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Building a Graph Neural Network Model for E-Commerce

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ABSTRACT

The article discusses the development of graph neural network (GNN) models for e-commerce, aimed at predicting user interactions with the content of the main page. The methods described focus on utilizing networks to improve relevance and personalize the user experience.

The purpose of this work is to examine the features of the graph neural network architecture specifically designed for e-commerce tasks. This architecture operates on graph data structures, allowing for the consideration of different levels of connections between users and products, and their various features.

The methodology employs graph node embedding algorithms such as GraphSAGE and Node2Vec, which transform any data into numerical vector representations. The sources used include scientific articles published by the author in the public domain, as well as materials available on the Internet, enabling a comprehensive exploration of the topic.

The results demonstrate that the proposed architecture enhances the accuracy of content personalization, as evidenced by increased click-through rates (CTR) and revenue. The implementation of this system modifies the algorithms for ranking content, thereby impacting the platform's effectiveness.

The article will be valuable for specialists working on recommendation systems, researchers, and developers of e-commerce solutions. The conclusions affirm the success of the proposed architecture in data analysis and user experience adaptation.

KEYWORDS: *deep learning, graph neural network models, deep and cross-network, recommendation systems, embeddings, prediction, browsing history.*

INTRODUCTION

E-commerce represents a rapidly evolving field where the personalization of user experience has become a critical component of business processes. The accumulation of data on user actions, preferences, and interactions with platforms necessitates the application of advanced analytical methods. Graph neural networks provide tools for exploring relationships among entities such as products, customers, and categories, including temporal dependencies.

Recommendation systems that leverage neural networks integrate these technologies with graph processing methods. However, challenges persist in scaling these technologies, adapting them to changing conditions, and integrating them into existing processes. Additionally, issues such as improving CTR prediction accuracy, accommodating a wide range of user preferences, and managing heterogeneous data remain significant.

The development of graph-based models for e-commerce has been widely discussed in academic literature due to their potential to enhance recommendation quality, predict user behavior, and optimize platform interactions. However, implementing such solutions faces challenges, including computational costs and the need to ensure the interpretability of results.

This article presents the architecture of a graph neural network designed to address e-commerce tasks. The proposed methodology focuses on improving the accuracy of user behavior predictions.

MATERIALS AND METHODS

The studies by Zhu L. and Liu W. et al. [1, 5] describe models such as Item-Relational Graph Neural Networks, analyzing connections between products through sparse graphs to improve recommendation accuracy. HiGNN, outlined in the work by Li Z. et al. [4], employs hierarchical structures, enhancing algorithm scalability. The DC-GNN method, presented by Feng C. et al. [2], optimizes data processing by segmenting the training stages. CC-GNN, discussed in the article by Xv G. et al. [3], addresses the issue of insufficient information. In Nguyen D. M. et al.'s work [10], the LightSAGE algorithm is presented, focusing on creating high-quality item embeddings through graph neural networks, addressing cold-start and long-tail challenges in large-scale e-commerce recommendations.

The study by Lu Y. W. and Li C. T. [9] describes temporal graph neural networks, which detect fraudulent activities through time series analysis. The algorithm presented in Yin H. et al.'s study [11] uses behavioral graphs to track user interactions, identifying anomalous behaviors.

Neural networks are widely used in data analysis. In Pan H. and Zhou H.'s article [12], convolutional neural networks are applied for sales prediction, aiding business strategy development. Li J. [6] outlines a model incorporating attention mechanisms and stochastic functions, improving recommendation quality. The research by Huang J., Niu S., and Zhang W. [7] describes a multilayer architecture for analyzing user sessions, enabling behavior prediction.

Data processing approaches vary across the studies. Articles such as those by Xv G. et al. [3] and Li Z. et al. [4] focus on the semantic attributes of products. However, challenges such as integrating external data sources (e.g., social networks) and automatically adapting models to dynamic changes still need to be solved.

Xu C. et al. analyze the use of attention-based graph networks for predicting sales volumes of new products. The study [13] emphasizes the importance of considering relationships between customer attributes, product features, and interaction data. The proposed architecture integrates sales information with network parameters, effectively modeling processes. This approach demonstrates the ability to uncover hidden patterns, particularly relevant for products with limited historical data.

