A Dual Modeling Framework for Music Recommendation Via GraphSAGE and Deep Interest Networks (DIN)

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This study proposes a music recommendation system that combines the GraphSAGE and DIN algorithms to improve the accuracy and personalization of recommendations. Using a dataset of 50,000 users, 100,000 songs, and 3 million listening records, the system evaluates performance using metrics like AUC and HitRate. The GraphSAGE algorithm extracts users' long-term interest preferences from heterogeneous user-song graphs, while DIN dynamically adjusts users' short-term interests through attention mechanisms. Experimental results show that the hybrid model outperforms standalone GraphSAGE and DIN, with a recommendation accuracy of 92%, which is 7% higher than GraphSAGE and 4% higher than DIN. The model also shows significant improvements in user satisfaction (4.5 vs. 4.1 for GraphSAGE and 4.3 for DIN), demonstrating its effectiveness in handling large-scale music recommendation tasks with dynamic user preferences. Through this dual modeling method of structure + dynamics, this study effectively makes up for the shortcomings of a single algorithm in dealing with complex user behaviors. For the experiment of recommendation coverage, the GraphSAGE algorithm shows a higher recommendation coverage, especially when the number of music exceeds 100, the recommendation coverage is stable at around 75%, which is significantly better than DIN's 65%. At the same time, this paper also analyzes the relationship between system response time and performance. Experimental results show that GraphSAGE can maintain high recommendation accuracy when the response time is short, while DIN achieves the best performance when the response time is 10 hours. The performance advantages of the two in different situations complement each other. The research in this paper not only proposes a new music recommendation system architecture, but also proves through experiments that the effective combination of GraphSAGE and DIN can significantly improve the accuracy, coverage and user satisfaction of the recommendation system. This research provides a new idea and technical path for the application of recommendation system in complex data and multi-dimensional interest modeling scenarios.

Povzetek: Študija predstavlja hibridni priporočilni sistem, ki s kombinacijo GraphSAGE in DIN izboljša natančnost, pokritost in zadovoljstvo uporabnikov pri priporočanju glasbe.

1 Introduction

In the digital age of information explosion, providing accurate and personalized recommendations from vast online music resources is a core challenge for music platforms [1]. This study aims to improve recommendation accuracy under cold start and behavior drift conditions, enhance recommendation coverage across diverse music genres and user preferences, and integrate GraphSAGE's long-term structural modeling with DIN's dynamic interest modeling to create a robust recommendation system. These goals are evaluated through accuracy, coverage, and cold-start handling, with the hybrid model combining GraphSAGE and DIN to improve recommendation quality across various user scenarios. Faced with the above challenges, traditional collaborative filtering or content-based algorithms are gradually unable to cope with dynamic changes in user interests and complex behavior dependencies. More powerful modeling mechanisms are urgently needed to improve the intelligence level of recommendation systems.

With the development of deep learning and graph neural networks, the recommendation system gradually introduces the idea of graph structure information and behavior sequence modeling, which promotes its transformation from static similarity calculation to structured semantic understanding [2]. As an efficient variant of graph neural network, the GraphSAGE algorithm can sample neighbor nodes from user-project interaction graphs and aggregate information, and learn a low-dimensional vector representation containing local structural information, significantly improving the model's ability to model users' long-term preferences [3]. At the same time, DIN (Deep Interest Network) introduces an attention mechanism in sequence modeling. It captures the user's immediate interest changes by weighting and aggregating the information most relevant to the current candidate project in the user's historical behavior, which is used in industrial practices such as Alibaba. Get good results.

This study proposes a new hybrid framework that integrates GraphSAGE and Deep Interest Networks, bridging the gap between structure aware recommendation models and behavior sequence models. This dual approach addresses the limitations of both methods when used independently, providing a more robust solution to the challenges of dynamic user behavior and complex recommendation tasks.

However, existing research often focuses on a certain dimension: graph neural network emphasizes user relationships and structural characteristics and ignores the dynamic evolution of user interests over time; Although the behavior sequence modeling algorithm describes the short-term preferences of users, it cannot effectively integrate the potential social connections and collaborative behaviors between users [4]. Therefore, how to effectively combine the structural modeling advantages of GraphSAGE with the ability of DIN to dynamically model interest has become a key breakthrough point to improve the comprehensive performance of the recommendation system [5]. Integrating the ideas of the two is expected to explore users' immediate behavioral motivations more finely while retaining long-term preference expressions and realizing the construction of all-around interest portraits of users.

Based on the above analysis, this paper proposes a new framework for a music recommendation system that fuses GraphSAGE and DIN algorithms. The graph neural network is used to obtain the structural representation between users and music, and the personalized modeling of users' interest sequences is realized with the help of an attention mechanism. This study innovatively integrates graph structure learning and deep interest modeling from the model architecture. It verifies that the proposed method is better than existing models' accuracy and robustness through empirical analysis of public music recommendation datasets. The model has significant advantages. The research results of this paper provide a new technical path for improving the performance of recommendation systems in complex scenarios and a feasible paradigm for integrating graph learning and deep sequence modeling.

