CS336 Language Modeling from Scratch

Lecture 7: Multi-Machine Parallelism for Large Language Models

Stanford University, Spring 2025

Abstract

This lecture covers multi-machine parallelism strategies for training large language models that exceed single-GPU capacity. Key topics include collective communication primitives (AllReduce, AllGather, ReduceScatter), data parallelism with ZeRO optimization stages, model parallelism (pipeline and tensor parallel), memory management strategies, and real-world implementation patterns used in modern LLM training. The lecture provides essential foundations for scaling language model training across multiple machines and understanding the trade-offs between different parallelization approaches.

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1 Introduction and Course Context

1.1 Lecture Overview

This lecture transitions from single-GPU optimization to distributed training across multiple machines, addressing the fundamental challenge that modern language models exceed the capacity of individual GPUs.

Key Point: Training Scale Reality

Large language models require exascale compute resources only available through multi-machine parallelism. Single GPUs are insufficient for training state-of-the-art models.

Learning Objectives:

1. Understand collective communication primitives
2. Master data parallelism and ZeRO optimization techniques
3. Analyze model parallelism strategies (pipeline and tensor)
4. Apply parallelism selection guidelines for real-world training

1.2 The Scaling Challenge

Modern language models face two fundamental bottlenecks:

Definition: Compute Scaling Challenge

While GPU FLOPS continue growing exponentially, training the largest models requires exascale compute resources only available in supercomputers with thousands of GPUs.

Definition: Memory Scaling Challenge

Models with billions of parameters cannot fit in single GPU memory (even 80GB H100s), requiring sophisticated memory distribution strategies.

[Insert diagram showing model size growth vs GPU memory capacity over time]

1.3 Hardware Architecture Foundation

Understanding GPU cluster topology is crucial for parallelization strategy selection:

Communication Hierarchy:

- **Intra-node NVLink**: 900 GB/s between 8 GPUs within single machine
- **Inter-node InfiniBand**: 100 GB/s across machines (8× slower)
- **Network Limits**: Fast all-to-all communication up to 256 GPUs

Warning: Hardware Implications

The 8× speed difference between intra-node and inter-node communication fundamentally shapes optimal parallelization strategies.

2 Collective Communication Primitives

2.1 Communication Fundamentals

Collective communication operations are the building blocks of all parallelization algorithms. Understanding their costs and relationships is essential for performance analysis.

Definition: AllReduce Operation

Performs a reduction (e.g., sum) across all participating devices and broadcasts the result to all devices. Communication cost: $2N$ where N is the data size.

Definition: Broadcast Operation

Copies data from one device to all other devices. Communication cost: N.

Definition: AllGather Operation

Each device contributes a portion of data, and all portions are gathered and replicated across all devices.

Definition: ReduceScatter Operation

Performs a reduction and distributes different parts of the result to different devices.

2.2 Critical Performance Identity

Key Point: AllReduce Decomposition Theorem

In bandwidth-limited regimes, AllReduce can be equivalently implemented as ReduceScatter followed by AllGather with identical communication cost.

Mathematical Relationship:

$$\text{AllReduce}(x) \equiv \text{AllGather}(\text{ReduceScatter}(x)) \tag{1}$$

This equivalence is fundamental to understanding ZeRO optimization strategies and enables "free" memory optimizations.

2.3 Hardware-Specific Considerations

GPU vs TPU Networking:

Performance: GPU Networking

- All-to-all connectivity up to 256 GPUs
- Hierarchical network beyond this scale
- Optimized for general-purpose parallel computing

Performance: TPU Networking

- Toroidal mesh topology
- Neighbor-to-neighbor communication only
- Specifically optimized for collective communications
- Can efficiently implement collective ops on mesh topology

3 Data Parallelism: From Naive to ZeRO

3.1 Naive Data Parallelism

Data parallelism is the most intuitive parallelization strategy, but naive implementations have severe memory limitations.

