

# Introduction to Neural Network Compression Techniques

EuroCC AI Training

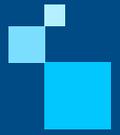
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25.10.2022



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# Agenda

Introduction

Neural Network  
Compression Techniques

Intel<sup>®</sup> Neural Compressor

# Introduction

# Introduction



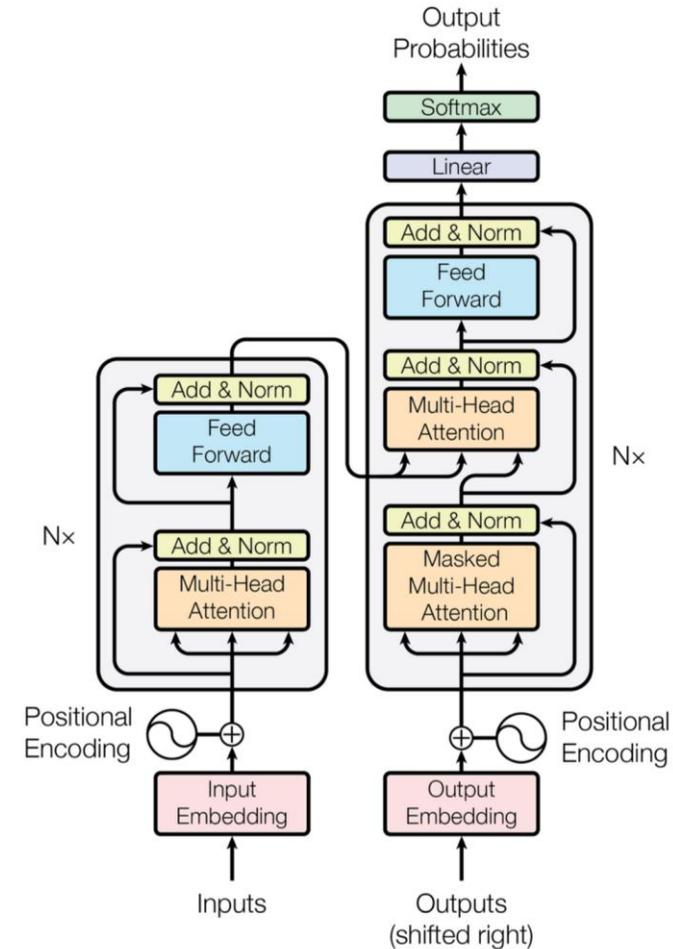
Need for neural network compression techniques?



Showcase: Transformer architectures!

# Introduction – Transformers

- Transformer architecture originates from machine translation tasks (NLP)
- Core-component: Multi-head (self-) attention
- Parallelization
- Most commonly known: BERT
- Huge increase of model parameters over the years





# Introduction – Transformers (GPT-3)

- Large Language Model (LLM) by OpenAI (backed by Microsoft)
- 175B parameters (cf. BERT base: 110M)
- 45TB of training data
- Cf. GPT-NeoX:
  - Trained on 96 [!] Nvidia A100s
  - For 3 months
- Estimated cost for training: 10—20 million dollars

# Introduction – Transformers

- Dominate NLP (via Hugging Face)
- BERT models (still) prevail
- **Optimization opportunities:**
  - Training/Finetuning
  - Inference
  - On a variety of hardware (CPU & GPU)
  - Aimed at speed-ups, memory reductions, sustainability.



# Neural Network Compression Techniques

# Neural Network Compression – Overview



Precision



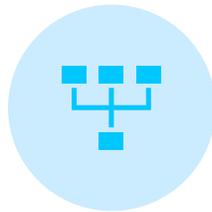
Quantization



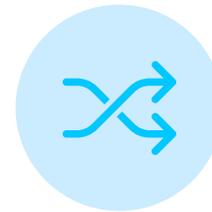
Pruning



Knowledge  
Distillation



Graph  
Optimization



Mixed Precision

# Neural Network Compression Techniques

Precision

# Floating Point – Precision

- Data precision:

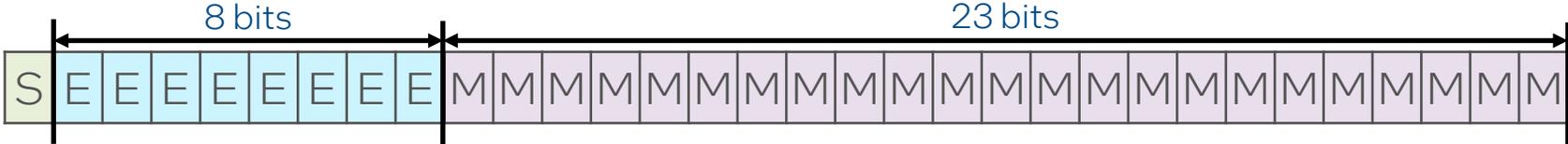
Number of bits used to store numerical values in memory

- Commonly found types of precision in Deep Learning:



