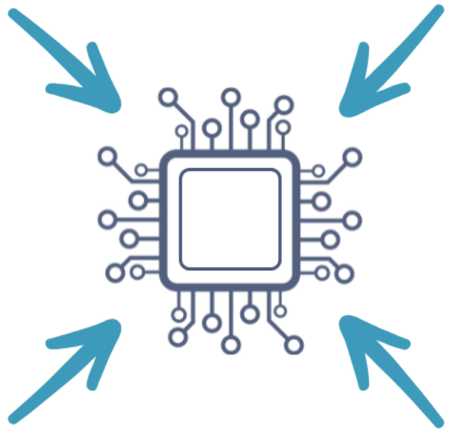
Applying dynamic quantization

SCALABLE AI MODELS WITH PYTORCH LIGHTNING

Sergiy Tkachuk
Director, GenAI Productivity

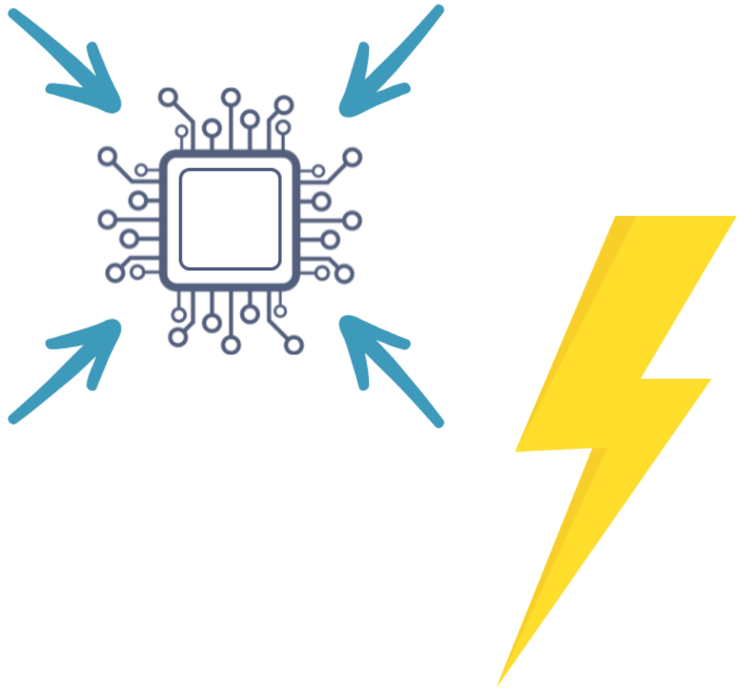
Why use quantization?

- Memory reduction



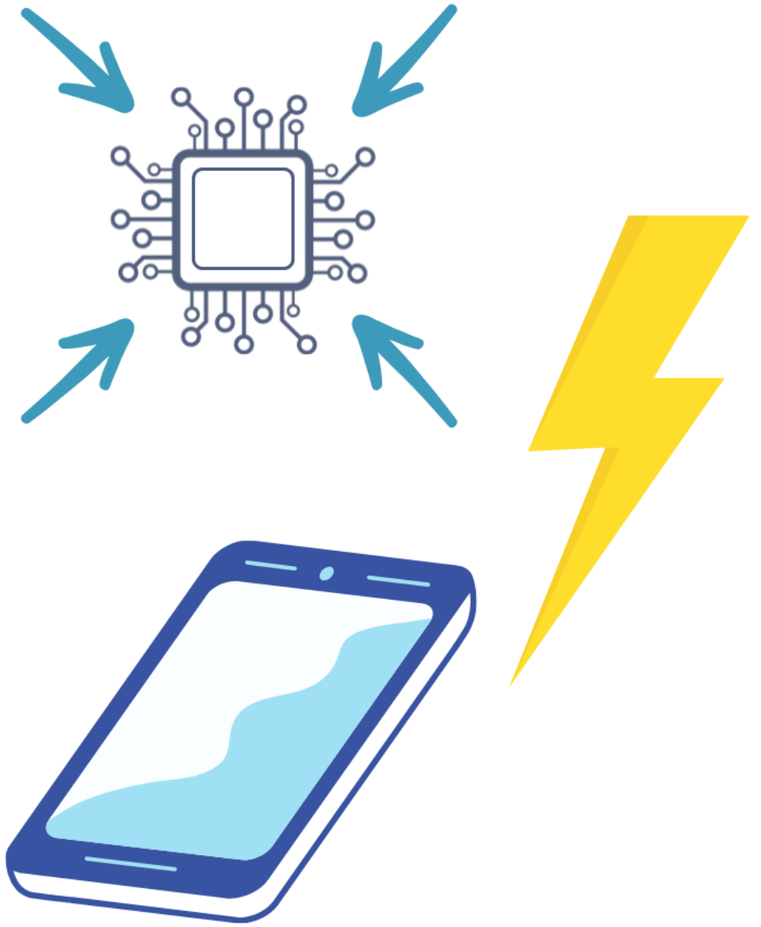
Why use quantization?