Definition: Data Parallelism Strategy

Model parameters are replicated across all devices, while the training batch is split among devices. Each device processes a subset of the batch.

Mathematical Formulation: For batch SGD with batch size B across M machines:

$$\theta_{t+1} = \theta_t - \eta \frac{1}{B} \sum_{i=1}^{B} \nabla_\theta \ell(\theta_t, x_i, y_i) \tag{2}$$

Performance: Naive Data Parallelism Analysis

Strengths:

- Excellent compute scaling: each GPU processes B/M examples
- Simple implementation and debugging
- No architectural dependencies

Critical Weakness:

- Poor memory scaling: all parameters replicated on each device
- Communication overhead: $2P$ per batch (where P = parameters)

3.2 The Memory Crisis

Understanding memory usage breakdown reveals why naive data parallelism fails for large models:

Warning: Memory Scaling Problem

A 7.5B parameter model requires 120GB total memory with naive data parallelism - exceeding single GPU capacity and scaling linearly with GPU count!

Component	Bytes per Parameter	Purpose
Model parameters (BF16)	2	Forward pass weights
Gradients (BF16)	2	Backward pass derivatives
Master weights (FP32)	4	High precision for updates
Adam first moments	4	Historical gradient means
Adam second moments	4	Historical gradient variances
Total	**16**	**8× memory overhead!**

Table 1: Memory requirements per parameter in naive data parallelism

3.3 ZeRO Stage 1: Optimizer State Sharding

The first ZeRO optimization addresses the largest memory consumer: optimizer states.

Definition: ZeRO Stage 1

Shard optimizer states (Adam moments) across devices while maintaining replicated parameters and gradients.

Algorithm: ZeRO Stage 1 Execution

1. Each GPU computes gradients for its batch slice
2. ReduceScatter gradients to responsible GPUs
3. Each GPU updates its parameter shard using local optimizer state
4. AllGather updated parameters back to all GPUs

Key Point: ZeRO Stage 1 Magic

Uses ReduceScatter + AllGather = AllReduce equivalence, providing memory savings with **zero additional communication cost**.

Memory Savings Example:

- **Naive approach**: 120GB total memory
- **ZeRO Stage 1**: 31.4GB total memory (74% reduction!)

3.4 ZeRO Stage 2: Gradient Sharding

Definition: ZeRO Stage 2

Extends Stage 1 by also sharding gradients across devices, requiring incremental communication during backward pass.

Algorithm: ZeRO Stage 2 Modifications

1. During backward pass, immediately reduce gradients for each layer to responsible GPU
2. Free local gradient memory after reduction
3. Maintain bounded memory usage throughout training
4. Same total communication cost as naive approach

Performance: ZeRO Stage 2 Characteristics

Memory Savings: Additional gradient sharding (31.4GB $\rightarrow$ 16.6GB)
Communication: Same bandwidth as naive ($2P$) but with incremental overhead
Complexity: Medium - requires layer-by-layer synchronization

3.5 ZeRO Stage 3: Full Sharding (FSDP)

Definition: ZeRO Stage 3 / FSDP

Full parameter, gradient, and optimizer state sharding with on-demand parameter communication. FSDP (Fully Sharded Data Parallel) is exactly ZeRO Stage 3.

Algorithm: ZeRO Stage 3 Execution

1. AllGather parameters for current layer
2. Perform forward computation
3. Free parameters immediately after use
4. Repeat for backward pass with ReduceScatter for gradient updates
5. Maximum memory savings: everything divided by GPU count

Memory Transformation:

- **Naive approach**: 120GB total memory
- **ZeRO Stage 3**: 1.9GB total memory (98.4% reduction!)

3.6 FSDP Communication-Computation Overlap

The key to FSDP efficiency is sophisticated prefetching and overlap strategies:
[Insert detailed timeline diagram showing overlapped AllGather, Forward, and Free operations]

Key Point: FSDP Efficiency Secret

Prefetch parameters for next layer while computing current layer, minimizing communication bubbles through careful scheduling.