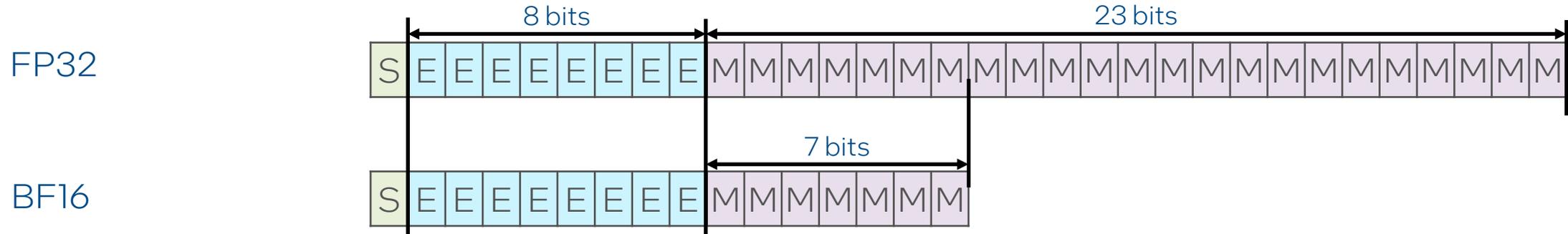
# Floating Point – Precision

FP32



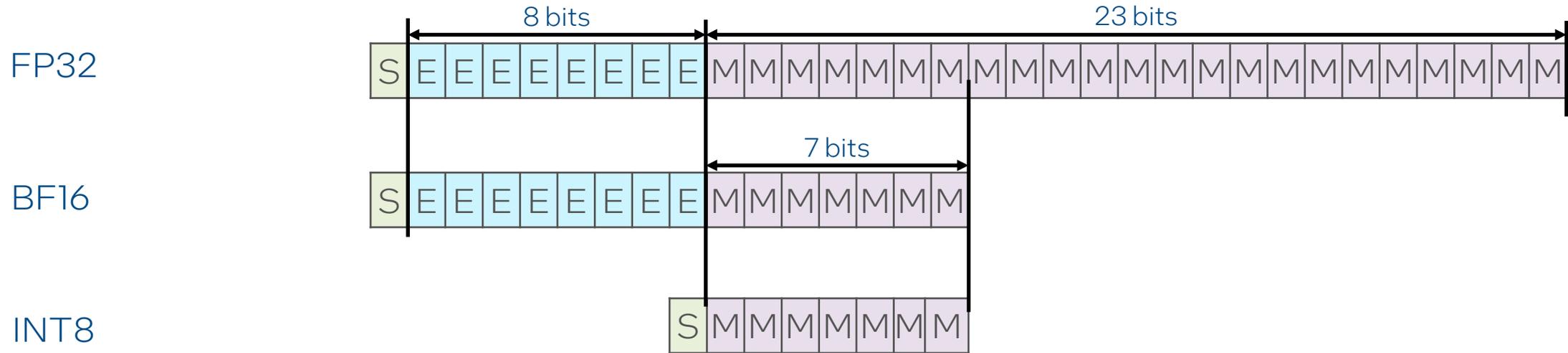
- FP32: The standard type for all neural network computations

# Floating Point – Precision



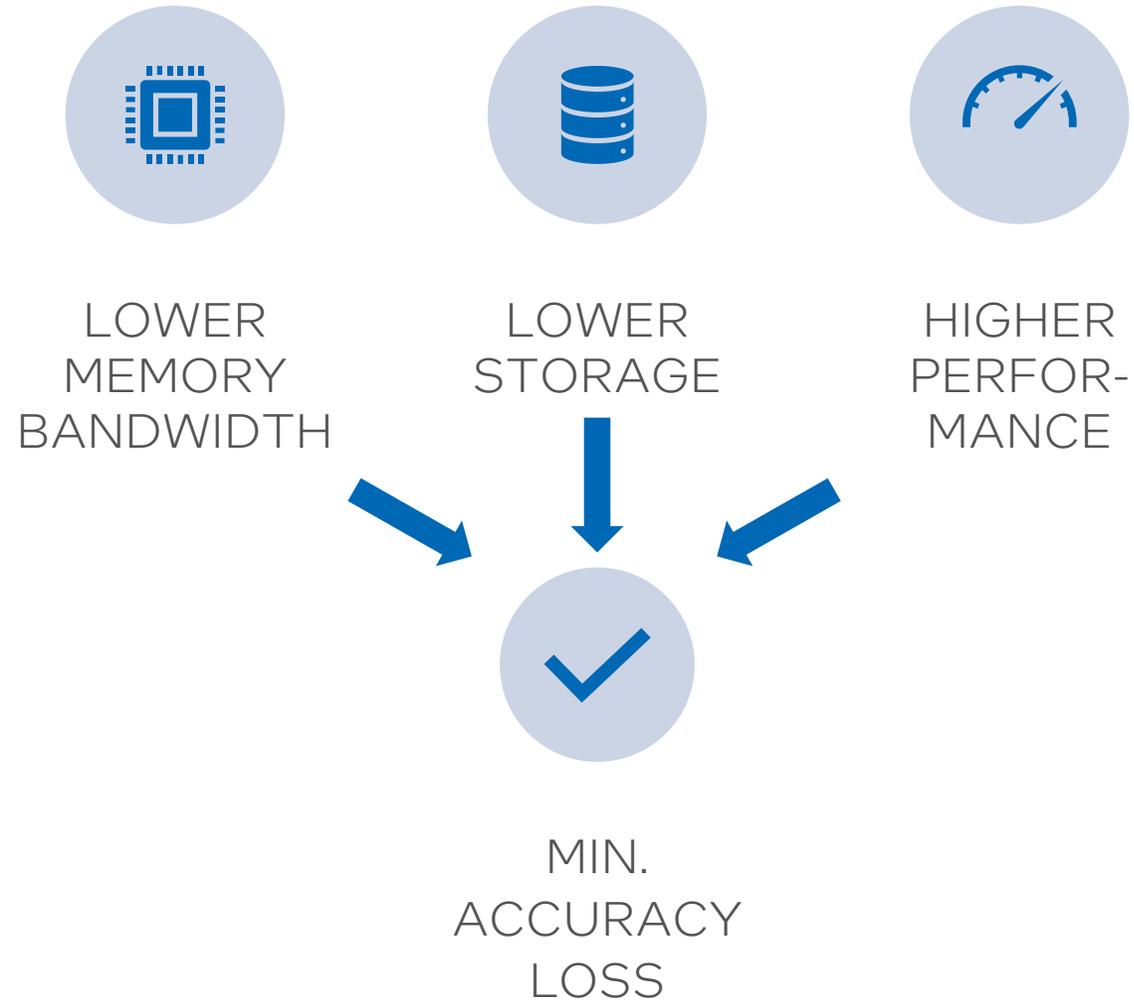
- FP32: The standard type for all neural network computations
- BF16: Efficient replacement for FP32 in training and inference

# Floating Point – Precision



- FP32: The standard type for all neural network computations
- BF16: Efficient replacement for FP32 in training and inference
- INT8: Significant speed-up in inference with small loss in accuracy

