Deployment on Constrained Devices

CS 203: Software Tools and Techniques for AI

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The "Edge" Challenge

Scenario: You trained a ResNet-50. It's 100MB.

You want to run it on a Raspberry Pi or a Mobile Phone.

Constraints:

1. **Memory**: Device has 2GB RAM, model needs 4GB.
2. **Latency**: Inference takes 5s, user needs <100ms.
3. **Power**: GPU drains battery in 20 mins.
4. **Storage**: App limit is 50MB.

Solution: Model Optimization.

Edge vs Cloud Deployment

Aspect	Cloud	Edge
Compute	Unlimited (scalable)	Limited (fixed hardware)
Latency	Network + Processing	Processing only
Privacy	Data leaves device	Data stays local

Use cases for Edge:

- Real-time (AR/VR, autonomous vehicles)
- Privacy-sensitive (medical, personal data)
- Offline scenarios (rural areas, airplanes)
- Cost at scale (millions of devices)

Hardware Constraints

Mobile devices (phones, tablets):

- CPU: ARM-based (different instruction set)
- RAM: 2-8GB
- Storage: Limited app size
- Power: Battery-constrained

IoT devices (Raspberry Pi, Arduino):

- CPU: Very limited (1-4 cores, < 2GHz)
- RAM: 512MB - 4GB
- No GPU or NPU in many cases

Edge servers (NVIDIA Jetson):

- Dedicated ML accelerators

Model Optimization Taxonomy

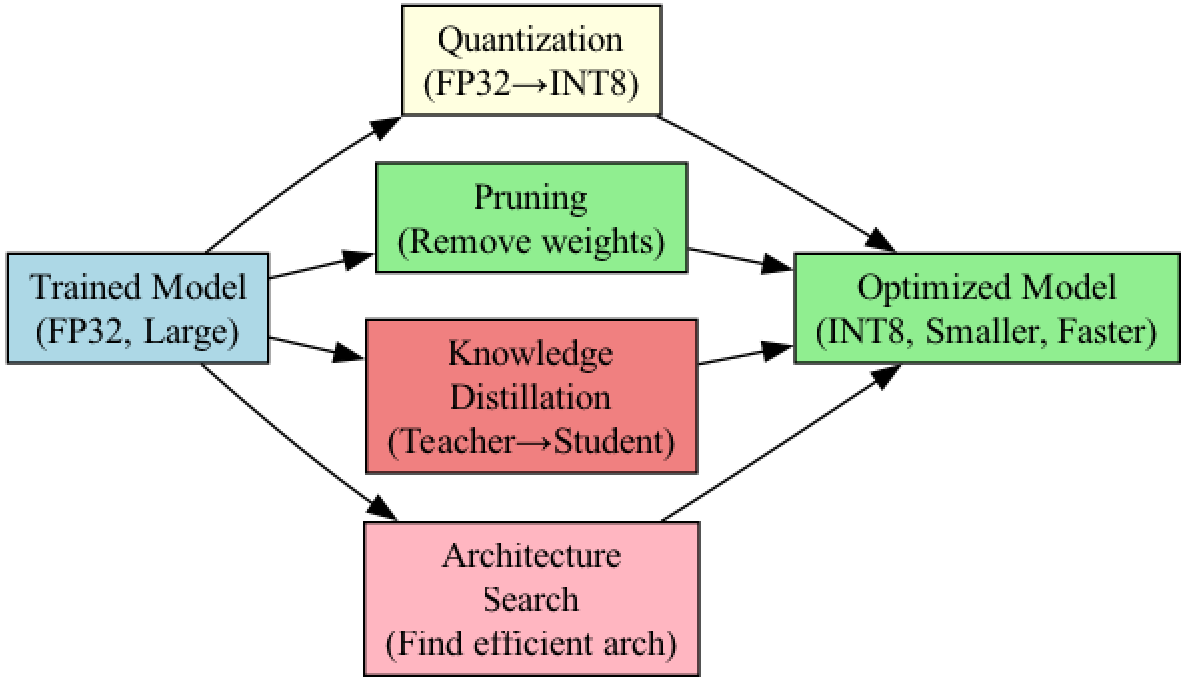
Size reduction:

