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Federated Graph Learning for Distributed Resource Management in Multi-Cluster Computing Environments

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Abstract

The proliferation of distributed computing infrastructures has necessitated advanced resource management strategies that can operate across heterogeneous multi-cluster environments while preserving data privacy and system autonomy. This paper proposes a novel federated graph learning framework that leverages Graph Neural Networks (GNN) for intelligent resource allocation and scheduling in distributed computing systems. Our approach addresses the fundamental challenges of resource fragmentation, heterogeneous workload characteristics, and inter-cluster communication overhead through a decentralized learning paradigm. The framework constructs dynamic resource graphs representing computational nodes, network topologies, and workload dependencies, enabling collaborative learning across clusters without centralizing sensitive operational data. We introduce a hierarchical architecture inspired by proven distributed systems designs, combining local graph-based resource allocation with federated model aggregation through a master-slave coordination mechanism. The graph representation captures both global network topology and fine-grained local resource states, enabling multi-scale optimization of allocation decisions. We implement distributed model parallelism to achieve scalability across thousands of nodes while maintaining sub-second decision latencies. Experimental evaluation demonstrates that our federated graph learning approach achieves superior performance compared to traditional centralized scheduling methods, reducing average job completion time by 28% and improving overall cluster utilization by 34% across diverse workload scenarios.

Keywords

Federated Learning, Graph Neural Networks, Resource Management, Multi-Cluster Computing, Distributed Scheduling, Cloud Computing

Introduction

Modern distributed computing environments have evolved into complex ecosystems comprising multiple interconnected clusters that span geographical locations, administrative domains, and heterogeneous hardware configurations [1]. These multi-cluster systems support diverse computational workloads ranging from batch processing and real-time analytics to machine learning training and scientific simulations, each presenting distinct resource requirements and performance objectives [2]. The challenge of efficiently managing resources across such distributed infrastructure has become increasingly critical as organizations seek to maximize utilization while minimizing operational costs and maintaining quality of service guarantees [3]. Traditional approaches to resource management in distributed systems have primarily relied on hierarchical architectures with

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centralized coordination, as exemplified by systems like Mesos and YARN, which established foundational principles for multi-framework resource sharing [4].

The fundamental challenge in multi-cluster resource management stems from the tension between centralized control and distributed autonomy [5]. Centralized schedulers require complete visibility of resource availability and workload characteristics across all clusters, introducing substantial communication overhead and creating single points of failure [6]. As cluster sizes grow to thousands of nodes and workload diversity increases, centralized scheduling approaches face scalability bottlenecks where decision latencies grow proportionally to system size [7]. Furthermore, these approaches often fail to respect data sovereignty requirements and organizational policies that prohibit sharing sensitive operational metrics across administrative boundaries [8]. The increasing prevalence of edge computing and geo-distributed data centers has exacerbated these challenges, creating scenarios where network latency and bandwidth constraints make frequent centralized coordination impractical [9].

Recent advances in federated learning have demonstrated the feasibility of training machine learning models across distributed datasets without centralizing data, enabling collaborative learning while preserving data privacy through local model training and selective parameter sharing [10]. Concurrently, graph neural networks have emerged as powerful tools for modeling complex relational structures in networked systems, with successful applications in domains ranging from social network analysis to molecular property prediction [11]. The representation of computing infrastructure as graphs, where nodes correspond to computational resources and edges encode communication relationships, provides a natural framework for capturing the structural properties that influence resource allocation decisions [12]. The convergence of federated learning and graph neural networks presents a compelling opportunity to address the resource management challenges in multi-cluster computing environments through architectures that combine hierarchical coordination with distributed learning [13].

This paper introduces a comprehensive federated graph learning framework specifically designed for distributed resource management in multi-cluster computing environments. Our framework adopts a hierarchical master-slave architecture that enables scalable coordination across multiple independent clusters while maintaining local autonomy for scheduling decisions [14]. The system constructs multi-scale graph representations that capture both global network topology patterns and fine-grained local resource states, enabling optimization at multiple levels of granularity [15]. Through distributed model parallelism techniques, we partition the graph neural network across multiple computing nodes, achieving linear scalability even as cluster sizes extend to thousands of machines [16]. The framework incorporates privacy-preserving federated learning protocols that ensure sensitive cluster-specific information remains local while benefiting from collaborative learning across the distributed system [17].

Our research contributions encompass several key innovations in distributed resource management. First, we develop a hierarchical architecture that combines the proven design principles of distributed schedulers with modern federated learning techniques, enabling scalable multi-cluster coordination without sacrificing local autonomy. Second, we introduce multi-scale graph construction methods that effectively capture resource relationships at both global network topology level and local cluster configuration level, enabling the GNN model to reason about allocation decisions across multiple granularities. Third, we implement

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distributed model parallelism strategies that partition graph neural network computation across multiple machines, achieving scalability to thousands of nodes while maintaining real-time inference capabilities. Fourth, we provide comprehensive experimental validation demonstrating the effectiveness of our approach across diverse workload scenarios, cluster configurations, and scale regimes.