# Lower Precision – Summary

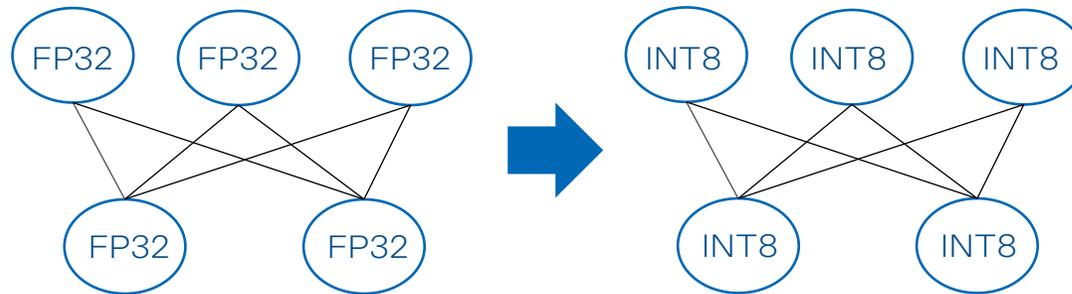


# Neural Network Compression Techniques

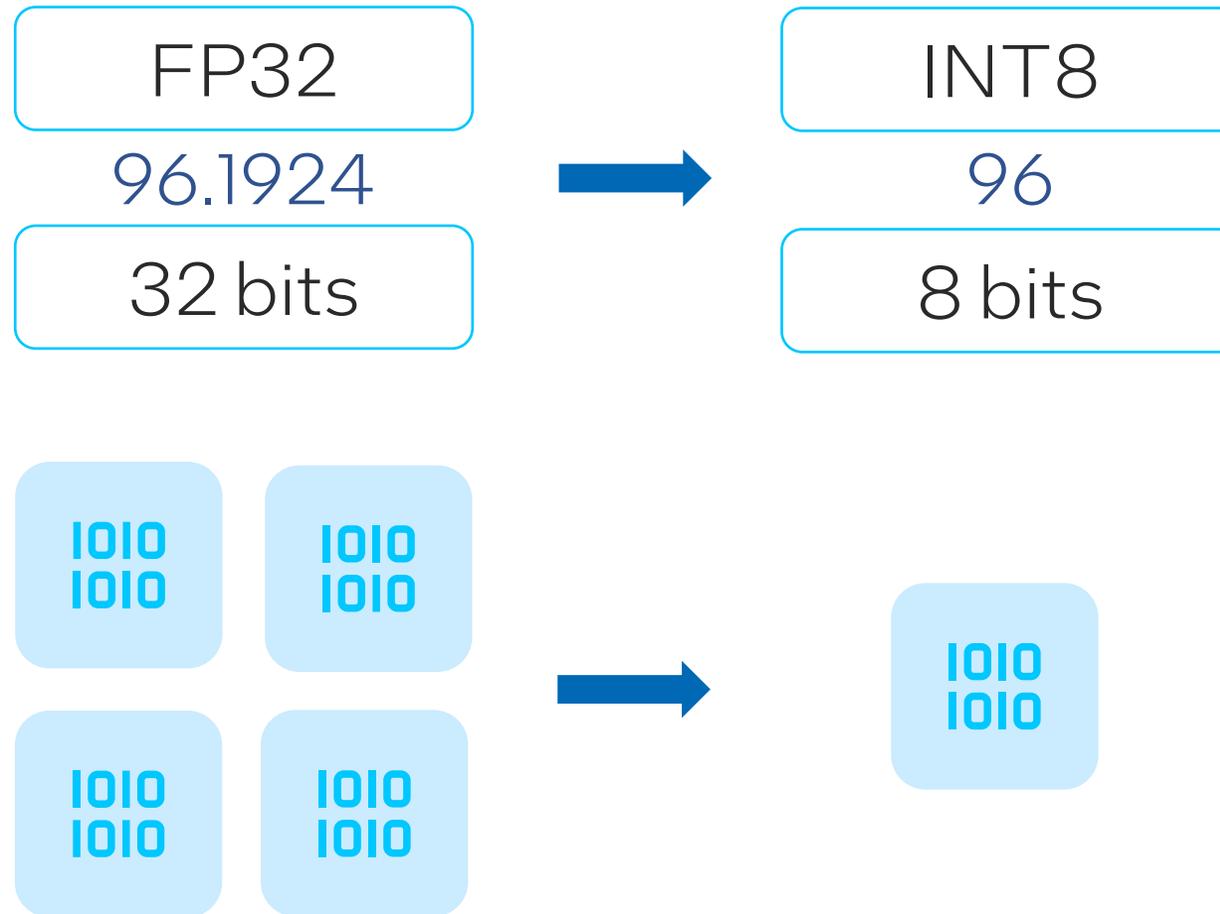
Quantization

# Quantization

- Systematic reduction of the precision of all or several layers within the model.
- Effectively, reduces the model size.
- Allows for faster inference.



# Quantization



# Quantization – Techniques (PTQ)

- **Post-Training Static Quantization (PTQ static):**
  - Performs quantization on already trained models.
  - It requires an additional pass over a dataset to work, only activations do calibration.
- **Post-Training Dynamic Quantization (PTQ dynamic):**
  - Multiplies input values by the scale factor, then rounds the result to the nearest.
  - It determines the scale factor for activations dynamically based on the data range observed at runtime.
  - Weights are quantized ahead of time, but the activations are dynamically quantized during inference.

# Quantization – Techniques (QAT)

- **Quantization-Aware Training (QAT):** Simulates low-precision inference-time computation in the forward pass of the training process.
  - All weights and activations are “fake quantized” during both the training forward and backward passes
  - FP32 values are rounded to mimic INT8 values, but all computations are still done with floating point numbers.
  - Weights are trained while being “aware” of the model will be quantized in the end.
  - Leads to higher accuracy than previous 2 quantization techniques but may take more time to deployment.

# Quantization – Summary

Systematic  
reduction of the  
model precision

Common  
procedure: FP32  
=> INT8

Common  
techniques: PTQ  
(static, dynamic)  
& QAT

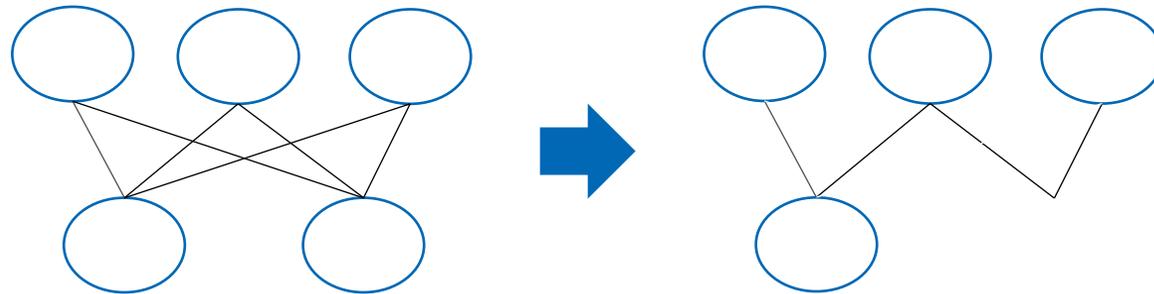
Faster inference  
& possible loss in  
accuracy

# Neural Network Compression Techniques

Pruning

# Pruning

- **Neural Network Pruning:** Reduces the size of a network by removing superfluous parts to achieve compact architectures with a minimal drop in accuracy.