1. **Quantization**: Lower precision (FP32 → INT8)
2. **Pruning**: Remove weights
3. **Knowledge Distillation**: Train smaller model
4. **Low-rank factorization**: Decompose weight matrices

Speed optimization:
5. **Operator fusion**: Merge operations
6. **Graph optimization**: Simplify computation graph
7. **Hardware acceleration**: Use specialized chips

Architecture design:
8. **Neural Architecture Search (NAS)**: Find efficient architectures
9. **Efficient architectures**: MobileNet, EfficientNet

Techniques Overview



Today's Focus:

1. **Quantization**: Lower precision math
2. **Pruning**: Removing useless connections
3. **Knowledge Distillation**: Train smaller student model
4. **ONNX**: Efficient cross-platform runtime

Optimization Techniques: Comparison

Technique	Size Reduction	Speed Improvement	Accuracy Impact	Implementation Complexity	When to U
Quantization (INT8)	4x (FP32→INT8)	2-4x faster	Minimal (<1%)	Low	Always (firs step)
Pruning (50%)	2x (half weights)	1.5-2x faster	Small (1-2%)	Medium	After quantizatio
Knowledge Distillation	Depends on student size	Significant	Can match	High	When you can retrain

Typical pipeline: Train → Prune → Quantize → Export (ONNX) → Deploy

Best bang for buck: Quantization (easy + effective)

Quantization: Theory

Standard Training: Float32 (32-bit floating point).

Quantization: Convert to Int8 (8-bit integer).

Formula:

$$Q(x) = \text{round}\left(\frac{x}{S} + Z\right)$$

- S: Scale (range / 255)
- Z: Zero-point (offset)

Impact:

- **Size**: 32 bits → 8 bits = **4x reduction**
- **Speed**: Integer math faster on CPUs (2-4x speedup)
- **Accuracy**: Minimal drop (<1%) for robust models

Quantization: Detailed Example

Float32 weights: `[-2.5, -1.0, 0.0, 1.5, 3.0]`

Quantization process:

```
# 1. Find min/max
min_val, max_val = -2.5, 3.0

# 2. Calculate scale
scale = (max_val - min_val) / 255  # 0.0216

# 3. Calculate zero-point
zero_point = -int(min_val / scale)  # 116

# 4. Quantize
quantized = round(weights / scale + zero_point)
# Result: [0, 70, 116, 185, 255]
```

Dequantize: `(quantized - zero_point) * scale`

Types of Quantization

1. **Post-Training Quantization (PTQ)**:
   - Train normal FP32 model
   - Calibrate with small dataset (~1000 samples)
   - Convert to INT8
   - **Pros**: Easy, no retraining
   - **Cons**: Slight accuracy drop

2. **Quantization-Aware Training (QAT)**:
   - Simulate quantization during training
   - Model learns to adapt to lower precision
   - **Pros**: Best accuracy
   - **Cons**: Slower training

Quantization Granularity

Per-tensor quantization:

- Single scale for entire tensor
- Faster but less accurate

Per-channel quantization:

- Separate scale per conv channel
- Better accuracy

Example:

```
import torch

# Per-tensor
model_int8 = torch.quantization.quantize_dynamic(
    model, {torch.nn.Linear}, dtype=torch.qint8
)
```

Pruning Theory

Observation: Neural networks are over-parameterized.