Code: FSDP Timeline Example

```
Forward Timeline:
AllGather W0 -> Forward W0 (start AllGather W1) ->
Forward W1 (start AllGather W2) -> Forward W2 -> ...

Backward Timeline:
AllGather W2 -> Backward W2 -> ReduceScatter gradients ->
Free W2 -> AllGather W1 -> ...
```

ZeRO Stage	Communication Cost	Memory Scaling	Implementation Complexity
Stage 1	$2P$ (same as naive)	Optimizer only	Low
Stage 2	$2P$	Gradients + Optimizer	Medium
Stage 3 (FSDP)	$3P$	Full scaling	High

Table 2: ZeRO stages comprehensive comparison

4 Model Parallelism Strategies

4.1 Moving Beyond Data Parallelism

Data parallelism limitations motivate model parallelism: splitting the model itself across devices rather than just the data.

Key Point: Model Parallelism Philosophy

Instead of replicating parameters and communicating them, permanently distribute parameters across devices and communicate activations instead.

Key Advantages:

- Can train models larger than single GPU memory
- Alternative scaling axis when batch sizes are limited
- Sometimes activations are much smaller than parameters

4.2 Pipeline Parallelism: Layer-wise Splitting

Definition: Pipeline Parallelism

Model parallelism strategy that partitions the model along layer boundaries, with different devices responsible for different consecutive layers.

Performance: Pipeline Parallelism Analysis

Intuitive Appeal: Natural layer boundaries make splitting conceptually simple
Critical Problem: Severe GPU underutilization due to sequential dependencies

Naive Pipeline Problems:
[Insert diagram showing GPU utilization timeline with large idle bubbles]

- GPUs active only $1/N$ of the time (where N = number of pipeline stages)
- Sequential dependency creates massive "bubble" periods of idle time
- Adding 4 GPUs gives throughput of 1 GPU - worst possible scaling!

4.3 Microbatching: Pipeline Optimization

Algorithm: Microbatching Strategy

1. Split batch into smaller microbatches
2. Pipeline microbatches through stages
3. Overlap computation and communication
4. Reduce bubble size through parallelism

Bubble Ratio Formula:

$$\text{Bubble Ratio} = \frac{\text{Number of Pipeline Stages} - 1}{\text{Number of Microbatches}} \tag{3}$$

Key Point: Batch Size Trade-off

Larger batch sizes reduce pipeline bubbles but consume the finite batch size resource that could be used for data parallelism.

4.4 Advanced Pipeline: Zero Bubble Optimization

Algorithm: Zero Bubble Pipeline (Dual Pipe)

Key Insight: Separate gradient computation into two independent parts:

1. **B operations**: Activation gradients (serially dependent)
2. **W operations**: Weight gradients (can be rescheduled)

Strategy: Fill bubble periods with weight gradient computations

[Insert diagram showing 1F-1B schedule with separated B and W operations]

Warning: Pipeline Implementation Complexity

Pipeline parallelism is "horrendously complicated" to implement correctly. Many frontier labs have only 1-2 people who understand their pipeline implementation.

4.5 Tensor Parallelism: Operation-wise Splitting

Definition: Tensor Parallelism

Model parallelism strategy that partitions individual operations (typically matrix multiplications) across devices rather than entire layers.

Core Concept: Since most computation is matrix multiplication, parallelize the matrix operations themselves.

Key Point: Matrix Decomposition Principle

Split large matrix multiplication $Y = XA$ as:

$$Y = X[A_1|A_2] = [XA_1|XA_2]$$

Each GPU computes a portion, then results are combined.

