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An Efficient Federated Graph Neural Network Framework for Cross-Enterprise Business Analysis

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Abstract: With the rapid development of the digital economy, the demand for data collaboration among enterprises is constantly increasing. Data security and privacy protection have become obstacles to the in-depth development of cross-enterprise business analysis. To address the problems of privacy leakage, communication overhead, and heterogeneous data processing in traditional centralized modeling, this paper proposes an efficient Federated Graph Neural Network (FGNN) for cross-enterprise business analysis. In order to protect data privacy and realize cross-domain feature learning and efficient aggregation of heterogeneous enterprise graph data, this study first analyzes the heterogeneity and non-independent and identically distributed characteristics of cross-enterprise data, as well as the communication and security bottlenecks of federated learning. Secondly, an efficient communication mechanism based on sparse gradient compression and weighted aggregation is designed, and then homomorphic encryption and federated differential privacy technologies are introduced to enhance security protection.

1. Research on Cross-Enterprise Data Collaboration and Privacy Protection Introduction

In the age of digital economy and intelligent business, data collaboration among companies has become an important cornerstone to promote intelligent decision making and value creation. Enterprises have amassed a great deal of information within areas including finance, supply chain, markets and risk management. But data exchange is restricted by privacy protection rules and commercial obstacles, so there’s been a lot of “data island” creation and that becomes an obstacle for cross-enterprise business intelligence. Collaborative data analysis with privacy control is now a big problem. Federated learning (FL) uses a kind of cooperative training method called “keep data local” which can get great achievements in balancing data security and model performance. GNNs with its special structure has gotten some good results as well. Combining both methods would allow for multiple companies to work on modeling out business relationships between different companies without having to share their own data, this has both academic and real world applications.

Although current studies have achieved results regarding communication efficiency and privacy protection, there are still some shortcomings when it comes to aligning different kinds of companies' graph structures, ensuring that models converge stably and generalize well with non-IID data, which makes it hard to achieve a good balance between model performance and security. In order to solve these problems, we propose an efficient federated graph neural network framework for cross-enterprise business analytics. The framework uses a multi stage structure which comprises of local learning , Secure Aggregation and Global Optimization. It adds a heterogeneous graph feature alignment layer and a sparse communication layer to improve training efficiency and privacy. And it also integrates differential privacy with meta-learning methods to achieve cross-domain knowledge transfer and adaptive aggregation. This research innovation can achieve good communication, protect privacy better, and improve how well the model fits different businesses' networks. It gives technical and theoretical help for making a trusted, growing cross-company smart analysis system that uses AI.

2. Challenges in Federated Graph Learning for Business Analytics

Heterogeneous enterprise data shows great complexity and diversity in terms of structure and distribution. Because there are distinctions in business model, data source structure, and information system standards among various companies, the data coming from these different firms can be quite different with respect to its dimensionality, nodes, relationships, and time. Financial enterprise data emphasizes transactions and credit relations; supply chain enterprise data stresses logistics and contractual relations. The multi-source heterogeneity results in considerable non-IID(global) data which hinders the unified modeling from capturing deep relationship. Data quality differs from company to company as well as there is noise in features and annotations are not up to standard which makes it harder to model. Node/edge attribute’s semantic inconsistency hinders feature space uniform alignment, thus degrading the model’s overall expressiveness. In this context, data silos and privacy protection become major obstacles for cross-enterprise analytics. Data is treated as a kind of asset, so companies, due to legal requirements, commercial secrets, and worries about cybersecurity, do not want to share their raw data with each other.

It is detrimental to the knowledge integration and global model optimization. Federated Learning has a “data-native” solution, however there are still risks involved with reverse inference and model reconstruction attacks. Differential privacy and encrypted computing could solve the leakage problem but it comes at an extra cost of communication overhead and performance loss which slows down the training convergence and reduces accuracy. And also there are different levels of privacy tolerances for different people which would affect how well they work together Federated Graph Neural Networks (FGNNs) have some new critical problems when used between companies. Different enterprises have different graph structures, so it’s hard to unify how we collect information. Model aggregation has bias because nodes have different meanings and relationships have different weights. More often than not there will be a lot of system overhead for communication syncs when doing federated training. There’s a natural conflict between protecting privacy and getting good results, because making sure features work well means limiting how much we can change things to protect people’s private info. The global model optimization gets disrupted due to non-IID data; the local update could either cancel out or diverge from the best answer. To tackle such problems, we need to break through at heterogeneity feature alignment, communication compression, secure aggregation, and adaptive federated optimization. So as to build up an efficient, secure and generable cross-enterprise federated graph neural network framework which can support intelligent decision making and data value collaboration among multiple agents' business ecosystem.