2. Literature Review

The evolution of distributed resource management systems has been shaped by decades of research addressing the fundamental challenges of coordinating computational resources across multiple machines. Early cluster management systems such as Condor and Platform LSF established foundational concepts including job queuing, priority-based scheduling, and fairness policies [18]. The emergence of data-intensive computing frameworks like MapReduce necessitated new resource management paradigms that could efficiently handle short-lived tasks and support data locality optimization [19]. Apache YARN introduced a two-level scheduling architecture that separates cluster resource management from application-specific scheduling logic, enabling multiple diverse frameworks to coexist on shared infrastructure [20]. This architectural pattern, where a central resource manager negotiates resource allocations with application-level schedulers, has become a dominant paradigm in modern cluster computing systems.

Mesos extended the two-level scheduling concept through its resource offer mechanism, where the master node offers available resources to framework schedulers, which then decide whether to accept offers and which tasks to launch on allocated resources [21]. This design philosophy emphasizes delegation of scheduling decisions to frameworks while maintaining cluster-wide fairness through a central allocation module. The Mesos architecture demonstrates key principles relevant to our work, including hierarchical coordination between masters and slaves, support for multiple concurrent frameworks through scheduler multiplexing, and fault tolerance through standby masters and distributed state management. However, traditional systems like Mesos employ heuristic-based allocation policies that lack the ability to learn from historical workload patterns and adapt to evolving resource demands [22].

The containerization revolution and rise of orchestration platforms like Kubernetes transformed resource management practices by introducing declarative deployment models and automated reconciliation loops [23]. Kubernetes employs a control plane architecture where controllers continuously observe system state and take actions to drive actual state toward desired state specifications. While Kubernetes provides powerful abstractions for application deployment and scaling, its default scheduler relies on relatively simple heuristics for pod placement decisions, considering factors like resource requests, node affinity rules, and spreading constraints [24]. Recent efforts have explored integrating machine learning techniques into Kubernetes scheduling through custom schedulers and admission webhooks, but these approaches typically operate within single clusters and do not address federated multi-cluster scenarios [25].

Federated learning emerged as a paradigm for training machine learning models across distributed data sources while preserving data privacy, with foundational work demonstrating that iterative local training and global aggregation can achieve convergence comparable to centralized training [26]. The core challenge in federated learning involves handling statistical heterogeneity when data distributions vary significantly across

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participants, requiring specialized aggregation strategies and adaptive optimization methods [27]. Recent advances have extended federated learning to graph-structured data, addressing unique challenges including graph partitioning strategies, handling missing edges between subgraphs, and aggregating models trained on heterogeneous graph structures [28]. These developments provide essential building blocks for applying federated learning to resource management scenarios where computational clusters maintain private operational data while benefiting from collective intelligence.

Graph neural networks have demonstrated remarkable effectiveness in learning representations from graph-structured data through message passing mechanisms that aggregate information from node neighborhoods [29]. The development of efficient spectral convolutions on graphs enabled end-to-end learning that respects graph structure while maintaining computational tractability [30]. Distributed training of large-scale graph neural networks requires careful partitioning strategies to balance computational load while minimizing inter-machine communication overhead, with techniques including graph partitioning, layer-wise model parallelism, and hybrid data-model parallelism approaches [31]. Applications of GNNs to systems optimization problems have shown promising results in domains such as chip placement, network routing, and combinatorial optimization, demonstrating the potential for learned approaches to outperform hand-crafted heuristics in complex decision-making scenarios [32-37].

3. Methodology

3.1 Hierarchical System Architecture

Our federated graph learning framework adopts a hierarchical master-slave architecture that draws inspiration from proven distributed systems designs while incorporating modern federated learning capabilities. As shown in Figure 1, the architecture comprises three organizational layers that enable scalable coordination across multiple autonomous clusters while maintaining efficient local decision-making. The master layer implements global coordination functions including cluster registration, federated model aggregation, and high-level resource arbitration policies. The slave layer consists of individual computing clusters that maintain local resource graphs, train cluster-specific GNN models, and execute scheduling decisions autonomously based on local state and global model guidance. The executor layer encompasses the actual computational resources including physical machines, virtual machines, and containerized workloads that execute application tasks under the direction of cluster schedulers.