- Memory reduction
- CPU acceleration



Why use quantization?

- Memory reduction
- CPU acceleration
- Mobile inference



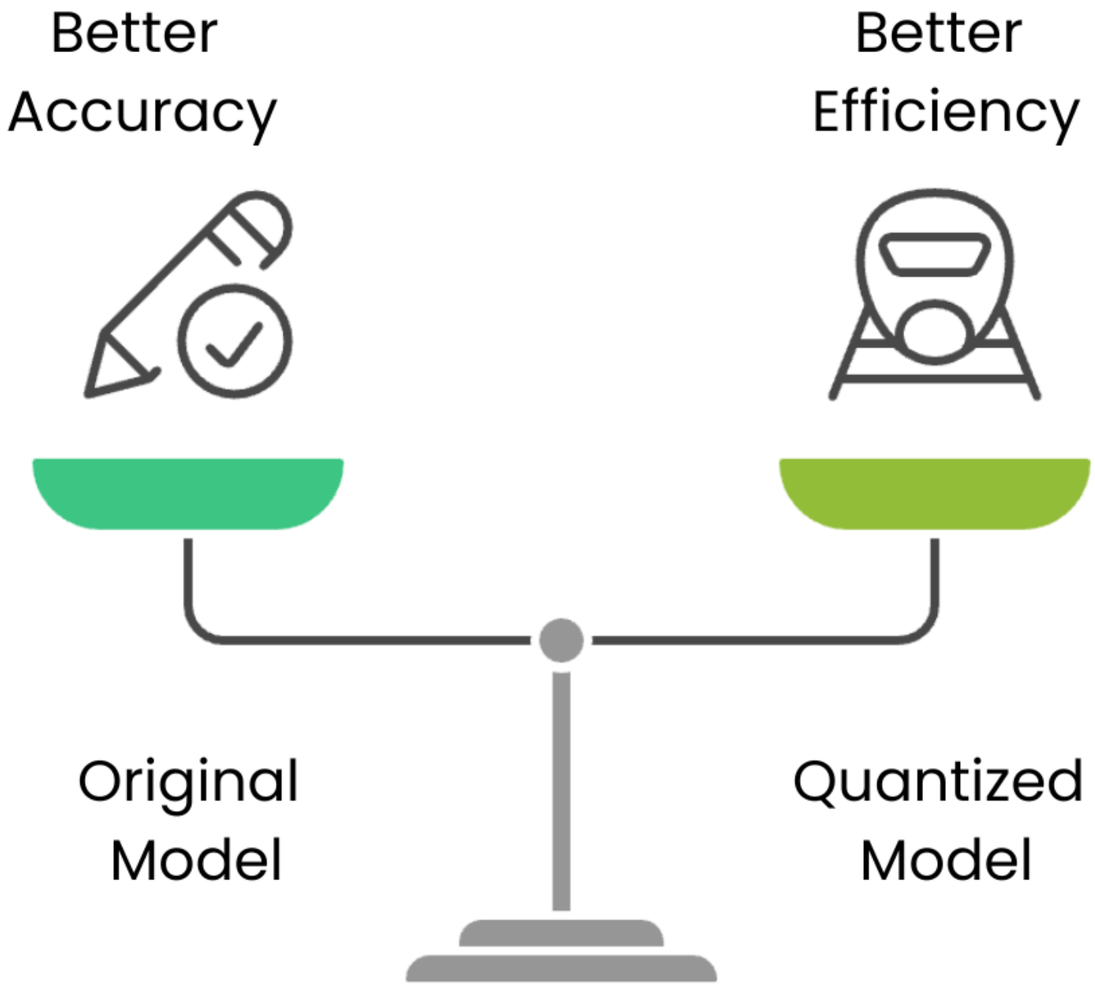
What is dynamic quantization?