# Pruning – Techniques

## ▪ Unstructured Pruning

- Finding and removing the least salient connections in the model where the nonzero patterns are irregular and could be anywhere in the matrix.
- Superfluous weight values are reduced to zero.
- Network architecture is unchanged, but induces sparsity in the network.

## ▪ Structured Pruning

- Finding parameters in groups, deleting entire blocks, filters, or channels according to some pruning criteria.
- Possibly, reduces width of layers and network.

# Pruning – Techniques

Pruning Type	Pruning Granularity	Pruning Algorithm
Unstructured Pruning	Element-wise	Magnitude
		Pattern Lock
Structured Pruning	Filter/Channel-wise	Gradient Sensitivity
	Block-wise	Group Lasso
	Element-wise	Pattern Lock

# Pruning – Summary

Remove  
superfluous parts  
in NN

Unstructured  
Pruning

Structured  
Pruning

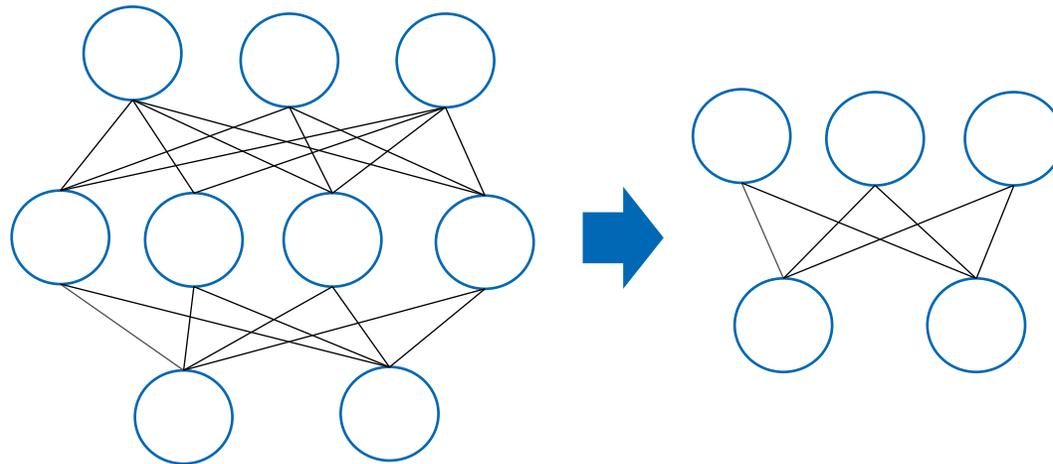
Faster inference  
& possible loss in  
accuracy

# Neural Network Compression Techniques

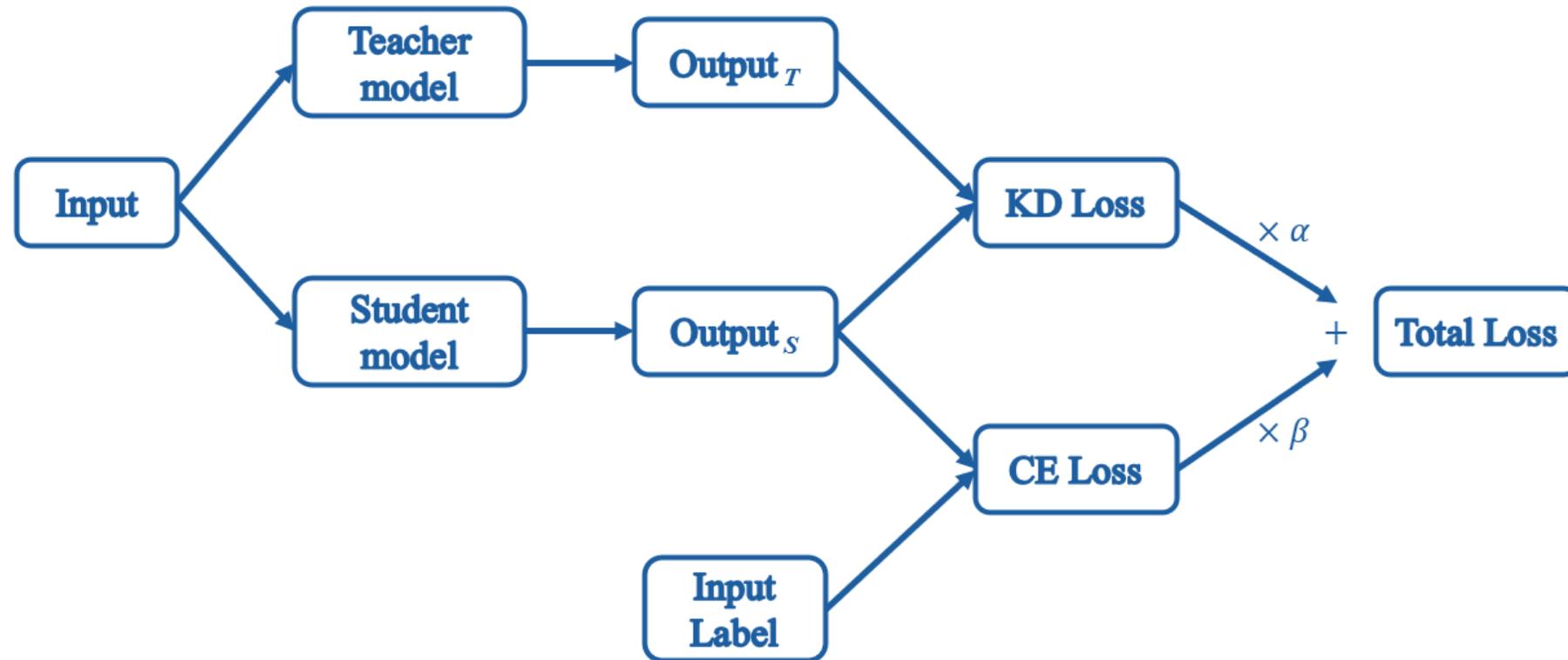
## Knowledge Distillation

# Knowledge Distillation

- A model compression method in which a small model is trained to mimic a pre-trained, larger model.
- The training setting is sometimes referred to as "teacher-student".
- Transfers knowledge from the teacher to the student without loss of validity.