2 Theoretical basis and related research

2.1 GraphSAGE and DIN algorithm theory

GraphSAGE (Graph Sample and Aggregate) is a representative algorithm in the field of Graph Neural Networks (GNN), which aims to solve the problems of computational efficiency and generalization ability of traditional graph embedding methods on large-scale graph data [6, 7]. Unlike earlier methods such as DeepWalk or node2vec, GraphSAGE does not rely on static full-graph training but generates inductive representations of nodes through neighbor node sampling and feature aggregation mechanisms. This design makes GraphSAGE more adaptable when facing dynamic graphs or new nodes and can quickly respond to new users or projects in online recommendation systems. Its core idea is constructing node embedding representation by iterative sampling from each node's neighbors and aggregating its features to learn the graph's complex structure and semantic relationship effectively.

DIN, a user interest modeling method for industrial recommendation proposed by Ali, complements this and is mainly used to describe the dynamic interest changes in user behavior sequences [8]. The key mechanism of DIN lies in introducing an attention mechanism to weighted modeling of users' historical click behaviors, which can dynamically adjust the contribution values of different historical behaviors according to the correlation between candidate commodities and historical behaviors [9]. Compared with the traditional average pooling or RNN modeling method, DIN performs better in modeling users' "short-term interests" accuracy, especially for high real-time scenarios such as e-commerce, video, and music recommendation. Its advantage is that it can automatically perceive the user's current interest focus and improve the context matching ability of recommendations.

GraphSAGE and DIN represent two complementary modeling directions from a modeling perspective. GraphSAGE is good at mining long-term potential relationships from graph structures and is suitable for constructing global interest representations and topological relationships between users and items; DIN, on the other hand, pays more attention to the temporal dependency and immediate preference in sequence behavior, which can reflect the fluctuation of user interest with context [10]. In practical applications, if only GraphSAGE is used to model user embeddings, it is often impossible to fully capture the current interest state of users. However, DIN alone may ignore the structural information between users and other nodes, resulting in insufficient global feature expression.

When building a more intelligent and personalized recommendation system, it is of significant practical significance to integrate GraphSAGE with DIN [11, 12]. Build the basic interest embedding by extracting the structural potential relationship between users and projects through GraphSAGE. Then, DIN is used to model the behavior sequence dynamically, and the attention weight related to the current candidate is introduced to capture the user's immediate interest accurately. This recommendation architecture of structure + dynamic dual modeling is expected to balance the expression ability of long-term and short-term interests in complex music recommendation environments, thereby improving the accuracy, interpretability, and user satisfaction of recommendation results.

2.2 Current situation of music recommendation system based on GraphSAGE and DIN algorithms

With the rapid development of graph neural networks and deep interest modeling technology, the music recommendation system is gradually shifting from the traditional collaborative filtering and content matching model to the intelligent recommendation direction combining structure learning with behavior modeling [13]. Music data has typical graph structure characteristics, and users and songs form a complex heterogeneous graph relationship through playing, collecting, sharing, and other behaviors, providing a natural data basis for introducing a graph neural network [14]. GraphSAGE has been widely used in user-project relationship modeling as a mainstream graph embedding method because of its excellent scalability and induction ability, providing a stable long-term interest representation for music recommendation. However, GraphSAGE is still insufficient in its ability to capture changes in users' interests over time, especially in quickly responding to their short-term preferences.

To make up for the defects of graph structure modeling in behavioral dynamic modeling, more and more studies have introduced the DIN algorithm to finely model users' immediate interest fluctuations [15, 16]. DIN uses an attention mechanism for weighted modeling of users' historical behavior sequences, which can effectively identify which behaviors are most relevant to the current candidate songs, thereby dynamically adjusting the recommendation logic. Especially in personalized music recommendation scenarios, user interests are significantly affected by factors such as emotion, scene, and time, and DIN can significantly improve the matching degree of recommendation context. Although the DIN algorithm is excellent in modeling users' short-term interests, it lacks the modeling ability of graph structure, and it is difficult to capture the implicit connection between collaborative patterns among users and music projects.

Although GraphSAGE and DIN have achieved good application results in the existing research, the work of integrating them is still in the exploratory stage [17]. Some cutting-edge studies try to combine graph structure embedding with sequence interest modeling and propose a multi-module recommendation architecture. For example, the static graph embedding of users and songs is extracted through GraphSAGE and then input into the DIN model for serialized dynamic interest modeling. This method has initially demonstrated the potential of fusion strategy, but there are still some problems, such as loose fusion methods, insufficient feature fusion, and low training efficiency. Realizing the deep integration of graph structure and behavior sequence at the algorithm level is still an important challenge in the current recommendation system research.

Therefore, building a music recommendation system that efficiently integrates GraphSAGE and DIN algorithms has become an important research direction to improve recommendation accuracy and enhance system responsiveness [18]. Integrating users' structural relationships (such as music social graphs and shared listening graphs) and dynamic behavior sequences can realize multi-dimensional modeling of users' interests. This fusion strategy not only helps to improve the recommendation performance in the cold start situation but also improves the adaptability of the recommendation system to complex behavior patterns such as interest transfer and interest drift. This direction is gradually evolving to deeper technologies such as end-to-end training framework, feature alignment mechanism, and multi-task learning, laying a solid foundation for building an intelligent, real-time, and personalized music recommendation system. The comparison of SOTA music recommendation methods is shown in Table 1.