4.6 Tensor Parallel Implementation Details

MLP Tensor Parallelism Example:

For MLP computation $Z = \text{dropout}(\text{GeLU}(XA)B)$:

Algorithm: Column-wise Tensor Parallelism

1. Split first matrix A column-wise: $A = [A_1|A_2]$
2. Each GPU computes: $Y_i = \text{GeLU}(XA_i)$
3. Split second matrix B row-wise: $B = [B_1; B_2]$
4. Each GPU computes: $Z_i = Y_i B_i$ locally
5. AllReduce to sum results: $Z = Z_1 + Z_2$

Communication Pattern:

- **Forward pass**: AllReduce after second matrix multiplication
- **Backward pass**: AllReduce for input gradients
- **Total**: 2 AllReduce operations per layer

4.7 Tensor Parallelism Performance Characteristics

Performance: Tensor Parallelism Trade-offs

Advantages:

- No pipeline bubbles or batch size consumption
- Relatively simple implementation
- Linear memory scaling

Critical Limitation:

- Very high bandwidth requirements
- Performance degrades rapidly beyond single node

Empirical Performance Data:

- **8 GPUs (single node)**: 10-12% overhead - acceptable
- **16 GPUs (cross-node)**: 42% performance loss - problematic
- **32 GPUs**: 65% performance loss - unusable

Key Point: Tensor Parallelism Rule

Apply tensor parallelism only within single nodes (typically 8 GPUs) where high-speed NVLink connections are available.

4.8 Pipeline vs Tensor Parallelism Comparison

Aspect	Pipeline Parallel	Tensor Parallel
Communication	Point-to-point activations	AllReduce per layer
Bandwidth Requirement	Low	Very High
Batch Size Impact	High consumption	No impact
Memory Scaling	Linear	Linear
Implementation Complexity	Very High	Low
Utilization Efficiency	Bubble problems	Excellent
Optimal Use Case	Slow network links	Fast intra-node links

Table 3: Model parallelism strategy comparison

5 Advanced Parallelism and Resource Management

5.1 Batch Size as a Limited Resource

Key Point: Batch Size Resource Principle

Batch size is a finite, precious resource that must be allocated wisely across different parallelism strategies, with diminishing returns beyond critical thresholds.

Critical Batch Size Concept:

- Below critical batch size: high gradient noise, valuable to increase
- Above critical batch size: diminishing returns from variance reduction
- Optimization becomes limited by gradient steps rather than noise

Warning: Parallelism Resource Conflicts

Data parallelism and pipeline parallelism both consume batch size. Must choose allocation carefully based on model size and hardware constraints.

5.2 Context/Sequence Parallelism

Definition: Context Parallelism (Ring Attention)

Parallelization strategy for handling very long sequences by distributing attention computation across devices in a ring pattern.

Implementation Concept:

- Each device handles different query positions
- Keys and values circulate between devices in ring fashion

- Enables training on sequences longer than single device memory
- Builds on Flash Attention tiling principles

5.3 Expert Parallelism for MoE Models

Definition: Expert Parallelism

Parallelization strategy for Mixture-of-Experts models where different experts are placed on different devices with sparse activation patterns.

Key Characteristics:

- Similar to tensor parallelism but with sparse routing
- Requires sophisticated load balancing
- Communication patterns less predictable than dense operations

5.4 Activation Memory Management

Warning: Activation Memory Scaling Problem

Unlike parameters and gradients, activation memory often cannot be fully parallelized and continues to grow with model size and sequence length.

Why Activations Don't Scale:

- Some activations (attention outputs) resist sharding
- Memory grows with both model depth and sequence length
- Becomes the limiting factor for very large models

Algorithm: Activation Checkpointing Strategy

Trade compute for memory:

1. Store only subset of activations during forward pass
2. Recompute intermediate activations during backward pass
3. Reduce memory usage at cost of additional computation
4. Enable larger effective batch sizes (helps other parallelism)

6 3D Parallelism: Combining Strategies

6.1 The Multi-Dimensional Approach

Modern large-scale training combines multiple parallelism dimensions simultaneously for optimal resource utilization.

Key Point: 3D Parallelism Formula

Combine Tensor Parallelism + Pipeline Parallelism + Data Parallelism to leverage the strengths of each approach while mitigating individual weaknesses.