# Knowledge Distillation



# Knowledge Distillation

- **Student model:**

- Shallow version of the teacher with fewer layers and fewer neurons per layer.
- Quantized version of the teacher.
- Pruned version of the teacher.
- Smaller, optimized network through neural architecture search (NAS).

- **E.g., DistilBERT:**

- 40% smaller than the teacher model, i.e., BERT base.
- 97% of performance retained in GLUE benchmark.
- 60% faster at inference.



# Knowledge Distillation – Summary

Student NN  
mimics teacher  
NN

Student:  
Shallower version  
of teacher

Knowledge  
transfer through  
combined loss

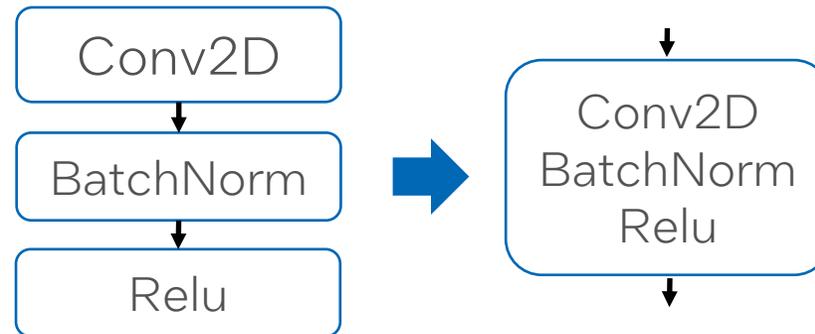
Faster fine-  
tuning &  
inference

# Neural Network Compression Techniques

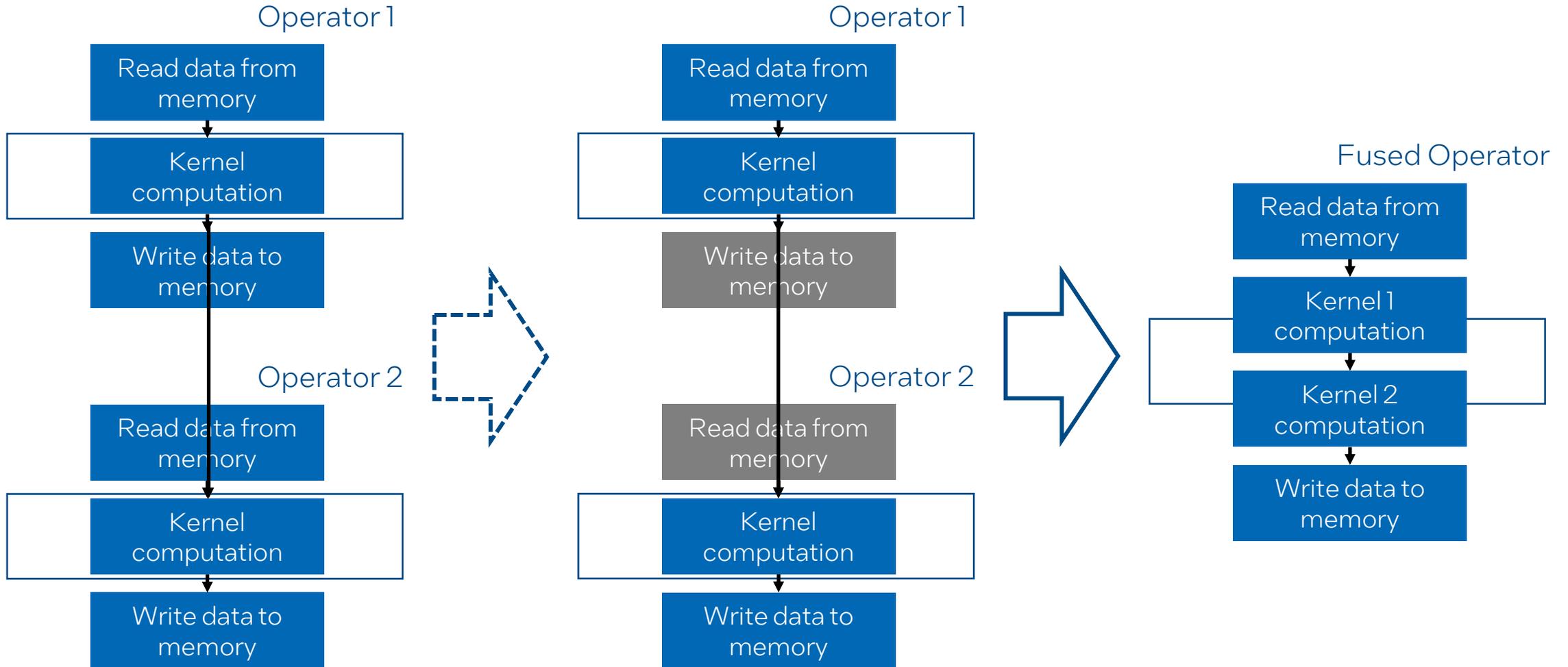
## Graph Optimization

# Graph Optimization

- Optimizes for inference of the model.
- Simplifies and fuses certain layers together.
  - Reduces complexity of the model.
- Optimizes graph (e.g., operators) and runtime (e.g., memory management).



# Graph Optimization – Operator Fusion



# Graph Optimization – FP32 & BF16 Fusion Patterns

- Conv2D + ReLU
- Conv2D + SUM
- Conv2D + SUM + ReLU
- Conv2D + Sigmoid
- Conv2D + Sigmoid + MUL
- Conv2D + HardTanh
- Conv2D + SiLU
- Conv2D + ELU
- Conv3D + ReLU
- Conv3D + SUM
- Conv3D + SUM + ReLU
- Conv3D + SiLU
- Linear + ReLU
- Linear + GELU
- Add + LayerNorm
- Div + Add + Softmax
- Linear + Linear + Linear
- View + Transpose + Contiguous + View

# Graph Optimization – INT8 Fusion Patterns

## ■ INT8 IN -> FP32 OUT

- dequant -> conv
- dequant -> linear
- dequant -> conv -> relu
- dequant -> conv -> sum
- dequant -> conv -> sum -> relu
- dequant -> linear -> relu
- dequant -> linear -> gelu
- dequant -> linear -> sigmoid
- dequant -> linear -> sum
- dequant -> bmm
- dequant -> bmm -> div