- Reduce precision of weights and operations
- Improves inference speed
- Ideal for deployment on resource-constrained devices

```
import torch
from torch.quantization
import quantize_dynamic

model_quantized = quantize_dynamic(
    model,
    {torch.nn.Linear},
    dtype=torch.qint8
)
```

Evaluating quantization impact



Performance comparison

- ⚡ Compare inference speed and memory footprint
- □ Determine acceptable accuracy trade-offs
- Decide on quantization suitability based on deployment needs

Comparing performance

```
import time

def measure_time(model, data_loader):
      model.eval()  # Set model to evaluation mode
    start_time = time.time()
    for inputs in data_loader:
        _ = model(inputs)
    end_time = time.time()
    return end_time - start_time

original_time = measure_time(model, test_loader)
quant_time = measure_time(model_quant, test_loader)

print(f"Original Model Time: {original_time:.2f}s")
print(f"Quantized Model Time: {quant_time:.2f}s")
```

Let's practice!

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Implementing model pruning techniques

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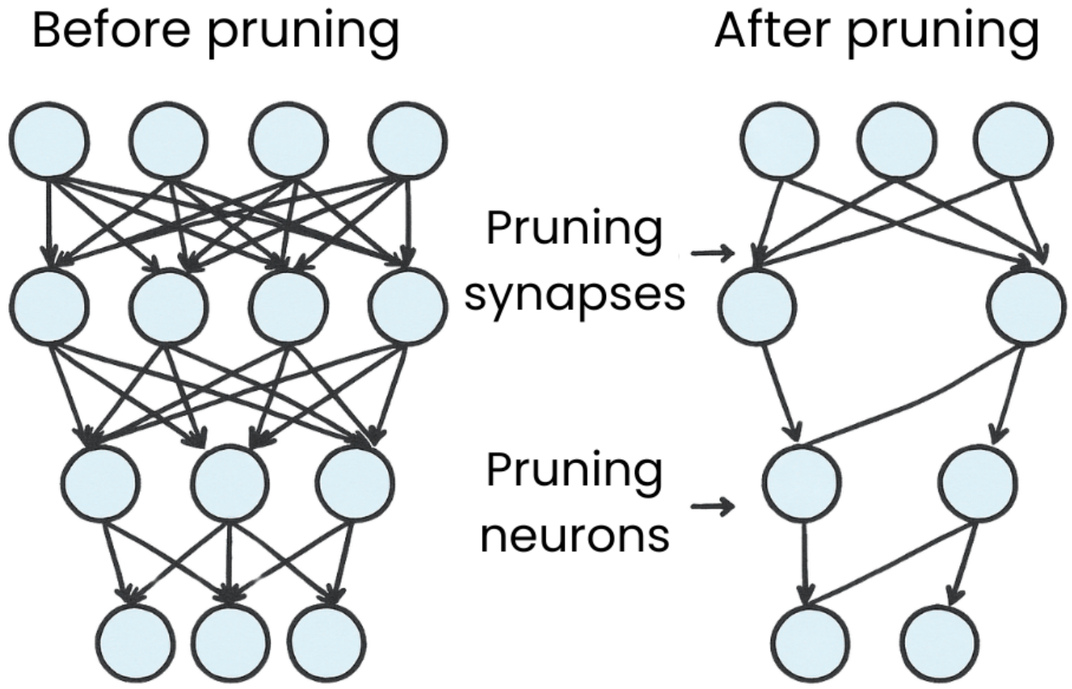
When to use pruning?