Dimensional Allocation Strategy:

1. **Tensor Parallelism**: Within nodes (8 GPUs max)
2. **Pipeline Parallelism**: Across nodes when models don't fit
3. **Data Parallelism**: Remaining GPUs for batch processing

6.2 Parallelism Selection Guidelines

Algorithm: Practical Parallelism Decision Framework

1. **Model Memory Check**: Does model fit in memory?
   - If yes → Use data parallelism
   - If no → Continue to step 2
2. **Within Node Scaling**: Use tensor parallelism up to 8 GPUs
   - High bandwidth NVLink connections
   - Minimal performance overhead
3. **Cross Node Scaling**: Choose between FSDP and Pipeline
   - High bandwidth → Consider pipeline parallelism
   - Limited bandwidth → Prefer FSDP/ZeRO-3
   - Implementation complexity → Strongly favor FSDP
4. **Remaining Resources**: Scale with data parallelism
   - Works well on slower network links
   - Simple implementation and debugging

6.3 Performance Trade-off Analysis

The choice of parallelism strategy depends critically on the ratio of communication to computation:

$$\text{Efficiency} = \frac{\text{Computation Time}}{\text{Computation Time} + \text{Communication Time}} \tag{4}$$

[Insert performance diagram showing communication vs computation regimes]

Strategy	Bandwidth Requirement	Batch Size Impact	Implementation Complexity
Data Parallel	Low	High consumption	Low
FSDP (ZeRO-3)	Medium	Medium consumption	Medium
Pipeline Parallel	Low	High consumption	Very High
Tensor Parallel	Very High	No impact	Low

Table 4: Comprehensive parallelism strategy characteristics

6.4 Gradient Accumulation Optimization

Key Point: Trading Batch Size for Communication Efficiency

When batch size budget is not fully consumed, use gradient accumulation to reduce communication frequency and improve efficiency.

Algorithm: Gradient Accumulation Strategy

1. Accumulate gradients over multiple microbatches locally
2. Synchronize gradients less frequently across devices
3. Trade batch size resource for reduced communication overhead
4. Particularly effective with small batch sizes

7 Real-World Case Studies and Implementation

7.1 Megatron-LM: Scaling to 1 Trillion Parameters

The Megatron-LM paper provides comprehensive empirical evidence for parallelization strategies across model scales.

Performance: Megatron-LM Results

Scale Range: 1.7B to 1T parameter models
Consistent Efficiency: 40-52% of theoretical peak FLOPS across all scales
Parallelization Patterns:

- Tensor parallel starts at 1, scales to 8, then caps
- Pipeline parallel increases with model size
- Data parallel fills remaining resources

Model Size	Tensor Parallel	Pipeline Parallel	Data Parallel	Efficiency
1.7B	1	1	Large	40-52%
22B	8	1	Medium	40-52%
175B	8	8	Small	40-52%
1T	8	64	Minimal	40-52%

Table 5: Megatron-LM parallelization strategy evolution

7.2 Modern LLM Training Examples

Recent Implementation Patterns:

Code: Real-World Parallelization Strategies

```
OLMo (7B parameters):
- Strategy: FSDP only (model fits comfortably)
- Reasoning: Simple, effective for moderate scale

DeepSeek V2/V3:
- Strategy: ZeRO-1 + Tensor + Pipeline parallel
- Reasoning: Massive scale requires all dimensions

Yi Models:
- Strategy: ZeRO-1 + Tensor + Pipeline parallel
- Expert Variant: Expert parallelism for MoE version

Llama 3:
- Strategy: Tensor(8) + Context + Pipeline + Data
- Reasoning: Long context requires sequence parallelism
```

7.3 Communication Optimization Patterns

Key Point: Bandwidth Hierarchy Utilization

Use parallelism strategies in order of bandwidth requirements: 1. Tensor parallel (highest bandwidth) 2. FSDP/Pipeline parallel (medium bandwidth) 3. Data parallel (lowest bandwidth, works on slow links)

Hierarchical Communication Strategy:

- **Fast intra-node links**: Tensor parallelism
- **Medium inter-node links**: FSDP or pipeline parallelism
- **Slow cross-rack links**: Data parallelism only

7.4 Implementation Complexity Considerations

Warning: Development Resource Requirements

Pipeline parallelism requires significant engineering expertise. Many organizations have only 1-2 people who understand their pipeline implementation.