Petroșanu D. M. et al. dedicated their study [14] to creating a directed acyclic graph for revenue prediction in e-commerce. The methodology relies on dynamically designed deep neural networks, accommodating changes in market conditions. Significant attention is given to model validation, adaptability to changing conditions, and ensuring computational accuracy amid data variability.

In the article by Yu Z. et al. [8], an adaptive semantic architecture for graph convolutional networks is introduced, designed for analyzing textual data in text-oriented graphs. The authors propose a methodology that integrates semantic information into the graph structure, enhancing tasks such as text classification and data extraction. The model adapts to the context of the text, enabling flexible graph customization and improving data processing accuracy.

Liu W. et al., in their article [15], proposed a graph neural network-based approach focused on analyzing interdependencies between products. The described model identifies relationships related to joint consumption and complementary purchases. This method improves calculation accuracy by accounting for non-trivial dependencies between product items.

The article examines graph analysis methods aimed at constructing structures that reflect interactions and relationships between elements. Algorithms like GraphSAGE and Node2Vec transform data into vector representations that capture graph patterns. Temporal graph layers adapt to changing conditions, facilitating the analysis of time-based changes. Attention mechanisms highlight significant connections, thereby enhancing model accuracy. Deep neural networks, including graph convolutional networks and recurrent architectures, optimize predictions and improve analysis quality.

RESULTS AND DISCUSSION

Designing an effective graph architecture is based on analyzing object characteristics and their relationships. The main elements of the architecture of a graph neural network model for e-commerce are presented in Table 1.

Table 1. Architecture elements of the graph neural network model for e-commerce

Component	Description	Implementation Example
Graph Type	Type of graph structure used in the model (directed, undirected, homogeneous, heterogeneous, weighted, etc.)	Customer purchase graph: nodes - users and products, edges - transactions
Nodes	Elements of the graph representing e-commerce objects	Users, products, product categories
Edges	Connections between graph nodes	Purchase, view, add-to-cart actions
Node Attributes	Characteristics of each node	User nodes: demographics, geolocation, purchase history
Edge Attributes	Characteristics of connections between nodes	Purchase edges: time, amount, device type
Model Type	Type of neural network used for graph processing	Graph Neural Network (GNN), Graph Convolutional Network (GCN)
Aggregation Function	Method for aggregating information from neighboring nodes	Mean pooling, Max pooling
Model Task	Objective of the graph model	Node classification - for user churn prediction, link prediction - for recommendation system

Evaluation Metrics	Methods for assessing model quality	Accuracy, Precision@K, Recall@K, NDCG, ROC-AUC
Data Source	Source of data for model training and testing	User activity logs, transaction data
Data Preprocessing	Libraries for transforming tabular data into graph format	Store users and items and sets of nodes, and store user interactions as user-item pairs
Tools and Libraries	Technologies for implementing graph neural networks	PyTorch Geometric, DGL, TensorFlow GNN
Model Complexity	Model complexity and computational requirements	O(V+E), where V - number of nodes, E - number of edges

An important aspect is the selection of encoding methods for nodes and edges, as their structure determines the model's ability to recognize complex dependencies [9,11]. Figure 1 illustrates the functionality of graph neural network architectures in e-commerce.