- Many weights near zero
- Removing them barely affects accuracy

Magnitude-based pruning:

1. Rank weights by absolute value
2. Remove smallest X% (e.g., 50%)
3. Fine-tune to recover accuracy

Structured vs Unstructured:

- **Unstructured**: Remove individual weights → sparse matrices
- **Structured**: Remove entire channels/neurons → smaller dense matrices

Pruning Strategies

One-shot pruning:

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

# Prune 30% of weights in layer
prune.l1_unstructured(module.conv1, name='weight', amount=0.3)
```

Iterative pruning (better accuracy):

1. Train to convergence
2. Prune small %
3. Fine-tune
4. Repeat

Lottery Ticket Hypothesis:

- Subnetwork exists that can train to same accuracy

Structured Pruning Example

Remove entire filters:

```
# Prune 40% of filters in conv layer
prune.ln_structured(
    module.conv1,
    name="weight",
    amount=0.4,
    n=2,       # L2 norm
    dim=0      # Filter dimension
)
```

Benefits:

- Actually reduces computation (not just params)
- No special hardware support needed
- Works well with quantization

Challenge: Harder to maintain accuracy than unstructured.

Knowledge Distillation

Idea: Compress knowledge from large "teacher" to small "student".

Process:

1. Train large teacher model (high accuracy)
2. Use teacher's soft outputs as targets
3. Train small student to mimic teacher

Loss function:

$$L = \alpha \cdot L_{CE}(y, \hat{y}) + (1 - \alpha) \cdot L_{KD}(T_{teacher}, T_{student})$$

Why it works:

- Soft targets contain more information than hard labels
- Student learns nuances from teacher

Knowledge Distillation Code

```
import torch.nn.functional as F

def distillation_loss(student_logits, teacher_logits, labels, T=3, alpha=0.5):
    # Hard loss (student vs true labels)
    hard_loss = F.cross_entropy(student_logits, labels)

    # Soft loss (student vs teacher)
    soft_student = F.log_softmax(student_logits / T, dim=1)
    soft_teacher = F.softmax(teacher_logits / T, dim=1)
    soft_loss = F.kl_div(soft_student, soft_teacher, reduction='batchmean') * T*T

    # Combined loss
    return alpha * hard_loss + (1 - alpha) * soft_loss
```

Temperature (T): Higher = softer probabilities.

Neural Architecture Search (NAS)

Goal: Automatically find efficient architectures.

Search space:

- Number of layers
- Layer types (conv, pooling, skip)
- Kernel sizes, channels

Search strategy:

1. **Random search**: Try random architectures
2. **Reinforcement learning**: RL agent proposes architectures
3. **Gradient-based**: DARTS (differentiable)

Hardware-aware NAS: Optimize for specific device constraints.

Efficient Architecture Families

MobileNet (Google):

- Depthwise separable convolutions
- 9x fewer parameters than VGG

EfficientNet (Google):

- Compound scaling (depth + width + resolution)
- State-of-art accuracy/efficiency trade-off

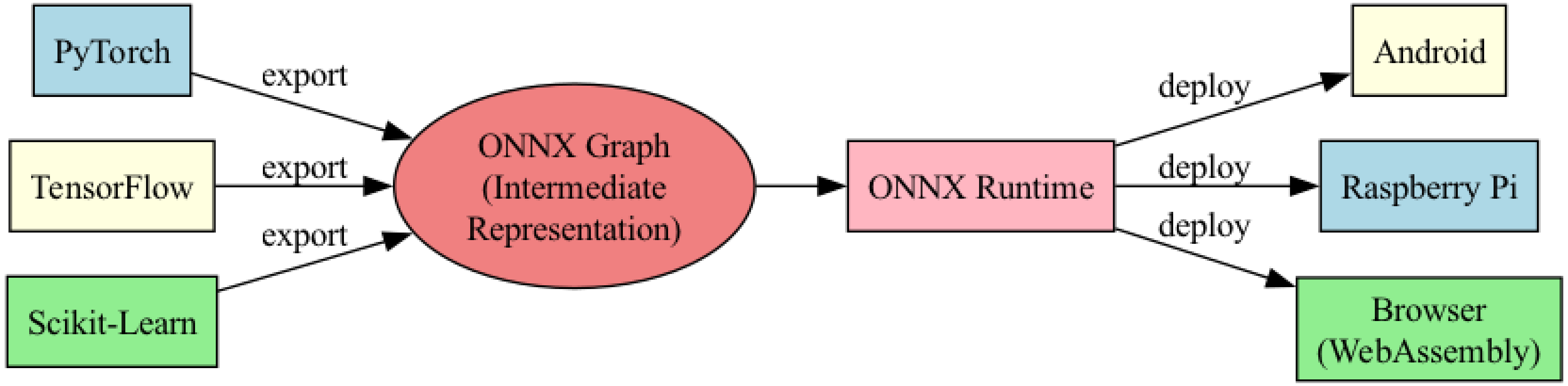
SqueezeNet:

- Fire modules (squeeze + expand)
- 50x smaller than AlexNet

TinyML architectures:

ONNX: Open Neural Network Exchange

The Universal Bridge



Why use it?

- **Interoperability**: Train in PyTorch, deploy in C++
- **Optimization**: Graph-level optimizations (fusion, constant folding)
- **Hardware support**: CPU, GPU, mobile accelerators

ONNX Export Example