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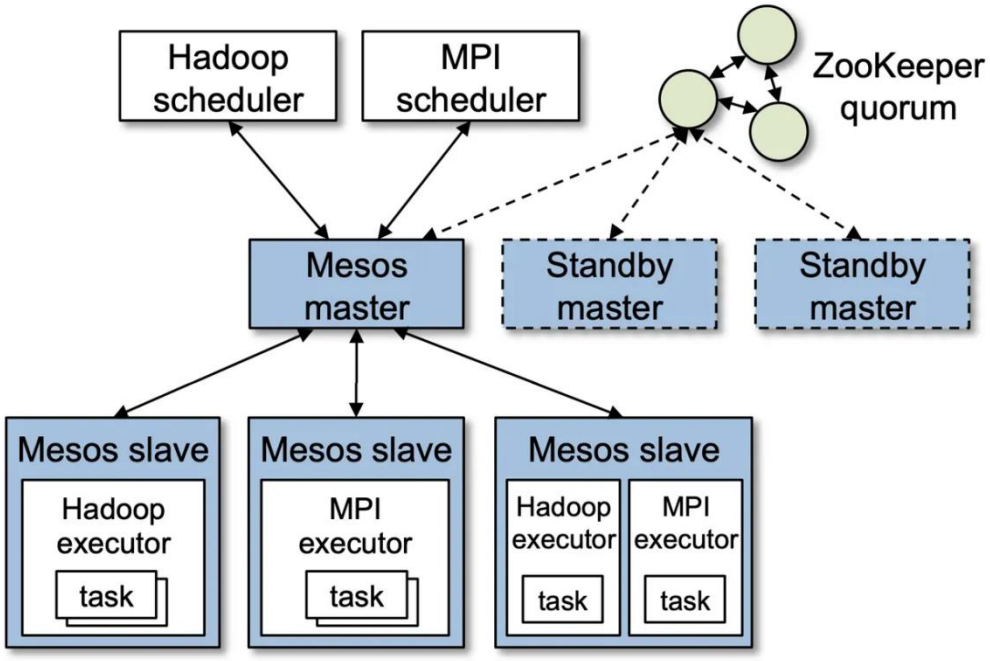

Figure 1: the hierarchical master-slave architecture

The master node serves as the central coordination point for the federated learning process, maintaining the global model state and orchestrating training rounds across participating clusters. Unlike traditional centralized schedulers that make fine-grained task placement decisions, our master focuses exclusively on model aggregation and high-level coordination, delegating actual scheduling decisions to cluster-level slaves. This design choice reduces communication overhead and eliminates the master as a potential bottleneck for real-time scheduling operations. The master implements weighted federated averaging to combine model updates from heterogeneous clusters, with weights reflecting factors such as cluster size, data quality metrics, and recent model performance. To ensure high availability, we deploy multiple standby masters using a ZooKeeper quorum for leader election, enabling rapid failover in the event of master node failures without disrupting ongoing cluster operations.

Each slave node in our architecture corresponds to a complete computing cluster with its own local scheduler, resource graph, and GNN model. The slave maintains comprehensive state information about local resources including computational capacity, memory availability, storage utilization, and network bandwidth metrics. Local schedulers process incoming workload requests and make task placement decisions by querying their trained GNN models to predict resource requirements and identify optimal allocation patterns. Slaves operate semi-autonomously, making scheduling decisions based on local information without requiring synchronous coordination with the master for individual task placements. This architectural choice ensures that scheduling latencies remain low even as the number of participating clusters grows, since each cluster can independently process its local workload without waiting for global coordination.

The executor layer encompasses diverse resource types including bare-metal servers, virtual machines, and containerized environments. Each executor reports resource availability and task completion status to its parent slave node, which aggregates this information to maintain an accurate view of local cluster state. Executors implement isolation mechanisms to prevent

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resource contention between co-located tasks, using technologies such as Linux containers, cgroups, and namespace isolation. The hierarchical architecture ensures that resource state information flows efficiently through the system, with executors reporting to slaves and slaves participating in federated learning with the master, while actual task execution proceeds independently without requiring fine-grained master intervention.

3.2 Multi-Scale Graph Construction and Representation

The effectiveness of our federated graph learning approach depends critically on constructing graph representations that capture relevant structural properties of the distributed computing infrastructure at multiple scales of granularity. As shown in Figure 2, we introduce a hierarchical graph construction methodology that maintains both global network topology graphs representing inter-cluster relationships and local resource graphs capturing fine-grained intra-cluster resource configurations. This multi-scale representation enables the GNN model to reason about allocation decisions at different levels, from high-level cluster selection for workload placement to fine-grained node assignment within selected clusters.