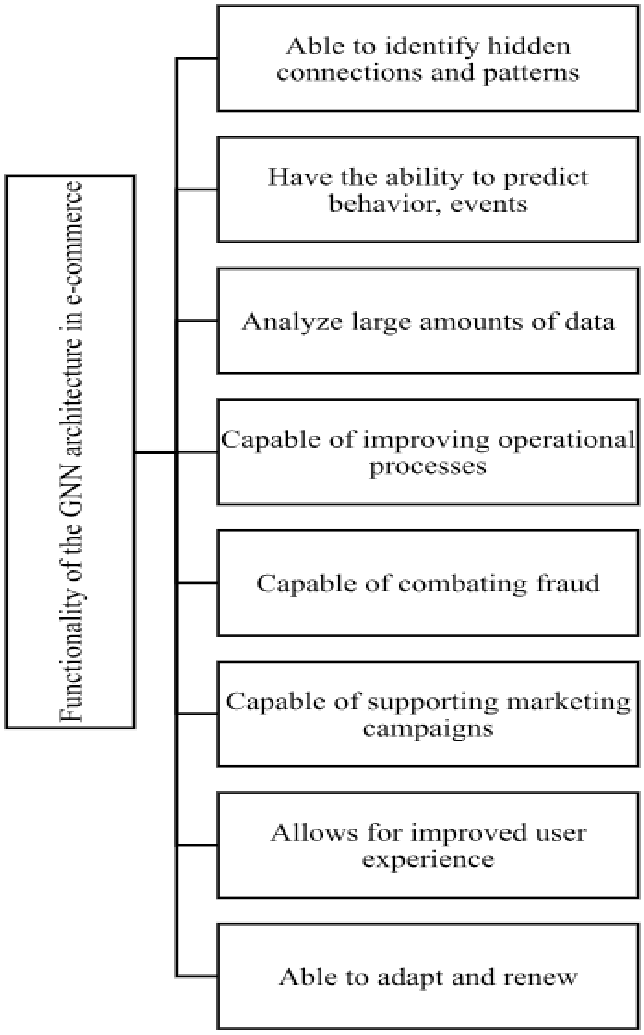

Fig.1. The functionality of the architecture of graph neural networks in e-commerce (compiled by the author)

In the context of e-commerce, particular attention should be paid to heterogeneous graphs, where elements, or nodes, differ in type and connections vary in their functional roles. Products, users, and categories form a multilayer structure that serves as the foundation for implementing recommendation systems and clustering algorithms. Temporal aspects are incorporated through time layers in graph networks, enabling adequate processing of data changes over time.

One of the initial steps in design is the selection of representations for objects and their relationships. Graph embeddings are created using methods aimed at transferring knowledge from the graph into dense vector spaces. Such approaches include algorithms like Node2Vec, which explores local and global patterns, and more complex mechanisms like GraphSAGE, which focuses on creating context-dependent embeddings [12].

For e-commerce tasks involving multilevel interactions, algorithms with adjustable parameters are employed. Weighted and labeled edges model the intensity and nature of interactions, such as reviews, purchases, and product additions to carts.

Training graph neural networks in this domain relies on combined approaches that include local and global data analysis. Combining graph convolutional networks (GCNs) with attention mechanisms allows the identification of connections, adapting the model to the characteristics of input data. For tasks requiring temporal changes, graph networks with recurrent layers analyze sequences of changes in object states [6,7].

Graph Attention Networks (GATs) are applied to work with heterogeneous structures. Attention mechanisms focus on significant parts of the graph, learning the importance of connections, and enhancing the processing of local and global patterns.

Researchers from Texas A&M University developed the Item Relationship Graph Neural Network (IRGNN) model, which identifies dependencies between products, including complementarity and substitutability. The model analyzes multiple connections between products, improving recommendations.

In 2022, a model for sales forecasting using a directed acyclic graph neural network was proposed. This approach enables long-term revenue forecasting by product categories, accounting for daily changes.

In 2024, the MycGNN model, inspired by the adaptive properties of mycelium, was introduced. Using graph neural networks, the model enhances recommendation diversity, improving accuracy in the e-commerce context [15].

Shopee developed the LightSAGE architecture, leveraging graph neural networks for product searches in advertising systems. The model combines user behavior data with collaborative filtering methods, constructing product graphs.

The Gaia model, introduced in 2022, uses graph neural networks with temporal changes to forecast gross merchandise value. The model analyzes correlations between sellers, aiding in accurate predictions of economic metrics.

The Content Collaborative Graph Neural Network (CC-GNN) model integrates content and collaborative graphs and incorporates content phrases into graph propagation, improving the understanding of phrase meanings and semantic changes. This enhances search accuracy on e-commerce platforms [13,14].