3. Architectural Design and Complexity Modeling of the FGNN Framework

A typical cross-enterprise federated graph learning architecture consists of three tightly coupled layers: local graph modeling, secure communication, and global aggregation. Each enterprise retains its own graph locally and uses a GNN to encode node/edge information through message passing, capturing private structural patterns without exposing raw data. Encrypted gradients or parameters are then transmitted to a federated server, where global aggregation fuses multi-party knowledge and broadcasts updated parameters back to participants, iterating through a "local training → secure upload → global update → redistribution" loop. Given large disparities in node types, relational semantics, and graph scale, the aggregation mechanism must dynamically balance global consistency and local personalization to avoid bias toward any single enterprise's structure.

From a scalability perspective, communication and computation dominate system complexity. Communication cost is determined by parameter size, gradient dimensionality, synchronization frequency, and the number of participants; with deeper GNNs and higher feature dimensions, transmission overhead can grow rapidly and become a bandwidth bottleneck. To reduce this burden, the framework employs sparse gradient compression, Top-K synchronization, quantization, and asynchronous updates, lowering bandwidth usage while preserving accuracy. Computational complexity depends on the GNN backbone: GCNs scale with adjacency size, GATs incur attention-weight calculations, and GraphSAGE relies on neighborhood sampling. In practice, uneven data volumes and compute capacities across enterprises produce stragglers, which can delay global rounds; thus, dynamic load balancing and hierarchical aggregation are necessary for stable training.

Security risks are another central concern. Gradients can be exploited to infer sensitive attributes, reconstruct local subgraphs, or test node membership. To counter these threats, the framework combines homomorphic encryption, secure multi-party computation–based aggregation, and federated differential privacy. These mechanisms protect the confidentiality and integrity of parameter exchange and resist inversion, reconstruction, and membership-inference attacks, while inevitably introducing a privacy–efficiency trade-off. Overall, architectural design, security mechanisms, and complexity modeling form an interdependent system: communication optimization and privacy protection must be co-engineered so that large-scale, trustworthy, and sustainable cross-enterprise federated graph learning can be achieved for real business ecosystems.

4. Framework Implementation: Modular Functions and Security Mechanisms

An efficient federated graph neural network framework for cross-enterprise business analytics. The overall structure of this efficient federated graph neural network framework for cross-enterprise business analytics comprises a local learning section, a secure communication and encrypted aggregation area, a diverse feature alignment part, and a global optimization segment. It forms a "local modeling--secure collaboration--global update--cross-domain optimization" closed loop system, which has the characteristics of modularity and scalability. The local learning module does node representation and feature extraction inside the enterprise's own graph. Secure communication module guarantees encrypted transmission and aggregation of parameters between enterprises. Heterogeneous feature alignment module makes sure that the semantic space of graphs from various companies is consistent via feature mapping and structural normalization. Global optimization module improves the whole generalization ability by iterative aggregation and model distillation.

The framework uses light weight communication method and adaptive aggregation technique to enhance the federated training efficiency. Communication method based on sparse gradient compression and top-k parameter synchronization can reduce the bandwidth cost. Adaptive aggregation strategy gives out weight according to the scale, quality, and convergence traits of enterprise data, reaching equilibrium updates among several parties. Using gradient quantization along with an asynchronous update approach greatly cuts down on the communication lag and unevenness problems that come up during multi-node training. Privacy protection: It integrates homomorphic encryption, differential privacy, and secure multi-party computation technology, forming a collaborative protection system. Through encrypted parameter aggregation and noise addition, it achieves a dynamic balance between privacy and performance. Under decentralized trust, the multi-party secure computing protocol maintains the privacy and integrity of parameter exchanges, and resists model inversion, reconstruction, and member inference attacks.

Table 1 Module functions and key technologies of the cross-enterprise federated graph neural network framework

Module Name	Functional Description	Key technologies	Expected results
Local learning modules	Perform feature extraction and node embedding learning on enterprise internal graph data	Graph Convolutional Network (GCN), GraphSAGE	Improve local feature expression capabilities
Secure Communication and Aggregation Module	Realize secure transmission and global aggregation of model parameters	Homomorphic encryption, differential privacy, FedAvg / FedProx	Ensure data privacy and model consistency
Heterogeneous feature alignment module	Map and normalize node features and relationship semantics of different enterprises	Meta-learning, feature normalization	Achieve cross-enterprise feature space alignment
Global Optimization Module	Integrate multi-party knowledge to improve model generalization performance	Model distillation, dynamic aggregation weight adjustment	Improve the stability and convergence speed of the global model
Evaluation and Feedback Module	Monitoring model performance and privacy leakage risks	Multi-metric joint evaluation (AUC, F1, DP budget)	Optimize the balance between system security and performance

Table 1 summarizes the main module composition, corresponding functions and key algorithm support of the federated graph neural network framework, which helps readers fully understand the technical system and design logic of the framework. In response to the heterogeneity of enterprise graph structures, the framework adopts a cross-domain parameter migration mechanism based on meta-learning. It first learns generalizable structural representations in the source domain enterprise and then adaptively migrates them to the target domain to achieve cross-enterprise knowledge sharing and semantic consistency; at the same time, it designs an adaptive graph attention mechanism to dynamically adjust the information propagation weight based on the semantic relevance of nodes, thereby enhancing the robustness and transferability of the model in multi-task scenarios. In the model training and evaluation system, the framework adopts a multi-round iterative federated optimization strategy, which relies on alternating updates of global and local models to achieve accelerated convergence.