Complexity Ranking (Low to High):

1. **Data Parallelism**: Framework support, simple debugging
2. **Tensor Parallelism**: Clear implementation patterns
3. **FSDP/ZeRO-3**: Moderate complexity, good framework support
4. **Pipeline Parallelism**: Very high complexity, custom infrastructure

7.5 Debugging and Monitoring Guidelines

Algorithm: Performance Monitoring Checklist

Critical Metrics to Track:

1. **GPU Utilization**: Should be high and balanced across devices
2. **Communication Overhead**: Ratio of communication to computation time
3. **Memory Usage Patterns**: Identify bottlenecks and imbalances
4. **Pipeline Bubble Ratios**: For pipeline parallel deployments
5. **Convergence Rates**: Ensure parallelization doesn't hurt training

Code: Monitoring Implementation

```
# Key performance indicators to track
def monitor_training_performance():
    - GPU utilization per device
    - Communication time vs computation time
    - Memory high-water marks
    - Gradient synchronization frequency
    - Loss convergence rates
    - Tokens per second throughput
```

8 Conclusion and Future Directions

8.1 Key Takeaways

Multi-machine parallelism is essential for training modern large language models, requiring careful orchestration of complementary strategies:

Key Point: Fundamental Principles

1. **No single solution**: Combine multiple parallelism strategies for optimal results
2. **Hardware awareness**: Match parallelism to communication topology
3. **Resource management**: Treat batch size as precious, finite resource
4. **Implementation complexity**: Balance performance gains against engineering costs

8.2 Strategy Summary

Performance: Parallelism Strategy Strengths

Data Parallelism (ZeRO):

- Excellent compute scaling and implementation simplicity
- ZeRO stages provide memory efficiency with minimal overhead
- Architecture-agnostic approach works with any model

Model Parallelism:

- Enables training models larger than single GPU memory
- Tensor parallel ideal for high-bandwidth intra-node scaling
- Pipeline parallel suitable for slow inter-node connections

8.3 Emerging Challenges and Research Directions

Current Research Areas:

- **Heterogeneous Computing**: Mixing different hardware types efficiently
- **Dynamic Parallelism**: Adapting strategies during training based on conditions
- **Fault Tolerance**: Handling hardware failures in large clusters gracefully
- **Auto-Parallelization**: Automatically selecting optimal strategies without human tuning

Technical Opportunities:

- Novel activation sharding strategies for better memory scaling
- Advanced pipeline scheduling algorithms beyond zero-bubble
- Communication-computation co-optimization techniques
- Parallelism-aware optimization algorithms

8.4 Practical Implementation Guidance

Algorithm: Recommended Development Approach

1. **Start Simple**: Begin with data parallelism (FSDP) for initial scaling**
2. **Profile Everything**: Use detailed profiling to identify actual bottlenecks**
3. **Scale Incrementally**: Add tensor parallelism within nodes first**
4. **Avoid Premature Optimization**: Don't implement pipeline parallel unless absolutely necessary**
5. **Monitor Continuously**: Track utilization, communication overhead, and convergence**