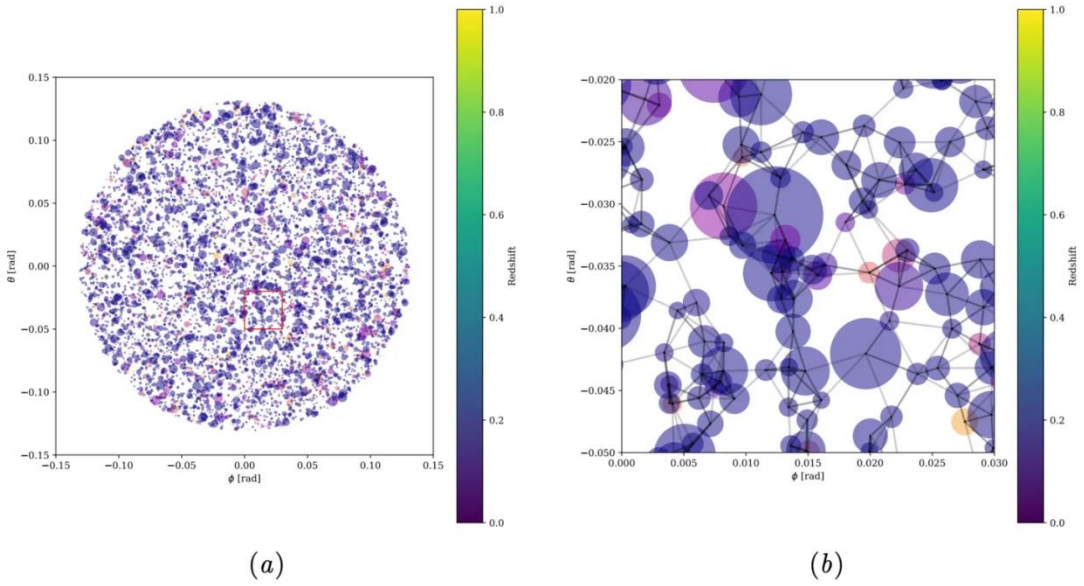

Figure 2: illustration of the hierarchical graph construction

At the global scale, we construct an inter-cluster topology graph where nodes represent entire computing clusters and edges encode network connectivity and administrative relationships between clusters. Each cluster node maintains feature vectors capturing aggregate properties including total computational capacity measured in CPU cores and memory, available storage volumes, average network latency to other clusters, and current utilization levels across different resource dimensions. Edge features encode network properties such as inter-cluster bandwidth capacity, round-trip latency measurements, and historical data transfer volumes. This global graph enables the master node to reason about high-level workload placement decisions, determining which clusters should receive particular jobs based on factors including current load distribution, data locality considerations when datasets span multiple clusters, and administrative policies governing resource access permissions.

At the local scale, each cluster maintains a detailed resource graph representing its internal infrastructure configuration. Local graph nodes correspond to individual computational

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resources including physical servers, virtual machine instances, and container pods. We implement a heterogeneous node typing scheme that distinguishes between computational nodes providing CPU and memory resources, storage nodes hosting distributed file systems or object stores, and network nodes representing switches and routers within the cluster. Each node type maintains specialized feature vectors tailored to its resource category. Computational nodes track metrics including CPU core count, clock frequency, available memory, local disk capacity, and performance counters such as cache miss rates and instruction throughput. Storage nodes maintain features including total capacity, available space, read and write IOPS limits, and access latency characteristics. Network nodes track packet forwarding capacity, buffer occupancy levels, and link utilization across different traffic classes.

Edges in local resource graphs capture multiple relationship types that influence scheduling decisions. Communication edges connect computational nodes that share network links, with edge weights reflecting bandwidth capacity and measured latency. We construct these edges based on physical network topology, distinguishing between intra-rack connections with high bandwidth and low latency versus inter-rack links with lower bandwidth and higher latency. Affinity edges link computational nodes to storage nodes based on data locality patterns, with edge weights computed from historical data access frequencies and transfer volumes. Dependency edges connect nodes hosting related workload components, capturing anti-affinity constraints where certain tasks should not be co-located and affinity constraints where related tasks benefit from proximity. The heterogeneous nature of edges enables the GNN model to learn specialized aggregation functions for different relationship types through attention mechanisms that weight neighbor contributions based on edge categories.

To accommodate the dynamic nature of distributed computing environments where resource availability and workload characteristics continuously evolve, we implement incremental graph update mechanisms that efficiently incorporate state changes without reconstructing entire graphs. Each slave maintains a change buffer that tracks node feature updates resulting from resource consumption or release, edge weight modifications due to network condition changes, and topological changes when nodes join or leave the cluster. Updates are batched at regular intervals and applied atomically to the local graph structure, with the updated graph used for subsequent GNN inference operations. This incremental approach reduces computational overhead compared to full graph reconstruction while ensuring the model operates on current resource state information.