```python
import torch
import torch.onnx

# Load PyTorch model
model = torch.load("model.pth")
model.eval()

# Create dummy input
dummy_input = torch.randn(1, 3, 224, 224)

# Export to ONNX
torch.onnx.export(
    model,
    dummy_input,
    "model.onnx",
    export_params=True,
    opset_version=14,
    input_names=['input'],
    output_names=['output'],
    dynamic_axes={'input': {0: 'batch_size'}}  # Variable batch size
)
```

ONNX Runtime Inference

```python
import onnxruntime as ort
import numpy as np

# Load ONNX model
session = ort.InferenceSession("model.onnx")

# Prepare input
input_data = np.random.randn(1, 3, 224, 224).astype(np.float32)

# Run inference
outputs = session.run(
    None,  # Output names (None = all outputs)
    {'input': input_data}
)

print(outputs[0])  # Prediction
```

Benefits: 2-3x faster than PyTorch on CPU.

ONNX Graph Optimizations

Operator fusion:

- Conv + BatchNorm + ReLU → Single fused op
- Reduces memory bandwidth

Constant folding:

- Pre-compute constants at export time

Dead code elimination:

- Remove unused branches

Quantization:

- ONNX Runtime supports INT8 quantization

Graph example:

Hardware Acceleration Options

Mobile (iOS/Android):

- **CoreML** (Apple): Optimized for iPhone/iPad
- **TensorFlow Lite**: Cross-platform mobile
- **ONNX Mobile**: ONNX Runtime for mobile

Edge TPU (Google Coral):

- Hardware accelerator for INT8 models
- 4 TOPS (trillion operations/sec)

NVIDIA Jetson:

- TensorRT for GPU optimization
- Mixed precision (FP16)

TensorFlow Lite Conversion

```python
import tensorflow as tf

# Convert Keras model to TFLite
converter = tf.lite.TFLiteConverter.from_keras_model(model)

# Enable optimizations
converter.optimizations = [tf.lite.Optimize.DEFAULT]

# Quantize to INT8
converter.representative_dataset = representative_data_gen
converter.target_spec.supported_ops = [tf.lite.OpsSet.TFLITE_BUILTINS_INT8]

# Convert
tflite_model = converter.convert()

# Save
with open("model.tflite", "wb") as f:
    f.write(tflite_model)
```

TensorRT (NVIDIA): Overview

High-performance inference engine for NVIDIA GPUs

Key optimizations:

- **Layer fusion**: Combine operations (Conv+BN+ReLU → single kernel)
- **Precision calibration**: Automatic FP32 → FP16 → INT8 conversion
- **Kernel auto-tuning**: Select fastest GPU kernels for your model
- **Memory optimization**: Reduce memory footprint

Performance gains:

- Typical speedup: 2-5x over PyTorch
- Latency reduction: 50-80% for large models
- Best for production deployment on NVIDIA GPUs

Use cases: Real-time inference, video processing, autonomous vehicles

TensorRT: Implementation