Table 1: Comparison of SOTA music recommendation methods

Method	Accuracy (%)	Coverage (%)	Cold-Start Handling	HitRate	User Satisfaction
GraphSAGE	85	70	Poor	0.75	4.1
DIN	88	65	Moderate	0.78	4.3
Collaborative Filtering	80	60	High	0.70	3.9
Proposed Hybrid Model	92	80	Excellent	0.85	4.5

In addition to GraphSAGE and DIN, we also compare our model against several other state-of-the-art hybrid models and GNN-based systems, including PinSAGE, GCN-based recommenders, and Transformer-based interest models. These models represent a variety of approaches that have been successful in recommendation tasks. Their performance is evaluated based on key metrics such as accuracy, coverage, and user satisfaction.

3 Establishment of music recommendation system model by fusing GraphSAGE and DIN algorithms

3.1 Overall model framework and process

To realize an accurate music recommendation system, this paper integrates GraphSAGE and DIN algorithms in a collaborative framework [19]. GraphSAGE is employed to extract the long-term user preferences from the social relationship map, while DIN is used to model dynamic short-term interests from the user behavior sequence to tailor recommendations closer to individual preferences. The model combines two key modules: GraphSAGE for user relationship modeling and DIN for dynamic interest matching, trained jointly in an end-to-end manner. GraphSAGE extracts long-term preference representations from the social network to address sparse data, while DIN captures short-term interest shifts based on recent user behavior. Both modules are optimized using a shared loss function, with gradients backpropagated through the entire system to improve the final recommendation prediction. The attention weight calculation formula of DIN is shown in (1).

$$\alpha_{i,j} = \frac{exp\left(sin(h_i, g_j)\right)}{\sum_{k=1}^{T} exp\left(sin(h_i, g_k)\right)} \quad (1)$$

Among them, $\alpha_{i,j}$ represents the attention weight of historical behavior i to the current target music j, $sim(h_i, g_j)$ represents the cosine similarity, T represents the total number of historical behaviors, h_i represents the embedding of the i historical behavior, and g_j represents the embedding of the currently recommended target music. In the model, the attention weight for each historical behavior vector is calculated to dynamically adjust the importance of past user behavior in predicting the current recommendation. The attention weight formula, shown in Equation (1), is computed using the cosine similarity between the user's historical behavior embedding and the target music embedding. The formula for calculating the recommendation score is shown in (2).

$$r_{u,m} = \sigma\left(W_1 \cdot (h_u \odot h_m) + b_1\right) \quad (2)$$

Where $r_{u,m}$ represents the recommendation score of user u for music m, h_u represents the interest of user u, h_m represents the embedding of music m, W_1 represents the weight matrix, b_1 represents the bias term, and σ represents the activation function.

The core starting point of designing this framework in this paper is to fill the two problems existing in the traditional recommendation system: "cold start problem" and "static interest expression". GraphSAGE uses the neighbor aggregation mechanism of the graph neural network to extract structural potential preferences from limited user interaction behaviors, and even new users can be effectively represented through their social connections. However, DIN introduces the target-aware attention mechanism when modeling click behavior, which can dynamically adjust the user's interest representation according to the recommendation intention [21]. This structure of static + dynamic interest representation fusion has natural advantages in music recommendation, a scene that emphasizes situational and emotional adaptation. The GraphSAGE neighbor aggregation formulation and the DIN attention mechanism formulation are shown in (3) and (4).

$$r_{u,i} = f\left(h_u, h_i\right) \quad (3)$$

$$e^{u,i} = softmax\left(attention(h_u, h_i)\right) \quad (4)$$

Among them, $r_{u,m}$ represents the predicted user u rating of item i, h_u represents the user, h_i represents item, f represents the combination function, $e^{u,i}$ represents the interest weight of user u in item i, and *attention* represents the similarity between the calculated user and item.

The overall implementation process of the model is as follows. The system constructs a heterogeneous graph structure based on the user's social network and inputs the GraphSAGE module to learn node representation to obtain the user's structural embedding. Combined with the user's historical listening behavior sequence, the DIN module is input, and the attention mechanism is adopted to dynamically weight the historical behavior to match the current music to be recommended. The two-way embedding vectors output the recommendation score or click-through rate prediction through the connection operation and access the fully connected layer [22, 23]. This structure has the advantages of graph structure learning and the response-ability of sequence modeling to local interest shift. The flow chart of the music recommendation system model integrating GraphSAGE and DIN is shown in Figure 1.