- 📱 Helpful when deploying models to edge or embedded systems
- 🔗 Can be combined with quantization for compound efficiency gains
- ⚡ Use when reducing latency or model size is a priority

What is model pruning?

- Removes less important connections in neural networks
- Leads to sparse models that are efficient to store and compute
- A common approach is L1 unstructured pruning



What is model pruning?

```
import torch.nn.utils.prune as prune

prune.l1_unstructured(model.fc, name="weight",
                      amount=0.4)

print(model.fc.weight.data)
```

```
tensor([[ 0.25, -0.13,  0.05,  0.70],
        [-0.88,  0.31, -0.02,  0.44]]) # Before pruning


tensor([[ 0.25, -0.13,  0.00,  0.70],
        [ 0.00,  0.31,  0.00,  0.44]]) # After pruning (40% weights set to 0)
```

Understanding pruning masks

- Pruning adds a binary mask to each targeted weight tensor.

- Mask = 1 --> weight kept.
- Mask = 0 --> weight set to 0 at forward time.

- Weights are still stored in memory until the mask is removed.

Making pruning permanent

- By default, pruned weights remain part of the original tensor
- To finalize pruning, remove reparametrizations
- Converts sparse layer into standard layer with zeroed weights

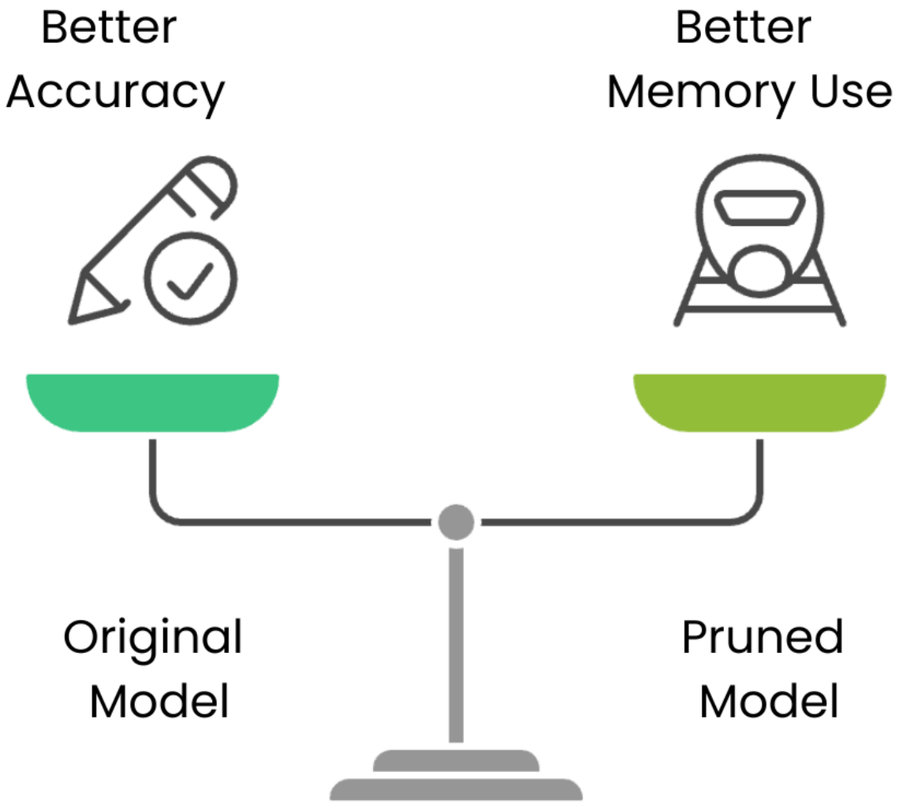
```
Sequential(
  (fc): Linear(
    in_features=128, out_features=64,
    bias=True
    (weight): PrunedParam()
  )
) # Before prune.remove
```

```
import torch.nn.utils.prune as prune

prune.remove(model.fc, 'weight')

# Print model structure
print(model)
```

```
Sequential(
  (fc): Linear(in_features=128,
               out_features=64,
               bias=True)
) # After prune.remove
```

Evaluating pruning impact

- Compare original and pruned model performance
- Expect slight drops in accuracy but major size/memory savings
- Helps assess if the trade-off is acceptable for deployment



Let's practice!