```python
import tensorrt as trt

# 1. Create builder and network
builder = trt.Builder(TRT_LOGGER)
network = builder.create_network()

# 2. Parse ONNX model
parser = trt.OnnxParser(network, TRT_LOGGER)
parser.parse_from_file("model.onnx")

# 3. Configure optimization
config = builder.create_builder_config()
config.set_flag(trt.BuilderFlag.FP16)  # Enable FP16

# 4. Build optimized engine
engine = builder.build_engine(network, config)
```

Next step: Save engine and load for inference

Benchmarking Models

Metrics to measure:

1. **Latency**: Time per inference (ms)
2. **Throughput**: Inferences per second
3. **Memory usage**: Peak RAM (MB)
4. **Model size**: Disk space (MB)
5. **Energy consumption**: Battery drain (mAh)

Tools:

- `torch.utils.benchmark` (PyTorch)
- `time` module (simple timing)
- `memory_profiler` (RAM usage)
- Device-specific profilers (Android Profiler, Xcode Instruments)

Latency Benchmarking Code

```
import time
import torch

model.eval()
input_data = torch.randn(1, 3, 224, 224)

# Warmup (JIT compilation, cache warming)
for _ in range(10):
    _ = model(input_data)

# Benchmark
times = []
for _ in range(100):
    start = time.time()
    with torch.no_grad():
        _ = model(input_data)
    times.append(time.time() - start)

print(f"Mean latency: {np.mean(times)*1000:.2f} ms")
print(f"Std latency: {np.std(times)*1000:.2f} ms")
print(f"P95 latency: {np.percentile(times, 95)*1000:.2f} ms")
```

Accuracy vs Efficiency Trade-off

Pareto frontier: No single "best" model.

Model	Size	Latency	Accuracy
ResNet-50	98MB	50ms	76%
+ Pruning 50%	49MB	40ms	75%
+ Quantization INT8	12MB	15ms	74%

Choose based on constraints:

- Strict latency → MobileNet quantized
- High accuracy needed → ResNet pruned
- Smallest size → MobileNet quantized

Deployment Checklist

Pre-deployment:

- [ ] Model optimized (quantized/pruned)
- [ ] Benchmarked on target device
- [ ] Accuracy validated
- [ ] Error handling implemented

Deployment:

- [ ] Model packaged (ONNX, TFLite, etc.)
- [ ] Inference code tested
- [ ] Fallback strategy (cloud API)

Post-deployment:

- [ ] Monitor latency in production

Summary

Key techniques:

1. **Quantization**: 4x smaller, 2-4x faster
2. **Pruning**: Remove redundant weights
3. **Knowledge Distillation**: Train small student model
4. **ONNX**: Universal deployment format
5. **Hardware acceleration**: TensorRT, CoreML, TFLite

Typical pipeline:

Train (FP32) → Prune → Quantize (INT8) → Export (ONNX) → Deploy

Lab: Hands-on optimization and benchmarking!

Additional Resources

Libraries:

- PyTorch quantization: https://pytorch.org/docs/stable/quantization.html
- ONNX: https://onnx.ai/
- TensorFlow Lite: https://www.tensorflow.org/lite

Papers:

- "Quantization and Training of Neural Networks for Efficient Integer-Arithmetic-Only Inference" (Google)
- "The Lottery Ticket Hypothesis" (MIT)
- "Distilling the Knowledge in a Neural Network" (Hinton et al.)

Hardware:

- NVIDIA Jetson: https://www.nvidia.com/en-us/autonomous-machines/jetson-store/