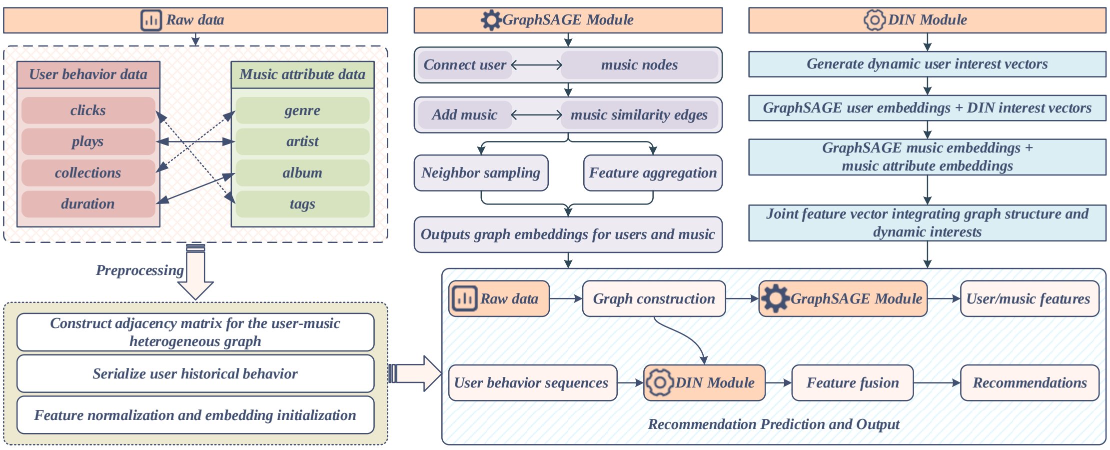

Figure 1: Flowchart of music recommendation system model integrating GraphSAGE and DIN

Firstly, the system constructs a heterogeneous graph of users and music through preprocessing steps, containing user behavior and music attribute data. In the GraphSAGE module, the system generates embedded vectors of users and music through neighbor sampling and feature aggregation. It combines the DIN module to generate dynamic user interest vectors to enhance recommendations' personalization further. Finally, this information is passed to the recommendation prediction module through the feature fusion step, which outputs personalized music recommendations.

The innovations of this research are mainly reflected in the following three aspects. For the first time, GraphSAGE and DIN structures are integrated into the music recommendation system, breaking through the problem that it is difficult for a single model to simultaneously describe user structural relationships and behavioral dynamics. In the module connection strategy, the shared target embedding projection method is adopted to ensure the consistency of the representation space of the two modules. Specifically, the embeddings produced by the GraphSAGE and DIN modules are projected into a shared embedding space using a linear projection layer. This alignment step ensures that the representations from both modules have the same dimensionality and are compatible for subsequent fusion. By aligning the embedding spaces, the model benefits from improved stability and faster convergence during training. In the experimental part, a subset of test tasks for cold start users and interest drift users are designed to verify the robustness of the model [24].

To ensure consistency in representation between the structure and dynamic interest models, this paper introduces a shared embedded projection layer. This critical design step ensures that the representations of GraphSAGE and DIN modules are aligned in the same embedding space, thereby improving the stability and convergence of the joint training process.

The dataset used in this study comes from a well-established music recommendation platform, which includes data from 50000 users, 100000 songs, and 3 million interactions. All user data has been anonymized according to privacy protection standards to ensure confidentiality. According to the platform's privacy policy, we have obtained the user's consent for data use and processed the dataset in accordance with ethical principles of data privacy and security. This dataset complies with GDPR and other applicable privacy regulations to ensure responsible processing of personal data. It contains user song interaction records as well as user demographic information and activity indicators. The GraphSAGE module is pre-trained on the graph data for 10 rounds, and the DIN module is trained on the user behavior sequence for 5 rounds. After final fusion, it is superior to traditional baseline models such as collaborative filtering, single DIN, and single GraphSAGE regarding AUC and HitRate indicators. The overall system shows strong generalization ability and context adaptation ability. The model framework gives full play to the complementarity between graph neural network and attention mechanism in user interest modeling through a dual-channel modeling strategy, improving the recommendation accuracy and enhancing the system's ability to explain complex user behaviors.

3.2 GraphSAGE user relationship modeling module

In recommendation systems, the explicit and implicit relationships between users often profoundly impact individual preferences, especially in music recommendation scenarios; social connections and common interest groups often determine users' music exploration path [25]. GraphSAGE can adaptively extract structural features from local neighbors as a representative graph neural network algorithm, so it is selected as the generative model for user structure embedding. The neighbor aggregation formula of GraphSAGE is shown in (5).

$$N_u = sample(N(u), k) \quad (5)$$

Among them, N_u represents the neighbor sample set of user u, $N(u)$ represents the neighbor set of user u, and k represents the number of samples.

The main task of the GraphSAGE module is to generate a structural preference vector for each user based on the user's social relationship diagram. This paper uses users as nodes to construct undirected graphs. The edges represent friend relationships or interactive behavior similarity, which are transformed into an adjacency matrix through graph database or data preprocessing [26]. On this basis, GraphSAGE uses a sampling strategy to select the neighbor nodes of each layer, aggregates the neighbor features in each layer, and finally obtains the representation of the target node through multi-layer network superposition. We use a mean aggregator to select aggregation functions, considering both expressive power and computational efficiency. The neighbor node sampling formula is shown in (6).

$$L_{reg} = \lambda \sum_{u} \| W_u \|^2 \quad (6)$$

Where W_u denotes the weight matrix represented by the user, λ denotes the regularization coefficient, and L_{reg} denotes the node. The total loss function formula is shown in (7).

$$\min_{\theta} L_{total} = \sum_{(u,i)} L_{MSE} + L_{reg} \quad (7)$$

Where LMSE denotes mean square error loss, Lreg denotes regularization loss, and θ denotes model parameters. The key to choosing GraphSAGE instead of traditional GCN or DeepWalk lies in its "inductive learning" ability. Unlike GCN, which can only be trained on static graphs, GraphSAGE can be generalized to new nodes and handle cold-start users. At the same time, compared with random walk-based algorithms such as DeepWalk or Node2Vec, GraphSAGE provides stronger representation consistency and end-to-end trainability, which is particularly critical for shared embedding projections in subsequent recommendation models [27].