## ■ INT8 IN -> INT8 OUT

- dequant -> conv -> quant
- dequant -> linear -> quant
- dequant -> conv -> relu -> quant
- dequant -> conv -> sum -> dequant
- dequant -> conv -> sum -> relu -> quant
- dequant -> linear -> relu -> quant
- dequant -> linear -> gelu -> quant
- dequant -> linear -> sigmoid -> quant
- dequant -> linear -> sum -> quant
- dequant -> bmm -> quant
- dequant -> bmm -> div -> quant
- dequant -> max\_pool2d -> quant

# Graph Optimization – Summary

Neural network  
as DAG

Operator &  
memory  
optimization

E.g., operator  
fusion

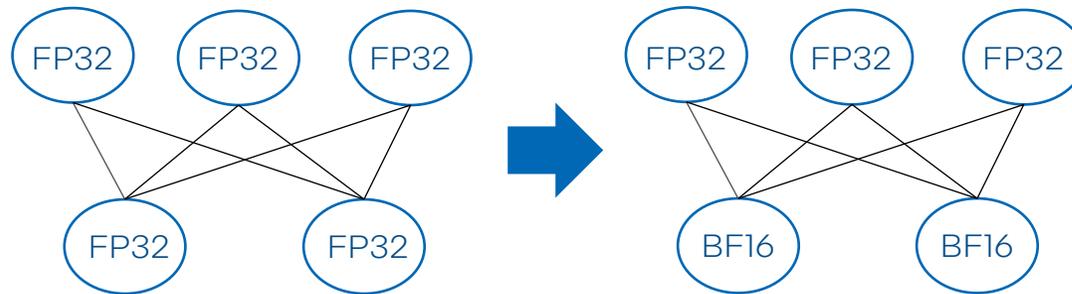
Faster inference

# Neural Network Compression Techniques

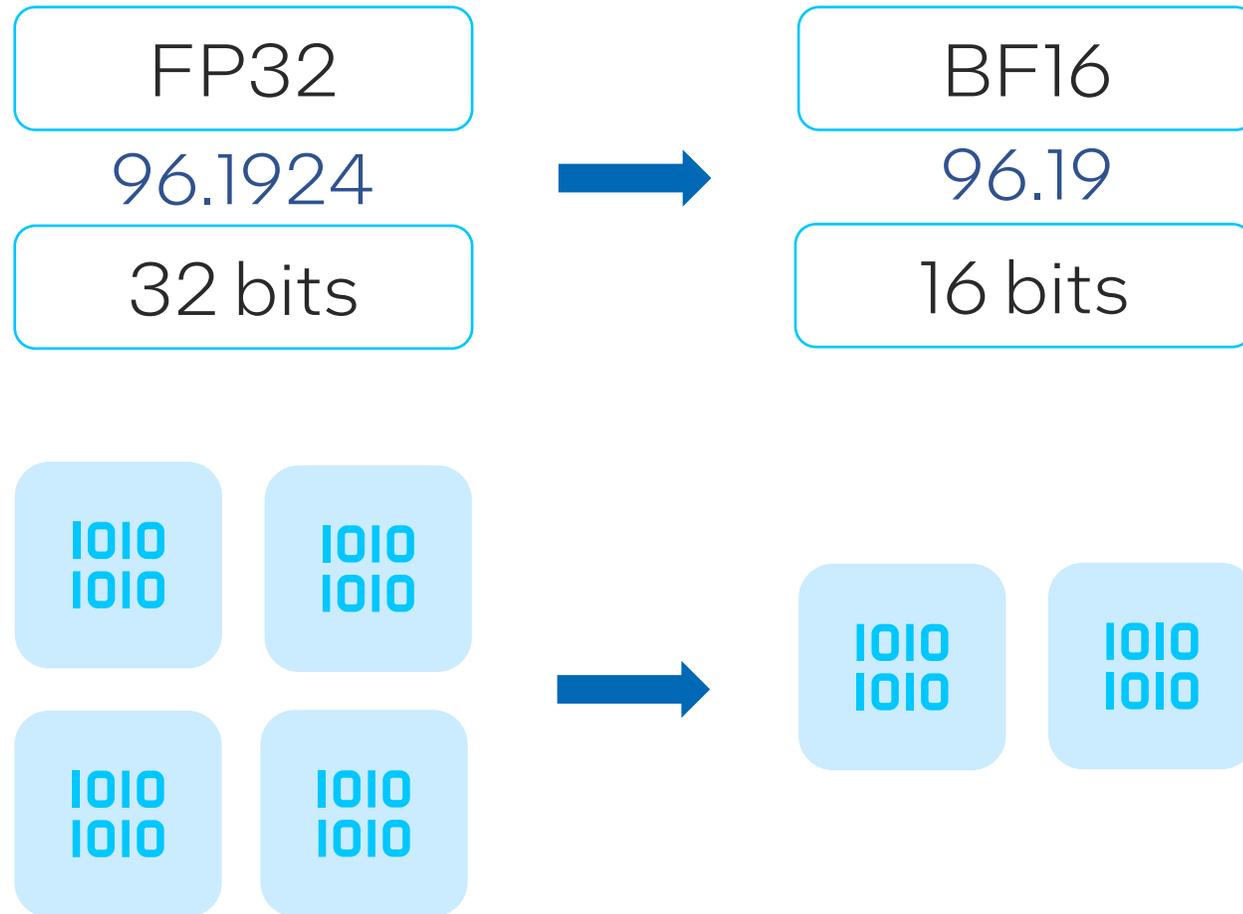
Mixed Precision

# Mixed Precision

- Combination of different numerical formats in one computational workload.
- Requires less memory.
- Allows for faster training and inference.