Warning: Implementation Reality Check

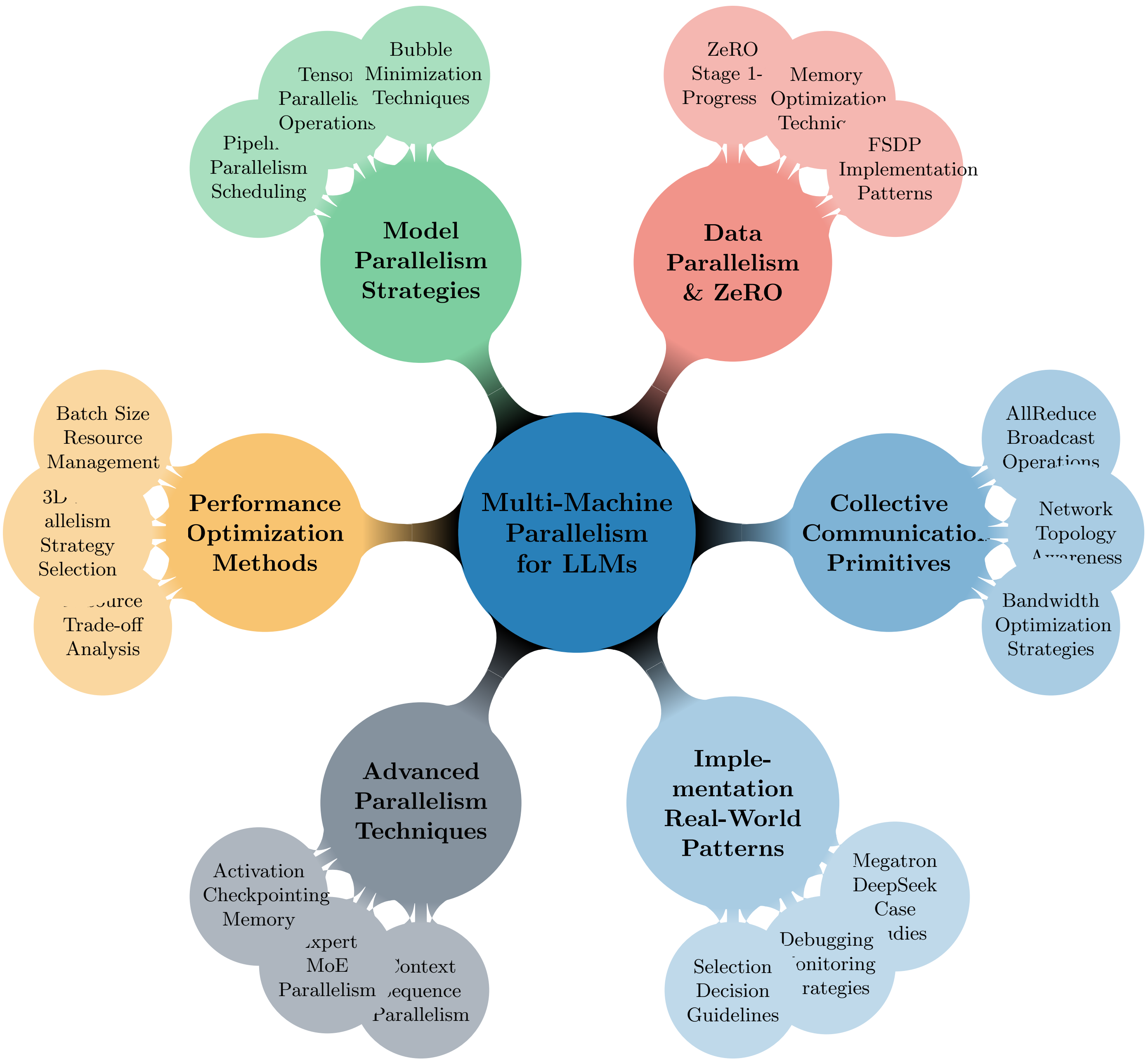
The field evolves rapidly with new architectures and optimization techniques emerging constantly. Focus on understanding fundamental principles rather than memorizing specific configurations.