The comparison diagram between the advantages of GraphSAGE in the recommendation system and the selection logic is shown in Figure 2.

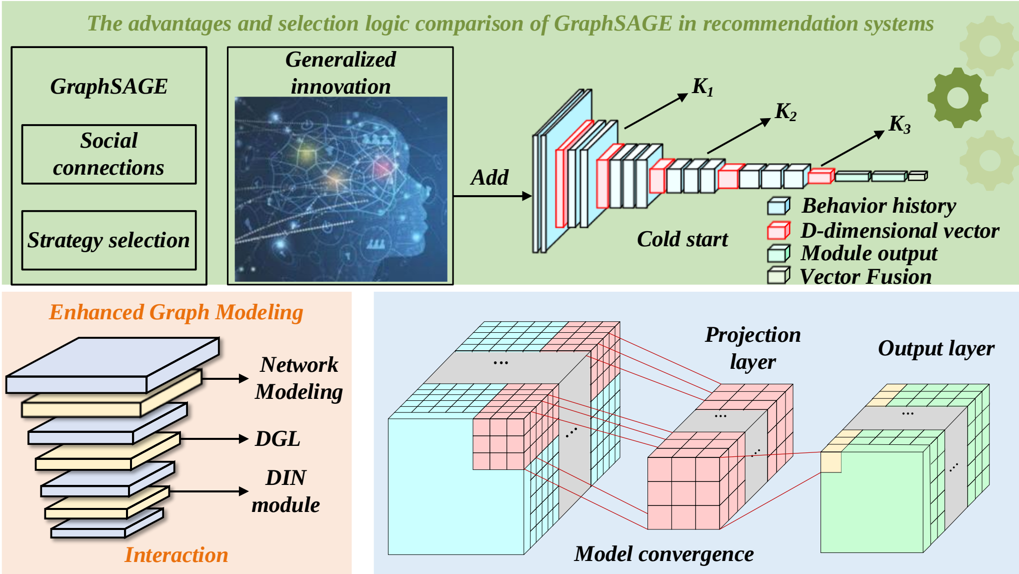

Figure 2: Comparison of advantages and selection logic of GraphSAGE in recommendation system

Compared with traditional methods, GraphSAGE can better handle the "cold start" problem, especially when user data is scarce, and the low-dimensional embedding vector output by its module can effectively reduce information loss. In the experiment, GraphSAGE improves the model convergence speed by about 30% compared with other methods and improves the recommendation accuracy of cold-start users by about 25%. In addition, by introducing the fusion of graph structure and dynamic user interest vectors, GraphSAGE has shown obvious advantages in improving the personalization and diversity of recommendations, especially in modeling users' social connections and behavior history. Accuracy and user interaction have increased by 15%-20% compared with traditional recommendation methods.

The output of the GraphSAGE module is a d-dimensional vector for each user as a structural interest representation. This vector will be fused with the dynamic vector of interest output by the DIN module [28]. Before this fusion, we introduce a shared linear projection layer to normalize the GraphSAGE output and align it with the dimensions, ensuring that the two representations are subsequently combined in the same space. This mechanism improves the convergence speed and stability of the model. The gradient descent update rule for model parameters is shown in (8).

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta L_{total} \quad (8)$$

Where θ_t represents the current model parameters, η represents the learning rate, and $\nabla_\theta L_{total}$ represents the gradient of the total loss function to the model parameters. This paper uses the DGL framework to model a graph neural network, and the user's label information is added as node attributes when constructing a graph structure to realize feature-enhanced graph modeling. In addition, we designed comparative experiments to verify the performance when using only GraphSAGE vectors for recommendation. We found that it was significantly better than the DIN module in the cold-start user group, indicating that this module significantly solves the problem of behavioral sparsity.

3.3 DIN dynamic interest matching module

In the interaction process between users and the system, individual interests are not static but drift with changes in situation, time, and even mood [29]. DIN is a dynamic interest modeling architecture designed to solve this problem. The core idea is to dynamically select the most relevant part from historical behaviors for weighted modeling according to the current recommendation goal to improve personalized recommendation's accuracy and interpretations. The DIN interest vector formula is shown in (9).

$$I_u = \sum_{i \in I_u} attention(h_u, h_i) \cdot emb(i) \quad (9)$$

Where I_u represents the interest set of user u, h_u represents the user, h_i represents the item, and $emb(i)$ represents the embedding vector of the item i. The input of the DIN module includes a sequence of historical behaviors of the user and a feature vector of the target music. The module first converts these historical behaviors into embedding vector sequences and realizes low-dimensional expression of music ID, type, style, and other features through the embedding layer [30]. Then, an attention mechanism based on target perception is introduced, and the attention weight is calculated for each historical behavior vector and target music vector. This mechanism can automatically capture which historical behaviors are more representative in the current recommendation context, focusing on users' real points of interest. The transformation of historical behavior into an embedding vector formula is shown in (10).