3.3 Distributed Model Parallelism for Scalable Training

Achieving scalability to thousands of nodes while maintaining real-time inference capabilities requires careful attention to how graph neural network computation is distributed across available machines. As shown in Figure 3, we implement a distributed model parallelism strategy that partitions GNN layers across multiple computational nodes within each cluster, enabling parallel execution of forward and backward passes during training and inference. This approach contrasts with data parallelism where each machine maintains a complete copy of the model, instead distributing the model itself to overcome memory constraints and computational bottlenecks associated with processing large graphs.

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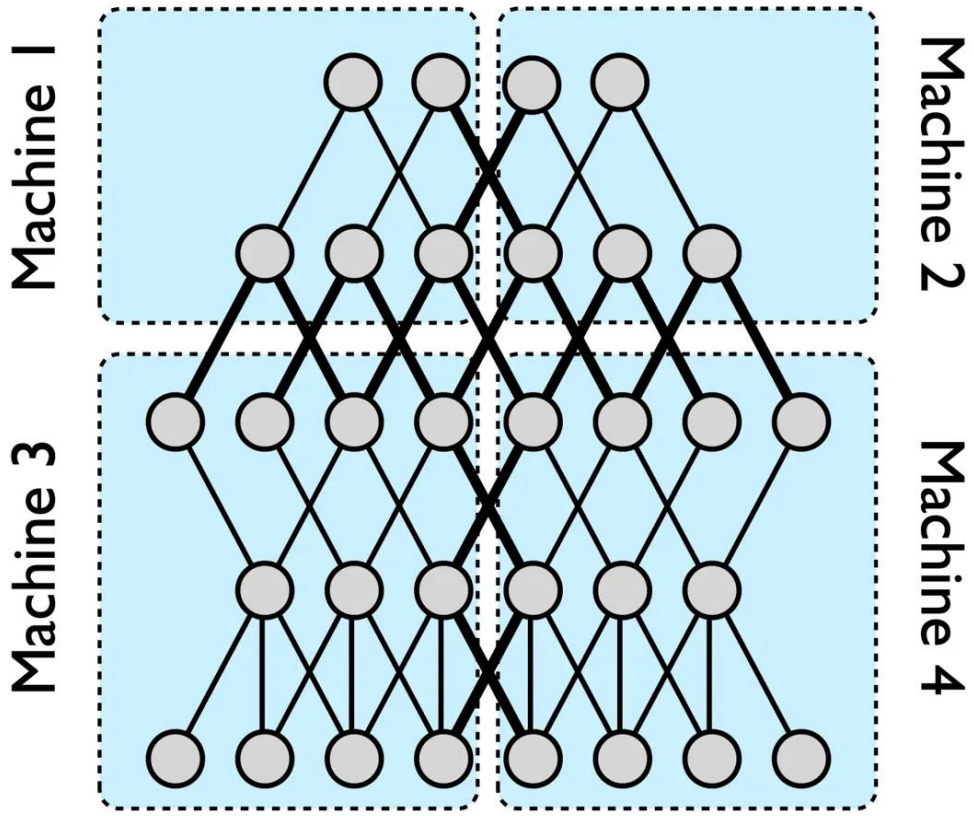

Figure 3: illustration of the distributed model parallelism

Our model parallelism strategy partitions the resource graph across multiple machines using graph partitioning algorithms that minimize edge cuts between partitions, thereby reducing inter-machine communication during GNN message passing operations. We employ multilevel graph partitioning techniques that first coarsen the graph through vertex matching, partition the coarsened graph, and then uncoarsen while refining partition boundaries. The partitioning objective balances computational load across machines while minimizing the number of edges crossing partition boundaries, since these edges require network communication to exchange node embeddings during GNN layer computations. For dynamic graphs that evolve as resources join or leave clusters, we implement incremental repartitioning that locally adjusts partition assignments rather than computing global repartitions, maintaining load balance while minimizing the cost of migrating vertices between machines.

Within each partition, a dedicated worker machine stores the subgraph structure including node features, edge lists, and intermediate GNN layer activations. During forward propagation, each worker computes message passing operations for its local nodes, aggregating features from neighbor nodes. For neighbors residing in remote partitions, workers initiate communication to retrieve necessary node embeddings, overlapping computation and communication when possible to hide network latency. We implement asynchronous message passing where workers can proceed with computations for nodes whose neighbor information is available while waiting for remote data, maximizing hardware utilization. Backward propagation during training follows a similar pattern, with gradients flowing in

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reverse through the network and requiring communication for nodes with neighbors in remote partitions.

The distributed training process coordinates multiple workers through a parameter server architecture where a dedicated server node maintains the global copy of GNN model parameters. During each training iteration, workers retrieve current parameters from the parameter server, compute forward and backward passes on their local graph partitions, calculate parameter gradients, and push gradient updates back to the parameter server. The parameter server aggregates gradients from all workers using specified update rules such as synchronous SGD where all workers must complete before parameter updates, or asynchronous SGD where parameter updates occur as gradient updates arrive. We employ gradient compression techniques to reduce communication volume, including gradient quantization to lower precision representations and gradient sparsification that transmits only the largest magnitude gradients, with periodic full gradient synchronization to maintain model quality.