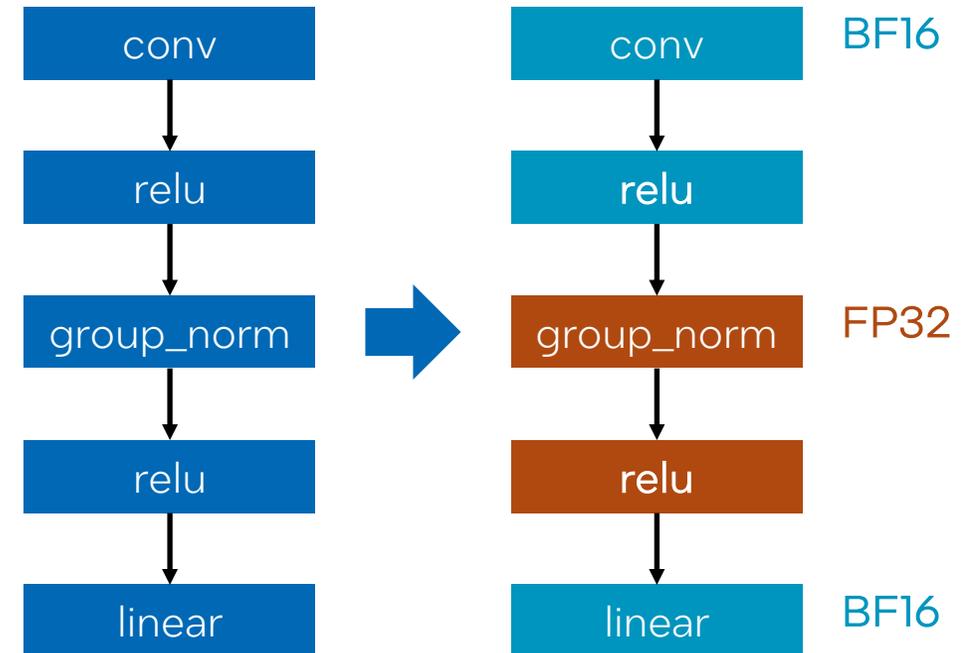


# Mixed Precision



# Auto Mixed Precision (AMP)

- 3 Categories of operators
  - **Lower precision**
    - Computation bound operators that could get performance boost with BF16.
    - E.g.: conv, linear
  - **Fallthrough**
    - Operators that runs with both FP32 and BF16 but might not get performance boost with BF16.
    - E.g.: relu, max\_pool2d
  - **FP32**
    - Operators that are not enabled with BF16 support yet. Inputs of them are casted into FP32 before execution.
    - E.g.: max\_pool3d, group\_norm



