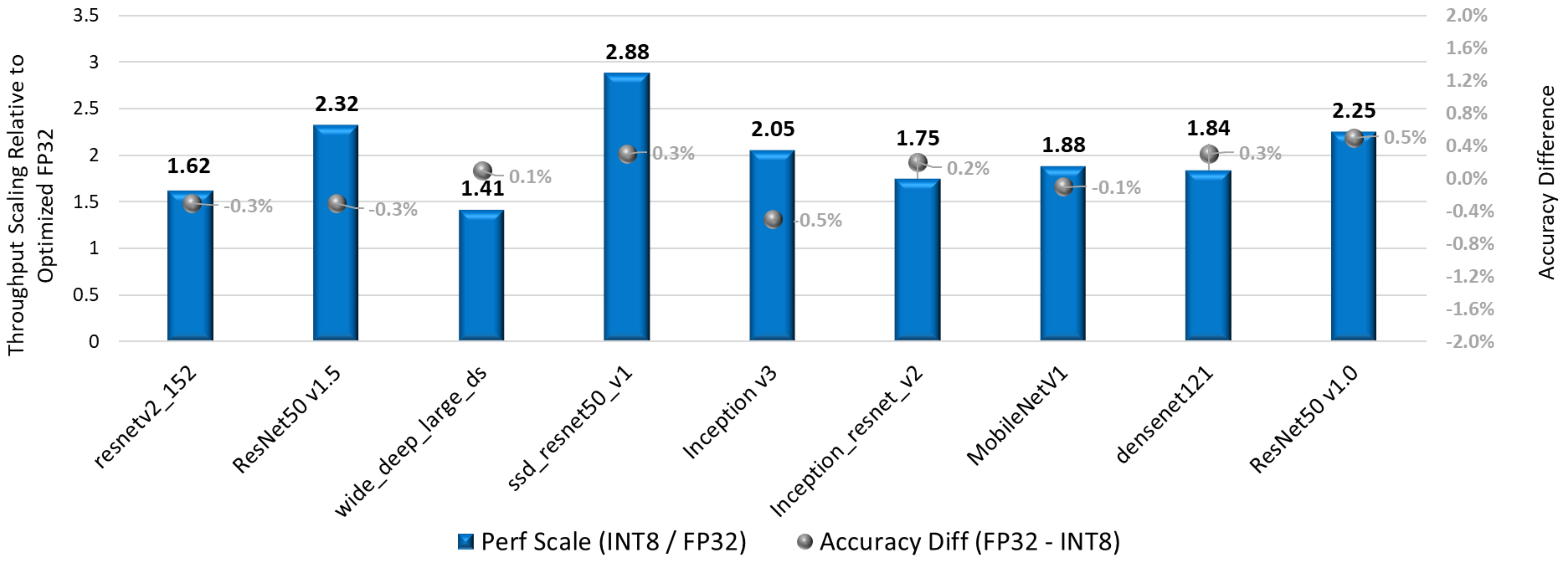


https://github.com/intel/neural-compressor

Installation:
pip install neural-compressor
conda install neural-compressor -c conda-forge -c intel

INT8 Quantized Inference Performance

Uses Intel® Optimization for Tensorflow and Intel® Neural Compressor



INT8 Inference Throughput Scaling up to 2.8x and Accuracy Drop within 0.6%

Model Zoo for Intel® Architecture

Language Modeling

Model	Framework	Mode	Model Documentation	Benchmark/Test Dataset
BERT large	TensorFlow	Inference	FP32 BFloat16 FP16	SQuAD
BERT large	TensorFlow	Training	FP32 BFloat16 FP16	SQuAD and MRPC
BERT large Sapphire Rapids	Tensorflow	Inference	FP32 BFloat16 Int8 BFloat32	SQuAD
BERT large Sapphire Rapids	Tensorflow	Training	FP32 BFloat16 BFloat32	SQuAD
DistilBERT base	Tensorflow	Inference	FP32 BFloat16 Int8 FP16	SST-2
BERT base	PyTorch	Inference	FP32 BFloat16	BERT Base SQuAD1.1
BERT large	PyTorch	Inference	FP32 Int8 BFloat16 BFloat32	BERT Large SQuAD1.1
BERT large	PyTorch	Training	FP32 BFloat16 BFloat32	preprocessed text dataset
DistilBERT base	PyTorch	Inference	FP32 Int8 BFloat16 BFloat32	DistilBERT Base SQuAD1.1
RNN-T	PyTorch	Inference	FP32 BFloat16 BFloat32	RNN-T dataset
RNN-T	PyTorch	Training	FP32 BFloat16 BFloat32	RNN-T dataset
RoBERTa base	PyTorch	Inference	FP32 BFloat16	RoBERTa Base SQuAD 2.0
T5	PyTorch	Inference	FP32 Int8	

TensorFlow BERT Large inference

Description

This document has instructions for running BERT Large inference using Intel-optimized TensorFlow.

Datasets

BERT Large Data

Download and unzip the BERT Large uncased (whole word masking) model from the google bert repo. Then, download the Stanford Question Answering Dataset (SQuAD) dataset file `dev-v1.1.json` into the `wwm_uncased_L-24_H-1024_A-16` directory that was just unzipped.

```
wget https://storage.googleapis.com/bert_models/2019_05_30/wwm_uncased_L-24_H-1024_A-16.zip
unzip wwm_uncased_L-24_H-1024_A-16.zip

wget https://rajpurkar.github.io/SQuAD-explorer/dataset/dev-v1.1.json -P wwm_uncased_L-24_H-1024_A-16
```

Set the `DATASET_DIR` to point to that directory when running BERT Large inference using the SQuAD data.

Quick Start Scripts

Script name	Description
`profile.sh`	This script runs inference in profile mode with a default `batch_size=32` .
`inference.sh`	Runs realtime inference using a default `batch_size=1` for the specified precision (fp32, bfloat16 or fp16). To run inference for throughtput, set `BATCH_SIZE` environment variable.

Key Features & Benefits

- Accelerate end-to-end AI and Data Science pipelines and achieve drop-in acceleration with optimized Python tools built using oneAPI libraries (i.e. oneMKL, oneDNN, oneCCL, oneDAL, and more)
- Achieve high-performance for deep learning training and inference with Intel-optimized versions of TensorFlow and PyTorch, and low-precision optimization with support for int8 and bfloat16
- Expedite development by using the open-source pre-trained deep learning models optimized by Intel for best performance via Model Zoo for Intel® Architecture
- Seamlessly scale Pandas workflows across multi-node dataframes with Intel® Distribution of Modin, accelerate analytics with performant backends such as OmniSci
- Increase machine learning model accuracy and performance with algorithms in Scikit-learn and XGBoost optimized for Intel architectures
- Supports cross-architecture development (Intel® CPUs/GPUs) and compute

Useful Links

- Intel® AI Analytics Toolkit (AI Kit)
- Intel® Extension for PyTorch*
- Intel® Extension for TensorFlow*
- Intel® Neural Compressor
- oneAPI-samples GitHub
- Model Zoo for Intel® Architecture GitHub

Notices & Disclaimers

Questions?