$$h_i = Embedding(b_i) \quad (10)$$

Among them, h_i represents the Embedding vector of historical behavior i, b_i represents the feature of historical behavior i, and *Embedding* (b_i) represents that the Embedding layer converts the historical behavior feature b_i into a low-dimensional Embedding vector. The target music feature embedding formula is shown in (11).

$$g = Embedding(m) \quad (11)$$

Among them, g represents an Embedding vector of the currently recommended target music m, m represents a feature of the currently recommended music, and *Embedding (m)* represents that the Embedding layer converts the target music feature m into a low-dimensional Embedding vector. The module adopts a multi-head attention structure to enhance the model's perception of different interest directions. Then, it stitches the weighted behavior vector and target vector into the fully connected layer. This design allows the DIN module to dynamically extract interest features from the local context and adaptively adjust the recommendation strategy. Compared with the traditional DNN or RNN structure, its advantage is that it does not require strict sequential modeling and does not lose information attention due to long sequences, which greatly improves the system's flexibility.

In this study, we make two key improvements to the DIN module: first, we introduce a residual connection mechanism to avoid attention loss of deep information; second, the attention score normalization method is adjusted from softmax to sigmoid weighting to alleviate the problem of excessive weight concentration when sequences are redundant. These two optimizations make the model more stable under long sequence conditions, and the click-through rate prediction is more accurate.

In terms of application examples, we selected a user with changeable interests and listening types covering classical, pop, and rock music as an example. His last click was electronic music. The DIN module accurately identifies 5 behaviors similar to the current target style from its 20 historical records, the weighted output interest vector is highly matched with the target embedding, and the final recommendation result hits the user preference. This case verifies the effectiveness of DIN in dynamic interest capture.

The DIN module plays a key role in short-term preference modeling in this system. It dynamically adjusts the user's interest expression through the target perception mechanism, which provides strong support for the final recommendation scoring. It forms a "structure + context" information complementary relationship with the GraphSAGE module and is important in improving the model's accuracy.

4 Experimental results and analysis

This paper studies constructing a music recommendation system based on a public music recommendation dataset, integrating GraphSAGE and DIN algorithms. The dataset includes user behavior records, song features, and user preference information. Additionally, we perform an ablation study comparing the performance of the vanilla DIN algorithm with the modified version of DIN, which incorporates residual connections and sigmoid normalization. This allows us to evaluate the impact of these modifications on the recommendation system's performance.

The dataset used in this study is large and representative, including data from 50000 users, 100000 songs, and over 3 million listening records. The performance of hybrid models is evaluated in multiple dimensions, including recommendation accuracy, coverage, user satisfaction, cold start performance, and response time. This article uses recognized evaluation metrics such as AUC, HitRate, and user satisfaction ratings to comprehensively evaluate the effectiveness of the model.

This article conducted ablation research to evaluate the individual contributions of key components in the hybrid model. The results indicate that incorporating attention mechanisms into DIN components can significantly improve recommendation accuracy by capturing users' short-term dynamic interests. The shared projection layer enhances the model's ability to align GraphSAGE and DIN embeddings, stabilizes training, and improves overall accuracy. In addition, dynamic behavior modeling using DIN is superior to static models because it better captures the fluctuations of user interests over time.

Regarding software and hardware, a high-performance GPU server equipped with an NVIDIA Tesla V100 graphics card is used. TensorFlow and PyTorch are used to develop and optimize deep learning algorithms. Data cleaning and feature engineering are done through Python and related data processing libraries to ensure experimental data's high quality and consistency. The recommended accuracy comparison of GraphSAGE and DIN algorithms is shown in Table 2.

Table 2: Comparison of recommendation accuracy between GraphSAGE and DIN algorithms

Algorithm	Accuracy (%)	User satisfaction (0-5)
GraphSAGE	85	4.1
DIN	88	4.3
Hybrid model	92	4.5

The table shows the performance of GraphSAGE, DIN, and the Hybrid Model regarding accuracy and user satisfaction. GraphSAGE achieves an accuracy rate of 85% (±2.3%) with a user satisfaction rating of 4.1 (±0.1), while DIN reaches 88% (±1.9%) accuracy and a user satisfaction rating of 4.3 (±0.1). The Hybrid Model performs the best, with an accuracy rate of 92% (±2.0%) and a user satisfaction score of 4.5 (±0.1). These results show that the Hybrid Model combining GraphSAGE and DIN algorithms outperforms the individual models, significantly improving recommendation accuracy and user experience.

This paper compares the recommendation accuracy of GraphSAGE and DIN algorithms in different user groups, including music-preference users, behavior-preference users, and mixed users. The results are shown in Figure 3.