9 Mind Map: Multi-Machine Parallelism

9.1 Central Concept

Multi-Machine Parallelism for Large Language Models

9.2 Main Conceptual Branches


Multi-Machine Parallelism for LLMs
Model Parallelism Strategies
Pipeli. Parallelism Scheduling
Tenso. Parallelis Operations
Bubble Minimization Techniques
Data Parallelism & ZeRO
ZeRO Stage 1- Progress
Memory Optimization Technic
FSDP Implementation Patterns
Collective Communicatio. Primitives
AllReduce Broadcast Operations
Network Topology Awareness
Bandwidth Optimization Strategies
Imple-mentation Real-World Patterns
Megatron DeepSeek Case ıdies
Debugging ʼonitoring rategies
Selection Decision Guidelines
Advanced Parallelism Techniques
Activation Checkpointing Memory
ɪxpert MoE Parallelism
Context ɪequence Parallelism
Performance Optimization Methods
Batch Size Resource Management
3D allelism Strategy Selection
ɪource Trade-off Analysis

9.3 Branch Details

1. **Collective Communication Primitives** (Blue Branch)

- **AllReduce, Broadcast Operations**: Understanding the fundamental communication primitives and their equivalence relationships (AllReduce = ReduceScatter + AllGather)
- **Network Topology Awareness**: Leveraging hardware communication hierarchies (NVLink vs InfiniBand) for optimal strategy selection
- **Bandwidth Optimization Strategies**: Communication-computation overlap techniques and hierarchical communication patterns

2. **Data Parallelism & ZeRO** (Red Branch)

- **ZeRO Stage 1-3 Progression**: From optimizer state sharding to full parameter sharding with memory scaling analysis
- **Memory Optimization Techniques**: Understanding the 16 bytes per parameter breakdown and reduction strategies
- **FSDP Implementation Patterns**: Communication-computation overlap, prefetching strategies, and practical deployment patterns

3. **Model Parallelism Strategies** (Green Branch)

- **Pipeline Parallelism Scheduling**: Microbatching strategies, bubble ratio optimization, and zero-bubble advanced techniques
- **Tensor Parallelism Operations**: Matrix decomposition strategies, column/row-wise splitting, and bandwidth requirement analysis
- **Bubble Minimization Techniques**: Advanced scheduling algorithms including 1F-1B and weight gradient separation strategies

4. **Performance Optimization Methods** (Orange Branch)

- **Resource Trade-off Analysis**: Memory vs communication vs computation trade-offs with quantitative performance models
- **3D Parallelism Strategy Selection**: Combining tensor, pipeline, and data parallelism with decision frameworks
- **Batch Size Resource Management**: Understanding batch size as finite resource and optimal allocation strategies

5. **Advanced Parallelism Techniques** (Gray Branch)

- **Context/Sequence Parallelism**: Ring Attention techniques for handling sequences longer than single device memory
- **Expert MoE Parallelism**: Mixture-of-Experts model scaling with sparse routing and load balancing strategies
- **Activation Checkpointing Memory**: Trading compute for memory with selective activation storage and recomputation

6. **Implementation Real-World Patterns** (Light Blue Branch)

- **Megatron, DeepSeek Case Studies**: Real-world scaling examples from 1.7B to 1T+ parameter models with empirical results
- **Debugging & Monitoring Strategies**: Performance monitoring, utilization tracking, and bottleneck identification techniques
- **Selection Decision Guidelines**: Practical decision frameworks for choosing parallelization strategies based on constraints

9.4 Visual Layout Description

The mind map should be organized as a radial diagram with the central concept at the center and six main branches extending outward in a hexagonal pattern. Each branch should use distinct colors matching the defined color scheme. Interconnections between branches should be shown with dotted lines to indicate relationships (e.g., how ZeRO stages relate to collective communication primitives, or how tensor parallelism connects to hardware bandwidth constraints). Key equations, performance metrics, and implementation guidelines should be highlighted in small boxes within each branch. The layout should emphasize the hierarchical decision-making process for selecting appropriate parallelization strategies based on model size, hardware constraints, and implementation complexity considerations.