# Mixed Precision – Summary

Combination of  
precision types

Common: FP32  
& BF16

E.g., AMP

Faster training &  
inference

# Intel Neural Compressor (INC)

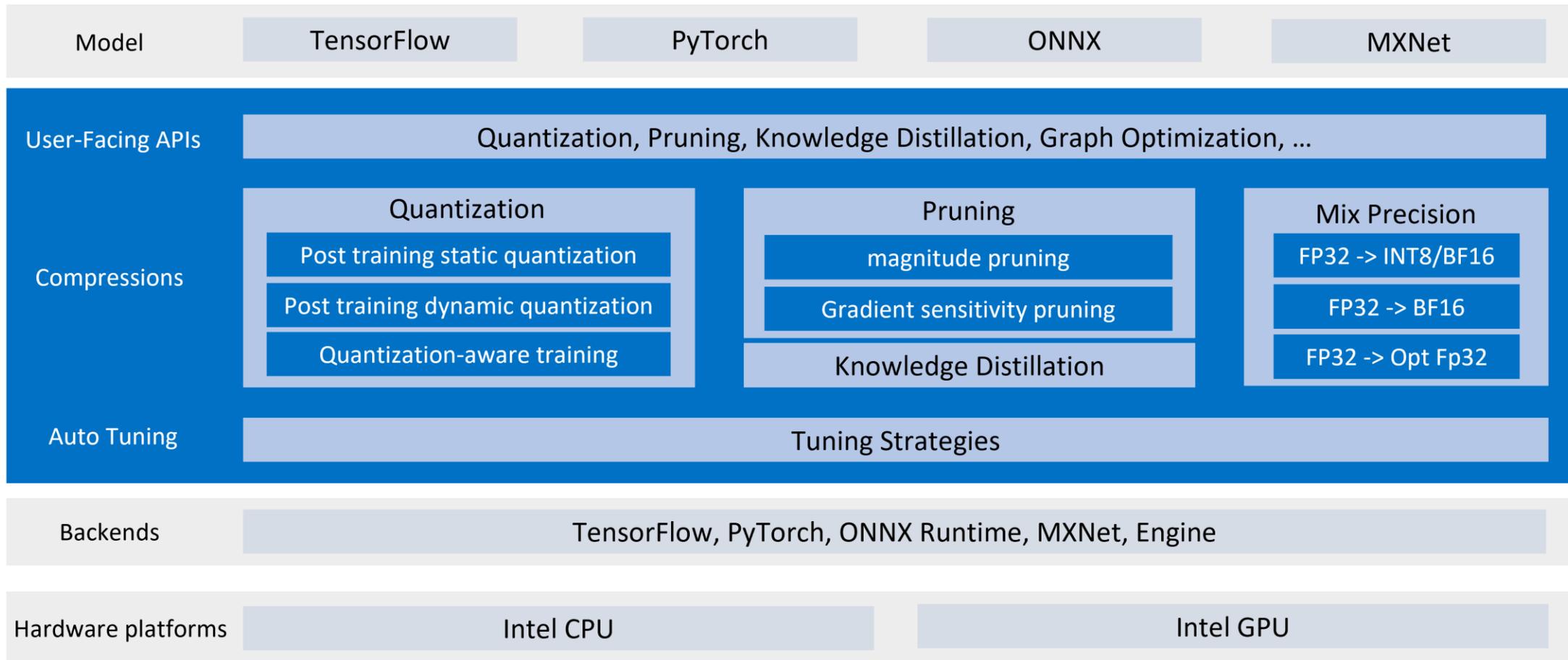
# INC: Intel Neural Compressor



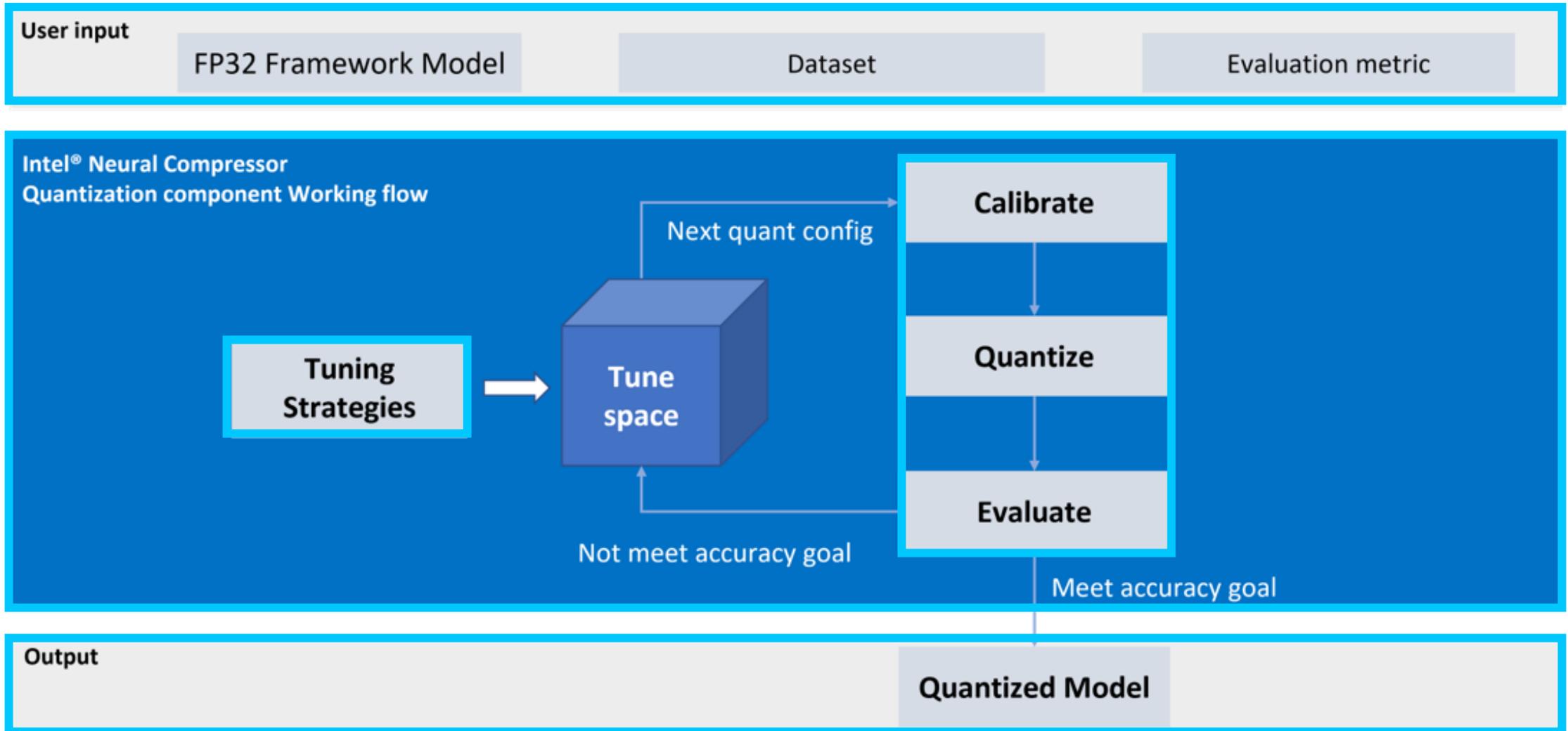
The Intel Neural Compressor, is an open-source Python library, which delivers unified interfaces across multiple deep learning frameworks for popular network optimization technologies.



It supports quantization, mixed precision, pruning, knowledge distillation, and graph optimizations, and uses accelerations by Intel Deep Learning Boost or Intel Advanced Matrix Extension in SPR.



# INC: Workflow



# Hugging Face



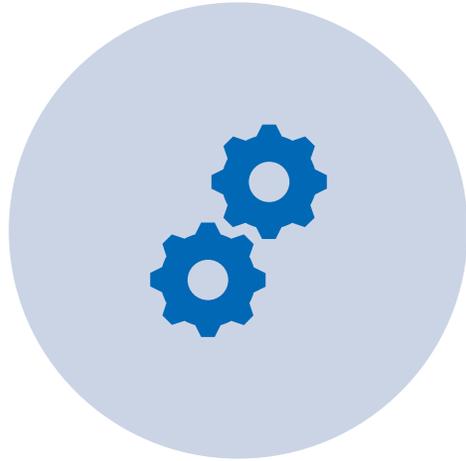
- Hugging Face  is an NLP-focused startup, which developed the popular Transformers library that exposes state-of-art transformer architectures to end-users.
- 2021 they released Optimum, a toolkit to compress Transformers, which also builds upon Intel Neural Compressor.

```
from optimum.intel.neural_compressor.quantization import IncQuantizerForSequenceClassification

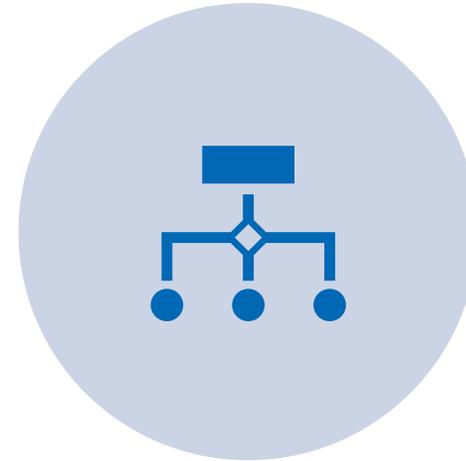
# Create quantizer from config
quantizer = IncQuantizerForSequenceClassification.from_config(
    "echarlaix/bert-base-dynamic-quant-test",
    config_name="quantization.yml",
    eval_func=eval_func,
)

# Apply dynamic quantization
model = quantizer.fit_dynamic()
```

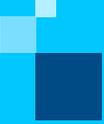
# INC: Intel Neural Compressor



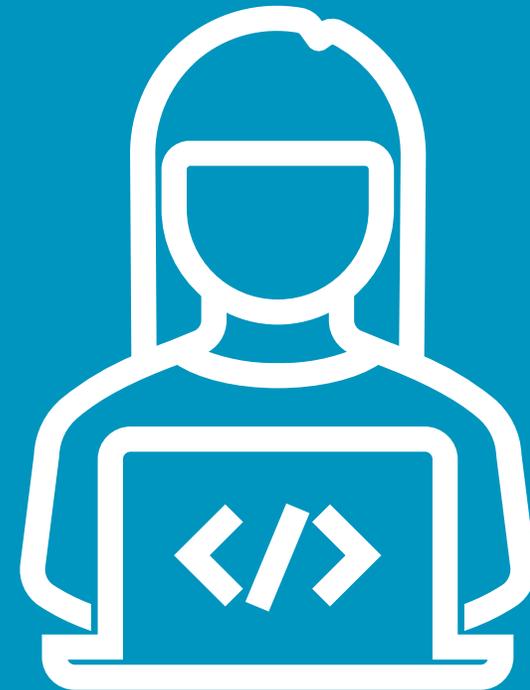
INTEL'S GENERAL PURPOSE MODEL  
OPTIMIZATION TOOLS, INCL.  
QUANTIZATION, PRUNING,  
DISTILLATION, ETC.



COVERING CV,  
RECOMMENDER, NLP, ETC.



# Demo



Thank you for your attention!

# Questions?

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