The Gramian Angular Summation Field (GASF) model employs graph neural networks with attention mechanisms to forecast sales of new products. It integrates structural and temporal data features, enabling accurate predictions of sales dynamics based on graph changes and user preferences [3,4]. Table 2 below outlines the advantages and disadvantages of using graph neural network architectures in e-commerce.

Table 2. Advantages and disadvantages of using GNNs for e-commerce (compiled by the author)

Advantages	**Disadvantages**
GNNs model both direct and indirect connections between users, products, and other entities, capturing intricate patterns that other methods may overlook.	Processing large-scale graphs, especially in e-commerce with millions of users and products, demands significant computational resources and specialized hardware.
By leveraging relationships within the graph, GNNs can deliver more accurate and relevant recommendations, enhancing the personalization of user experiences.	As the number of users, products, and interactions grows, efficiently scaling GNN models to handle massive graphs may pose a challenge.
By introducing different types of edges and assigning various weights to them, GNNs allow us to easily model multimodal content interactions: views, clicks, video completion rates, purchases	The performance of GNNs heavily depends on having comprehensive, high-quality data: maintaining an additional graph data preparation pipeline creates technical overhead
GNNs can effectively recommend new products by leveraging their connections to existing nodes in the graph (like brands), mitigating the cold-start problem.	Developing, training, and fine-tuning GNNs necessitates specialized knowledge in both graph theory and machine learning.
GNNs can predict future user behaviors, such as the likelihood of interactions or purchases, by analyzing the evolving connections in the graph.	Continuously constructing and updating graphs can be resource-intensive and slow, especially when data changes frequently or is not structured efficiently.
By modeling relationships between objects and their contexts, GNNs can enhance search relevance, delivering more accurate search results to users.	GNNs can be highly complex, and their outputs are often difficult to interpret, which may hinder decision-making by business analysts and reduce model transparency.

Further analysis within this work focuses on the practical application of a graph neural network model known as the application of a graph neural network for the purpose of predicting clicks on Zalando homepage**.** The objective was to enhance the quality of personalized content displayed on the homepage, thereby increasing user interactions with interface elements and driving revenue growth from hosted advertisements. The project included a study of user actions on the platform, such as clicks, views, and purchases. It also considered content properties, including textual information, visual characteristics, thematic associations, and data on geography, devices, and session time parameters.

The collected data were transformed into a graph structure, where nodes represented users and content, and the edges described the nature of their interactions. Vector representations captured the characteristics of users and content. The model operated using a message-passing mechanism to account for connections within the graph. Additionally, a mechanism for initial features processing and identifying the most significant interactions was employed.

The training was conducted using historical data. The model was trained to predict the existence of a click edge in the graph given a view edge between a user and a content node. Specialized computational systems were utilized to enhance computation performance: data preprocessing and conversion into graph format was performed using PyTorch Geometric library on Spark Databricks cluster. The GNN itself was trained on a GPU machine to ensure a fast experimentation cycle.

Integration of a recommender system fully running on graph neural networks is highly complex as it requires maintenance and constant updates of the full user-content graph, as well as running inference on a GNN requires a completely different ecosystem. Therefore full GNN integration is still a work in progress, and the current suggested approach is to utilise GNN to train user and content embeddings and use them in the downstream click prediction task. Adding these embeddings as features into the production model has improved our main offline evaluation metric, ROC-AUC, by 0.6 percentage points which helped to further improve content relevance for the user. There is still a lot of room for improvement on both sides: fine-tuning the hyperparameters of the production model with GNN features, as well as testing architectural enhancements to train GNN embeddings.

The implementation of this solution improves the quality of content personalization because the GNN embeddings are not just some features of clients and entities, but features trained specifically for the task of click prediction which allows the model to encode not only constant properties of the content but also its evolving connections with users, leading to more accurate and context-aware predictions.

The developed modeling approach demonstrated the effectiveness of modern technologies in enhancing e-commerce platform performance. On top of improving the accuracy of click prediction, GNNs offer even more powerful capabilities that allow modeling complex aspects such as novelty and diversity of content recommendations. This can help companies steer user engagement not only through relevance but also through diverse and inspiring content. Thus, graph neural networks present new opportunities for creating personalized recommendation systems that account for complex data interrelations. Future advancements in this approach involve integrating online learning models and hybrid architectures, which will improve data processing efficiency and personalization quality.

