Dynamic Sparse Training (DST)

A Decade of Sparse Training: Why Do We Still Stick to Dense Training?

AAAI 2026 Tutorial

The Paradox

The Problem

- Neural networks are **over-parameterized**
- Most weights are redundant or unnecessary
- Can we train with **95% fewer parameters**?

The Paradox

- DST is algorithmically mature
- Can perform on par with dense training
- **But most implementations remain dense!**

Why? Let's find out...

What is Sparse Training?

Dense Network:

- All weights active
- 1.3M parameters
- Full memory usage

Sparse Network (95%):

- Only 5% weights active
- $\sim$65K parameters
- 95% memory reduction

95% Sparsity

Dense	Sparse
1.3M	65K
100%	5%

The Promise

Drastic 95% parameter reduction! Can we achieve this with minimal performance loss?

Simulated vs Truly Sparse

Simulated Sparsity (Dense+Mask)

- Binary mask over dense weights
- Still stores ALL weights
- Still computes with dense ops
- Easy to implement
- No memory savings

Truly Sparse (CSR)

- Sparse matrix formats (CSR/COO)
- Stores only non-zeros
- Custom sparse kernels
- Complex to implement
- Real memory savings

Key Insight

Most research uses **simulated sparsity** - convenient but doesn't deliver true efficiency!

Network Architecture

Simple CNN for MNIST

- **Conv Layers:** 2 conv layers (16, 32 channels)
- **FC Layers:** 4 fully connected layers
- **Total:** 1.3M parameters
- **Dataset:** MNIST (60K train, 10K test)

Masked Implementation

- `MaskedConv2d` - masked convolutional layers
- `MaskedLinear` - masked fully connected layers
- Binary mask: $1 =$ active, $0 =$ pruned
- Mask applied during forward pass

Dynamic Sparse Training (DST)

Core Algorithm

Prune-and-Regrow Strategy:

1. **Prune:** Remove small-magnitude weights
2. **Regrow:** Add random new connections
3. **Maintain:** Constant sparsity level

Magnitude Pruning:

- Remove weights with smallest $|w|$
- Intuition: Small weights contribute less

Applied every 2 epochs during training

Random Regrowth:

- Explore new connectivity
- Reinitialize to small random values
- Alternative: Gradient-based (RigL)

Training Results

MNIST Classification (10 epochs, 95% sparsity)

	Dense	Dense+Mask
Test Accuracy	98.98%	96.71%
Test Loss	0.0449	0.0992
Parameters	1.3M	65K (95% sparse)
Performance Gap		**-2.27%**

Remarkable Results!

- **Drastic 95% parameter reduction** (1.3M $\rightarrow$ 65K)
- **Only 2.27% accuracy drop** - metrics barely affected!
- Achieves **96.71% accuracy** with just 5% of weights
- DST maintains sparsity while dynamically exploring connectivity

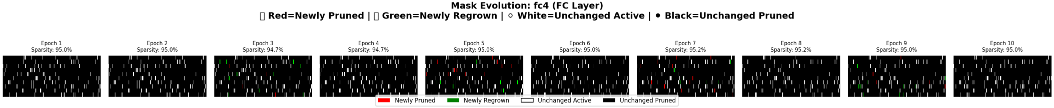
Mask Evolution During Training

Sparsity Maintained

- Initial: 95% sparsity (random)
- After DST: ∼95% sparsity maintained
- Topology changes dynamically

Visualization (Last Layer)

Red: Newly pruned **Green:** Newly regrown **White:** Unchanged active **Black:** Unchanged pruned



FC4 Layer: Deletion and regrowth over epochs

Benchmarking: Simulated vs Truly Sparse

Inference Time Comparison (100 samples, 10 runs)

Method	Time (ms)
Dense+Mask (GPU)	0.68
Dense+Mask (CPU)	25.03
Truly Sparse CSR (CPU)	1351.50
Truly Sparse CSR (GPU)	1.04
GPU Comparison	**Dense+Mask 1.53x faster**

Critical Finding

- **Trade-off:** Slight slowdown in inference (1.53x)
- **But:** Drastic 95% parameter reduction
- Truly sparse requires specialized implementations

Why Do We Still Stick to Dense Training?

The Barriers

1. **Simulated Sparsity**
   - Convenient but no real-world savings
   - Still uses dense operations
2. **Truly Sparse Implementation**
   - Requires sparse formats (CSR/COO)
   - Needs custom kernels
   - Significant engineering effort
3. **System-Level Barriers**
   - Hardware optimized for dense ops
   - Frameworks favor dense operations
   - Sparse overhead for low sparsity

Key Takeaways

What We Learned

1. **Sparse training works!** Drastic 95% parameter reduction with only 2.27% accuracy drop
2. **DST adapts topology** dynamically during training (prune + regrow)
3. **Simulated vs Truly Sparse:** Big difference in real-world efficiency
4. **The paradox:** Algorithm works brilliantly, but implementation remains challenging

The Promise

- **95% parameter reduction** - from 1.3M to just 65K!
- **Metrics barely affected** - only 2.27% accuracy loss
- Significant memory and energy savings

Next Steps: Hardware-software co-design for sparse training

Conclusion

Dynamic Sparse Training:

- Algorithmically mature
- **Drastic 95% parameter reduction**
- **Metrics barely affected** (only 2.27% drop)
- Performs on par with dense

But implementation remains challenging

The gap between research and practice
needs hardware-software co-design