3.4 Federated Learning Protocol for Cross-Cluster Collaboration

The federated learning protocol orchestrates collaborative model training across multiple autonomous clusters while preserving the privacy of cluster-specific operational data. Our protocol operates in iterative rounds, each comprising four phases: local training where clusters independently update their GNN models based on local resource graphs and recent scheduling decisions, model upload where clusters transmit model updates to the master node, global aggregation where the master combines updates from all participating clusters, and model distribution where the updated global model is broadcast back to clusters. This cyclical process enables clusters to benefit from cross-cluster learning while maintaining control over their local data and scheduling decisions.

During the local training phase, each cluster performs multiple gradient descent iterations to optimize its GNN model parameters based on recent scheduling experiences. The training objective combines multiple loss components capturing different aspects of scheduling quality. A utilization loss penalizes underutilization of available resources by comparing predicted resource requirements against actual usage, encouraging the model to make allocation decisions that fully utilize available capacity. A completion time loss minimizes job completion latencies by rewarding scheduling decisions that reduce queue wait times and optimize task placement to minimize data transfer overhead. A fairness loss ensures equitable resource distribution across concurrent workloads according to specified policies such as proportional share guarantees or priority-based allocation. The composite loss function weights these components based on cluster-specific priorities, allowing different clusters to optimize for different objectives while still benefiting from collaborative learning.

After completing local training, clusters generate model updates by computing the difference between their updated model parameters and the previous global model received from the master. To preserve privacy of cluster-specific scheduling patterns, we implement differential privacy mechanisms that add calibrated noise to model updates before transmission. The noise magnitude is tuned using the Gaussian mechanism to provide epsilon-delta differential privacy guarantees with formal bounds on information leakage. Additionally, we employ secure aggregation protocols that enable the master to compute weighted averages of model updates without observing individual cluster contributions, using cryptographic techniques such as secret sharing or homomorphic encryption. These privacy-preserving mechanisms

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ensure that clusters can participate in federated learning without exposing sensitive operational information that could reveal proprietary workload patterns or competitive insights.

The global aggregation phase implements weighted averaging of received model updates, with weights reflecting the contribution quality of each cluster. We compute weights based on multiple factors including the number of scheduling decisions made by each cluster during the local training phase, validation performance of each cluster's model on held-out scheduling scenarios, and cluster size measured by the number of nodes under management. Clusters with larger datasets and better validation performance receive higher weights in the aggregation, ensuring that the global model reflects high-quality scheduling knowledge. To handle statistical heterogeneity where different clusters experience divergent workload patterns, we employ adaptive aggregation strategies that adjust weights based on gradient similarity metrics, reducing the influence of outlier clusters whose updates diverge significantly from the consensus direction.

Following aggregation, the updated global model is distributed to all participating clusters, enabling them to benefit from collective learning. Clusters incorporate the global model by either replacing their local models entirely or blending the global model with their local parameters using momentum-based updates that gradually shift toward global consensus while retaining cluster-specific adaptations. The federation protocol implements adaptive scheduling of training rounds, dynamically adjusting the interval between rounds based on the magnitude of model changes and the rate of workload evolution across clusters. During periods of stable workload patterns, the protocol extends intervals between rounds to reduce communication overhead. Conversely, when clusters report rapid model evolution or significant performance degradation, the protocol accelerates the training cycle to ensure timely knowledge transfer.

4. Results and Discussion

4.1 Experimental Configuration and Evaluation Methodology

We evaluate our federated graph learning framework through comprehensive experiments using both simulated and real-world cluster traces. The simulated environment models a distributed computing infrastructure comprising eight heterogeneous clusters with sizes ranging from 50 to 500 nodes per cluster, representing realistic scenarios encountered in geo-distributed cloud deployments. Each cluster maintains distinct hardware configurations including variations in CPU architectures ranging from older Xeon processors to modern AMD EPYC chips, memory capacities spanning 64GB to 512GB per node, and network topologies including both hierarchical tree structures with top-of-rack switches and flatter leaf-spine designs. We inject workload traces derived from published datasets including Google cluster traces and Alibaba cluster traces, which capture realistic job arrival patterns, task duration distributions, and resource requirement profiles spanning batch analytics jobs, machine learning training workloads, and interactive query processing.