SCALABLE AI MODELS WITH PYTORCH LIGHTNING

Exporting models with TorchScript

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Sergiy Tkachuk
Director, GenAI Productivity

What is TorchScript?

- Independent of Python
- Efficient in production
- Examples:
  - Deployment on mobile devices

What is TorchScript?

- Independent of Python
- Efficient in production
- Examples:
  - Deployment on mobile devices
  - High-performance inference in production systems

Converting models to TorchScript

Two methods for conversion:

- `torch.jit.trace` : Uses example inputs to trace execution
- `torch.jit.script` : Compiles the model by analyzing Python code

When to use:

1. Use `trace` for simpler models
2. Use `script` for models with control flow (e.g., loops)

```
import torch
import torch.nn as nn
class SimpleModel(nn.Module):
    def forward(self, x):
        return x * 2
model = SimpleModel()
scripted_model = torch.jit.script(model)
```

Saving and loading TorchScript models

- Saving the model:
  - `torch.jit.save` : Save the scripted model to a file
- Loading the model:
  - `torch.jit.load` : Load the model back for inference

```
# Save the model
torch.jit.save(scripted_mod,"model.pt")

# Load the model
loaded_model=torch.jit.load("model.pt")
```

Performing inference with TorchScript

- Steps:
  - Load the TorchScript model
  - Pass inputs to the model for predictions
  - Outputs are identical to PyTorch predictions

```
# Perform inference
input_arr = [1.0, 2.0, 3.0]
input_tensor = torch.tensor(input_arr)
output = loaded_model(input_tensor)
print(output)
```

Example Input:

- Input Tensor: `[1.0, 2.0, 3.0]`

Example Output:

- Output Tensor: `[2.0, 4.0, 6.0]`

TorchScript in a nutshell

- `torch.jit.trace` : Works for static models
- `torch.jit.script` : Handles dynamic control flow
- `torch.jit.save` : Saves the scripted model
- `torch.jit.load` : Reloads for inference

Let's practice!

SCALABLE AI MODELS WITH PYTORCH LIGHTNING

Recap: Scalable AI Models with PyTorch Lightning

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Director, GenAI Productivity

Building scalable models with PyTorch Lightning

- Neural network structuring
- Effective training logic
- LightningModule implementation

```
import lightning.pytorch as pl
import torch.nn as nn

class ClassificationModel(pl.LightningModule):
    def __init__(self, input_dim,
                 hidden_dim, num_class):
          # Initialize parent class
        super().__init__()
        # First layer
        self.layer1 = nn.Linear(input_dim,
                                hidden_dim)
        # Activation function
        self.relu = nn.ReLU()
        # Output layer
        self.layer2 = nn.Linear(hidden_dim,
                                num_class)
```

Advanced techniques in PyTorch Lightning

- Data management and preprocessing
- Validation and testing methods
- Lightning callbacks optimization

```
from lightning.pytorch import Trainer
from lightning.pytorch.callbacks import EarlyStopping, ModelCheckpoint

checkpoint = ModelCheckpoint(
    monitor='val_accuracy',
    save_top_k=2,
    mode='max')
early_stopping = EarlyStopping(
    monitor='val_accuracy',
    patience=5,
    mode='max')
```

Optimizing models for scalability

- Model quantization strategies
- Model pruning for efficiency
- TorchScript for deployment

```
import torch
import torch.nn as nn

class SimpleModel(nn.Module):
    def forward(self, x):
        return x * 2

scripted_model = torch.jit.script(SimpleModel())

torch.jit.save(scripted_mod,"model.pt") # Save the model
loaded_model=torch.jit.load("model.pt") # Load the model
```

Congratulations!

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