CONCLUSION

This study examined the architecture of a graph neural network model designed for personalization tasks in e-commerce interactions. The developed structures incorporated temporal aspects and relationships between system elements such as users, products, and categories.

Graph embeddings were used for data representation, employing algorithms capable of capturing both local patterns and global connections. The introduction of temporal layers enhanced adaptability to changing conditions, while attention mechanisms accounted for preference dynamics. Examples of implementation on global platforms demonstrate the approach's effectiveness in content personalization.

REFERENCES

1. Zhu L. E-Commerce Recommendation Algorithm based on Graph Neural Network //Highlights in Science, Engineering and Technology. – 2023. – Vol.. 39. – pp. 1264-1268.
2. Feng C. et al. DC-GNN: Decoupled graph neural networks for improving and accelerating large-scale e-commerce retrieval //Companion Proceedings of the Web Conference 2022. – 2022. – pp. 32-40.
3. Xv G. et al. E-commerce Search via Content Collaborative Graph Neural Network //Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining. – 2023. – pp. 2885-2897.
4. Li Z. et al. Hierarchical bipartite graph neural networks: Towards large-scale e-commerce applications //2020 IEEE 36th International Conference on Data Engineering (ICDE). – IEEE. - 2020. – pp. 1677-1688.
5. Liu W. et al. Item relationship graph neural networks for e-commerce //IEEE Transactions on Neural Networks and Learning Systems. – 2021. – Vol. 33 (9). – pp. 4785-4799.
6. Li J. Application on E-Commerce Knowledge Graph Recommendation Model Integrating Attention Mechanism and Random Features //Proceedings of the 2022 4th International Conference on Robotics, Intelligent Control and Artificial Intelligence. – 2022. – pp. 919-923.
7. Huang J., Niu S., Zhang W. Session-Based Recommendation with Multi-layer Parallel Graph Neural Network //Proceedings of the 2023 9th International Conference on Computing and Artificial Intelligence. – 2023. – pp. 249-257.
8. Yu Z. et al. AS-GCN: Adaptive semantic architecture of graph convolutional networks for text-rich networks //2021 IEEE International Conference on Data Mining (ICDM). – IEEE. - 2021. – pp. 837-846.
9. Lu Y. W., Li C. T. Fraudulent User Detection with Time-enhanced Graph Neural Networks on E-Commerce Platforms //2023 International Conference on Consumer Electronics-Taiwan (ICCE-Taiwan). – IEEE. - 2023. – pp. 49-50.
10. Nguyen D. M. et al. LightSAGE: Graph Neural Networks for Large Scale Item Retrieval in Shopee's Advertisement Recommendation //Proceedings of the 17th ACM Conference on Recommender Systems. – 2023. – pp. 334-337.
11. Yin H. et al. Behavioral graph fraud detection in E-commerce //2022 IEEE International Conference on Data Mining Workshops (ICDMW). – IEEE. - 2022. – pp. 1-8.
12. Pan H., Zhou H. Study on convolutional neural network and its application in data mining and sales forecasting for E-commerce //Electronic Commerce Research. – 2020. – Vol. 20 (2). – pp. 297-320.
13. Xu C. et al. Graph attention networks for new product sales forecasting in e-commerce //Database Systems for Advanced Applications: 26th International Conference, DASFAA 2021, Taipei, Taiwan, April 11–14, 2021, Proceedings, Part III 26. – Springer International Publishing. - 2021. – pp. 553-565.
14. Petroșanu D. M. et al. E-commerce sales revenues forecasting by means of dynamically designing, developing and validating a directed acyclic graph (DAG) network for deep learning //Electronics. – 2022. – Vol. 11 (18). – p. 2940.

15. Liu W. et al. Item relationship graph neural networks for e-commerce //IEEE Transactions on Neural Networks and Learning Systems. – 2021. – Vol.33 (9). – pp. 4785-4799.

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