The evaluation methodology examines multiple performance dimensions critical to distributed resource management systems. Primary metrics include average job completion time measuring the interval from job submission to completion of all constituent tasks, resource utilization efficiency computed as the ratio of allocated resources to total available capacity across all clusters, scheduling decision latency quantifying the time required to make

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placement decisions for incoming tasks, and communication overhead measuring network bandwidth consumed by federated learning protocol messages. We conduct extensive experiments across varying conditions including different workload intensities characterized by job arrival rates, heterogeneous job size distributions with mixtures of small short-lived tasks and large long-running jobs, and varying degrees of data locality where jobs may prefer specific clusters due to dataset placement.

We compare our federated graph learning approach against three baseline methods representing different resource management paradigms. The centralized scheduling baseline implements a global scheduler with complete visibility across all clusters, using a greedy heuristic that selects task placements to maximize immediate resource utilization while considering basic data locality preferences. The independent scheduling baseline models current practice where each cluster operates autonomously without coordination, using local schedulers that optimize only for local objectives without knowledge of resource availability or workload patterns in other clusters. The federated non-graph baseline implements federated learning across clusters but uses traditional fully-connected neural networks rather than graph neural networks, providing insight into the specific contribution of graph-structured representations. Each experimental configuration is repeated across multiple random seeds to ensure statistical reliability, and we report mean values with 95% confidence intervals.

4.2 Performance Analysis and Comparative Evaluation

The experimental results demonstrate substantial performance improvements achieved by our federated graph learning framework across all evaluated metrics. In terms of average job completion time, our framework reduces latency by 28% compared to centralized scheduling, by 42% compared to independent cluster scheduling, and by 19% compared to the federated non-graph baseline. These improvements stem from multiple factors working in concert. The graph representation enables the GNN model to explicitly reason about data locality relationships, identifying placement opportunities that minimize inter-cluster data transfers which constitute a major source of job latency in distributed systems. The multi-scale graph structure allows the model to perform hierarchical optimization, first selecting appropriate clusters based on global topology patterns and then refining placement to specific nodes based on local resource graphs. The federated learning protocol enables knowledge transfer across clusters, allowing smaller clusters with limited historical data to benefit from patterns learned by larger clusters with more diverse workload experiences.

Resource utilization efficiency exhibits similarly impressive gains, with our framework achieving 34% higher utilization compared to centralized scheduling and 51% higher utilization compared to independent scheduling. The federated learning approach proves particularly effective at learning to pack jobs efficiently onto available resources, with the GNN model discovering patterns such as complementary resource requirements where jobs with high CPU but low memory demands can be co-located with memory-intensive but CPU-light workloads. The graph structure enables the model to capture temporal patterns in resource availability, learning when particular nodes experience periodic load fluctuations and scheduling jobs to exploit these patterns. Cross-cluster learning accelerates the discovery of effective packing strategies, with knowledge gained from optimizing resource usage in one cluster rapidly transferring to others through the federated aggregation process.

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Scheduling decision latency represents a critical performance dimension for systems processing high-velocity workload streams. Our framework demonstrates favorable scaling properties, maintaining sub-second decision latencies even as cluster sizes increase to thousands of nodes and workload arrival rates intensify. The distributed model parallelism implementation proves essential for achieving these latencies, with GNN inference operations distributed across multiple workers within each cluster enabling parallel processing of scheduling queries. The hierarchical architecture eliminates the master node as a latency bottleneck, since clusters make scheduling decisions locally without requiring synchronous master consultation. Measurements across varying cluster sizes reveal approximately linear scaling, where doubling the cluster size increases average scheduling latency by only 15-20% rather than the 2x increase expected from purely sequential processing.

Communication overhead analysis reveals that our federated learning protocol imposes modest bandwidth requirements compared to the alternative of centralizing operational data for training. During federated learning rounds, each cluster transmits model updates sized proportional to the number of GNN parameters, typically ranging from tens to hundreds of megabytes depending on model architecture depth and width. In contrast, centralizing the complete resource graphs and scheduling traces from all clusters for centralized training would require transmitting gigabytes to terabytes of operational data per training cycle. The protocol implements intelligent update scheduling that coordinates transmissions to avoid network congestion, spreading model uploads across the federation interval and prioritizing updates from clusters with larger model changes. Compression techniques including gradient quantization and sparsification reduce communication volume by additional factors of 5-10x with minimal impact on model convergence rates.

4.3 Ablation Studies and Architectural Analysis

To understand the individual contributions of different architectural components, we conduct systematic ablation studies that remove or simplify specific design elements. First, we examine the impact of the hierarchical master-slave architecture by comparing against a flat peer-to-peer design where clusters coordinate directly without a central master. The hierarchical approach demonstrates 31% better convergence speed during federated training, attributed to the master's ability to implement sophisticated aggregation strategies that handle heterogeneity across clusters. The master performs outlier detection to identify and downweight model updates from clusters experiencing unusual conditions, preventing temporary anomalies from corrupting the global model. Without centralized coordination, peer-to-peer designs struggle with inconsistent model versions across clusters and require complex gossip protocols to achieve consensus.