The evaluation indicators include multi-dimensional standards such as accuracy, AUC, F1-score, communication cost, and privacy leakage rate. The experiments are conducted with the help of real enterprise cooperation network datasets and synthetic cross-domain graphs, covering tasks such as cross-bank credit risk prediction and supply chain anomaly detection. The experimental results show that the existing methods are significantly inferior to the framework in terms of model accuracy, communication efficiency and privacy protection, indicating that it is feasible to achieve privacy controllable, efficient collaboration and heterogeneous integration in a complex business ecosystem, becoming a systematic solution and theoretical support source for building a secure and reliable cross-enterprise intelligent analysis system.

5. Application Scenarios and Empirical Results

Table 2 Summary of experimental scenarios and performance comparison results

Application Scenario	Comparison Model	Accuracy	AUC value	Communication cost reduction rate	Privacy leakage rate	Performance Improvement Notes
Cross-bank credit risk prediction	Traditional centralized model	0.84	0.87	—	high	High privacy risk and unstable performance
	Common federated learning model	0.86	0.89	20%	middle	Convergence is slow, generalization is average
	This article's FGNN framework	0.91	0.94	45%	Low	Improve recognition rate and security
Supply Chain Anomaly Detection	Traditional isolated detection model	0.79	0.81	—	high	Unable to capture the global risk chain
	Federated Aggregation GNN Model	0.83	0.86	18%	middle	Limited local detection capabilities
	This article's FGNN framework	0.89	0.91	42%	Low	Improve global detection sensitivity
Collaborative optimization of the industrial chain	Traditional forecasting models	0.82	0.85	—	high	Insufficient optimization capabilities
	Distributed GNN model	0.86	0.88	25%	middle	Slow convergence
	This article's FGNN framework	0.92	0.93	40%	Low	Significantly improve collaborative efficiency and robustness

It covers three typical business analysis scenarios: cross-bank credit risk prediction, supply chain collaborative anomaly detection, and intelligent optimization of the industrial chain. The efficient federated graph neural network framework has powerful capabilities in cross-enterprise modeling and knowledge integration. When predicting cross-bank credit risk, the framework integrates distributed credit data from multiple financial institutions to achieve joint modeling and risk assessment without sharing original customer information. Banks use nodes such as customers, accounts, and transaction behaviors to build heterogeneous financial graph networks. The neighborhood aggregation mechanism of graph neural networks depicts potential financial connections, relying on federated learning to achieve cross-institutional knowledge sharing. Homomorphic encryption and differential privacy technologies are used to prevent the leakage of sensitive information. Traditional centralized methods are significantly inferior to the model in terms of AUC, recall rate, and default prediction accuracy. This makes it possible to achieve the result of secure credit collaborative assessment among multiple banks. InModel experiments using supply chain data simulations demonstrate that this mechanism significantly improves production collaboration efficiency and inventory turnover, while enhancing the risk resilience of the supply network.

This federated graph neural network framework achieves cross-domain feature alignment and distributed optimization with the help of privacy-controllable conditions, successfully building an intelligent analysis system for complex business ecosystems. It has shown significant practical application value and academic research significance in the fields of cross-bank financial risk control, supply chain security, and industrial chain collaborative decision-making. Table 2 compares three typical tasks: cross-bank credit risk prediction, supply chain anomaly detection, and industrial chain collaborative optimization. The main performance indicators involve different models, namely traditional centralized models, ordinary federated learning models, and the FGNN framework proposed in this paper, showing the advantages of the proposed method in multi-task business analysis.

6. Conclusion, Limitations, and Future Directions

This paper focuses on data sharing and privacy protection in cross-enterprise business analysis scenarios, demonstrating the construction of an efficient federated graph neural network framework that prevents the exposure of raw data, thereby enabling multi-enterprise collaborative modeling and intelligent analysis. The research systematically designs and verifies four aspects: architecture, communication optimization, privacy security, and heterogeneous data fusion. The introduction of sparse gradient compression and Top-K aggregation strategies significantly reduces communication overhead; homomorphic encryption and federated differential privacy techniques effectively defend against model inversion and statistical reconstruction attacks; and a meta-learning-based heterogeneous graph alignment mechanism enhances the model's generalization and migration capabilities across different enterprise data distributions. Experimental results verify the superiority of this framework in typical scenarios such as cross-bank credit risk prediction and supply chain anomaly detection, demonstrating its practicality and scalability.

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