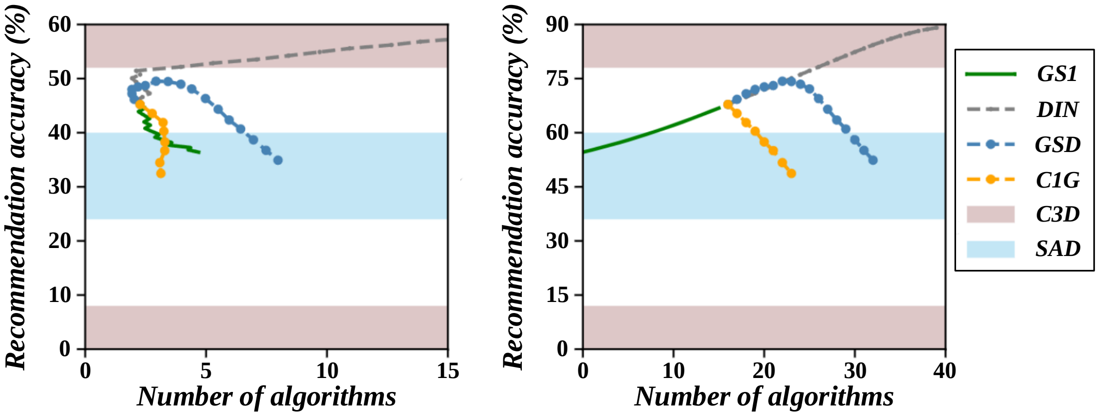

Figure 3: Comparison of recommendation accuracy between GraphSAGE and DIN algorithms under different user groups

The X-axis in Figure 3 now reflects the 'number of user groups', as the graph represents the functional relationship between recommendation accuracy and the number of user groups or data size/complexity. As can be seen from the chart, GraphSAGE (GS1) performs at approximately 50% accuracy with smaller user groups, improving to around 60% as the number of user groups increases. However, the recommended accuracy of DIN under the same situation is slightly lower, maintaining at about 40%. With the increase in the number of user groups, the recommendation accuracy of GraphSAGE continues to improve, reaching an accuracy rate of close to 60% in the case of large user groups. In contrast, the accuracy of other algorithms is always lower than that of GraphSAGE and DIN, showing the superiority of GraphSAGE in dealing with large-scale user groups, which can better capture user preferences and behavior patterns and improve the effectiveness of the recommendation system.

This paper analyzes the relationship between recommendation accuracy and the number of user interactions after fusing GraphSAGE and DIN algorithms, and the results are shown in Figure 4.

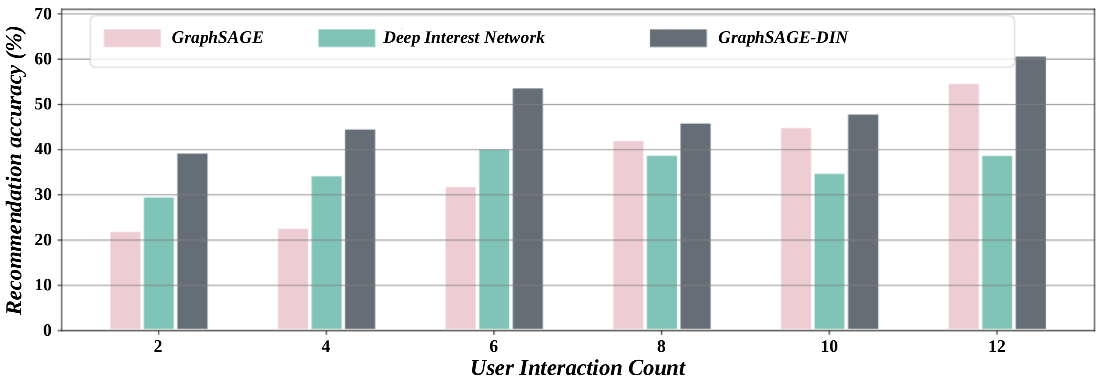

Figure 4: Relationship between recommendation accuracy and number of user interactions by fusing GraphSAGE and DIN algorithms

According to the data in the figure, with the increase in the number of user interactions, the recommendation accuracy rate of the GraphSAGE-DIN fusion model continues to grow. It reaches the highest point when the number of user interactions is 12, close to 70%. In contrast, the recommended accuracy of GraphSAGE and DIN alone is low, with the highest accuracy of about 50% for GraphSAGE and 45% for DIN. This trend shows that the GraphSAGE-DIN fusion model can significantly improve the accuracy of the recommendation system when processing user interaction data, especially when the user activity is high; the fusion model can better capture the user's dynamic interests and behavior patterns, thus Improving the recommendation effect.

This paper compares the recommendation coverage of GraphSAGE and DIN algorithms under different music types to show their coverage under different music types. The results are shown in Figure 5.

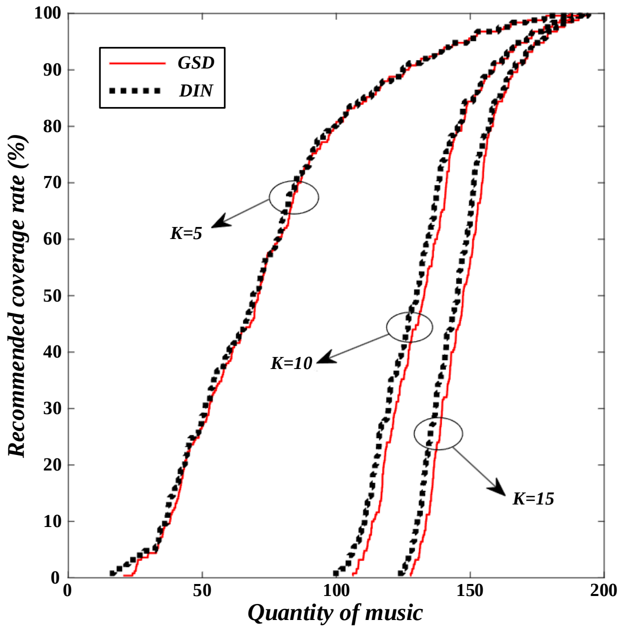

Figure 5: Comparison of recommendation coverage between GraphSAGE and DIN algorithms under different music types