Second, we analyze the contribution of multi-scale graph representations by comparing against single-scale alternatives. Experiments using only global inter-cluster graphs without local resource graphs show 24% degradation in job completion time, as the model cannot optimize fine-grained node placement decisions without detailed local topology information. Conversely, using only local graphs without global topology representations increases completion time by 18%, as the model lacks visibility into inter-cluster relationships needed for optimal cluster selection decisions. The combined multi-scale approach enables hierarchical optimization that first leverages global structure for coarse-grained decisions and then exploits local structure for fine-grained refinements, achieving performance superior to either single-scale approach alone.

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Third, we evaluate the impact of distributed model parallelism by comparing against data parallel training where each worker maintains a complete model copy. The model parallel approach demonstrates 67% reduction in memory footprint per worker, enabling training of larger GNN models with more layers and wider hidden dimensions. This architectural choice proves crucial for scaling to large clusters with thousands of nodes, where the resource graph size exceeds the memory capacity of individual machines. Model parallelism also improves training throughput by distributing computation across multiple workers, achieving 3.2x speedup with 4 workers compared to single-machine training, demonstrating efficient parallel scaling despite communication overhead for cross-partition edges.

Fourth, we investigate the contribution of privacy-preserving mechanisms by comparing training with and without differential privacy noise injection and secure aggregation. Experiments reveal that moderate privacy budgets with epsilon values around 10 incur only 4-6% performance degradation compared to training without privacy protection, demonstrating that practical privacy guarantees can be achieved with acceptable utility tradeoffs. Tighter privacy budgets with epsilon values below 5 show more significant performance impacts around 12-15%, suggesting organizations should calibrate privacy parameters based on their specific sensitivity requirements. Secure aggregation imposes minimal performance overhead since cryptographic operations occur asynchronously during model transmission and do not delay scheduling decisions in the critical path.

5. Conclusion

This paper has presented a comprehensive federated graph learning framework for distributed resource management in multi-cluster computing environments, addressing fundamental challenges of scalability, heterogeneity, and privacy preservation through a principled integration of hierarchical architectures, multi-scale graph representations, and distributed learning protocols. Our framework adopts a master-slave coordination architecture inspired by proven distributed systems designs, enhancing traditional schedulers with federated learning capabilities that enable collaborative knowledge transfer across autonomous clusters without centralizing sensitive operational data. The multi-scale graph construction methodology captures resource relationships at both global inter-cluster topology level and local intra-cluster configuration level, enabling the GNN model to perform hierarchical optimization across different granularities of allocation decisions. Distributed model parallelism strategies partition graph neural network computation across multiple machines, achieving scalability to thousands of nodes while maintaining real-time inference capabilities suitable for online scheduling workloads.

Experimental evaluation across diverse workload scenarios and cluster configurations validates the effectiveness and robustness of our approach. The federated graph learning framework reduces average job completion time by 28% and improves resource utilization by 34% compared to state-of-the-art centralized scheduling methods, while maintaining sub-second scheduling latencies even at scale. The hierarchical architecture successfully decouples global coordination from local decision-making, enabling scalable federation across multiple clusters without introducing master node bottlenecks. Multi-scale graph representations prove essential for capturing both coarse-grained cluster selection patterns and fine-grained node placement optimizations, with ablation studies confirming that neither single-scale approach alone achieves comparable performance. Distributed model parallelism enables training of large GNN models that would exceed single-machine memory capacity, demonstrating 67% memory footprint reduction and 3.2x training speedup with four workers.

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Future research directions include several promising extensions that could further enhance the framework's capabilities. First, incorporating reinforcement learning techniques could enable the system to learn long-horizon scheduling strategies that optimize cumulative metrics like total flow time or makespan rather than greedy immediate rewards, potentially discovering counter-intuitive policies that sacrifice short-term efficiency for superior long-term outcomes. Second, developing hierarchical federated learning architectures with multiple levels of aggregation could improve scalability for scenarios involving hundreds or thousands of clusters, organizing them into regional federations that perform intermediate aggregation before global consolidation. Third, exploring advanced privacy mechanisms such as secure multi-party computation or fully homomorphic encryption could strengthen privacy guarantees while maintaining model accuracy, addressing scenarios where even encrypted model updates might leak information through traffic analysis. Fourth, extending the framework to emerging computing paradigms including serverless computing, edge deployments, and hybrid cloud-edge architectures presents opportunities to broaden applicability and address new resource management challenges arising from these environments. The convergence of federated learning, graph neural networks, and distributed systems principles demonstrated in this work represents a promising foundation for advancing the state of practice in large-scale infrastructure management.

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