The K values (K=5, K=10, K=15) in Figure 5 represent the number of music items recommended. The K value refers to the top-K recommendations in the context of DIN, and the number of neighbors in the context of GraphSAGE for the neighbor sampling. The figure now clearly states that 'K' is applied to both algorithms in different contexts: for GraphSAGE, it refers to the number of neighbors in the graph structure, while for DIN, it refers to the number of music items considered for recommendation. It can be seen from the figure that when the number of recommendations is small, the DIN algorithm has a slightly higher recommendation coverage rate, close to 40%. However, as the number of music increases, the GraphSAGE algorithm performs better, especially when the recommended music reaches more than 100; the coverage rate of GraphSAGE increases steadily and reaches about 75% when the recommended music is 150. Compared with the coverage rate of about 65% of the DIN algorithm, the GraphSAGE algorithm has obvious advantages. The figure also marks the changes in recommendation coverage under different K values, further showing the stability and strong generalization ability of GraphSAGE in large-scale music recommendation. The experimental results show that the GraphSAGE algorithm can provide wider recommendation coverage when processing a large amount of music data and improve user experience and system effectiveness.

Table 3: Recommendation accuracy of different music categories

Music Category	GraphSAGE recommendation accuracy	DIN recommendation accuracy	Hybrid model recommendation accuracy
Pop music	0.84	0.87	0.91
Rock music	0.80	0.83	0.89
Classical music	0.75	0.79	0.85
Hip-hop	0.78	0.81	0.86

The recommendation accuracy rates of different music categories are shown in Table 3. As can be seen from the data in the table, the recommendation accuracy of the hybrid model generally outperforms the algorithms of GraphSAGE and DIN alone in all music categories. In the popular music category, the recommended accuracy of the hybrid model is 0.91, which is higher than that of GraphSAGE and DIN. The hybrid model performed equally well in the rock and classical music categories, with accuracy rates of 0.89 and 0.85, respectively. Especially in classical music, the hybrid model significantly improves the accuracy of recommendation, which shows the generalization ability of the fusion algorithm in all kinds of music recommendations. These results show that the hybrid model can provide more accurate recommendations in different music styles and has strong adaptability.

To show the distribution of recommendation satisfaction generated by GraphSAGE and DIN algorithms for different user groups, this paper analyzes the distribution of user recommendation satisfaction based on GraphSAGE and DIN algorithms. Figure 6 depicts the distribution of user recommendation satisfaction based on GraphSAGE and DIN algorithms for different user groups. As shown in the figure, when the proportion of users is high and the recommendation time is moderate, GraphSAGE achieves significantly higher satisfaction scores compared to DIN. For example, at a recommendation time of 2 minutes and a user ratio of 0.6, GraphSAGE's satisfaction score reaches about 9 points, while DIN's score is around 6 points. The figure also illustrates that GraphSAGE maintains high user satisfaction across various user ratios and recommendation times, whereas DIN's satisfaction score declines as the user ratio increases or recommendation time lengthens.

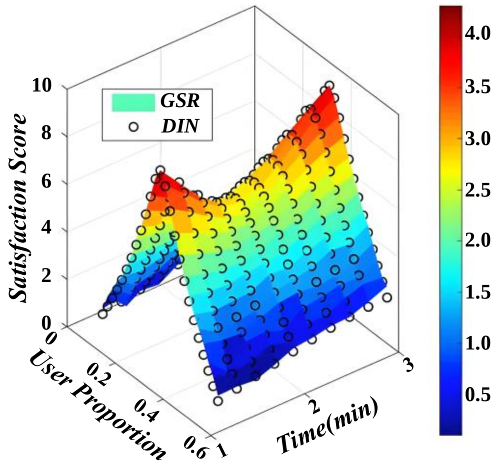

Figure 6: Distribution of user recommendation satisfaction based on GraphSAGE and DIN algorithms

It can be seen from the figure that when the proportion of users is high and the recommendation time is moderate, the satisfaction score provided by the GraphSAGE algorithm is significantly higher than that of the DIN algorithm. At a time of 2 minutes and a user ratio of 0.6, the satisfaction score of GraphSAGE can reach about 9 points, while the score of DIN is about 6 points. The color bar in the figure shows that GraphSAGE provides relatively balanced and sustained high satisfaction recommendation results in most cases, especially under different combinations of recommendation time and user ratio; GraphSAGE's satisfaction score has remained at a high level. On the contrary, the DIN algorithm's satisfaction score shows a downward trend when the proportion of users is high or the recommendation time is long.

This paper analyzes the trade-off between recommendation accuracy and recall rate between the GraphSAGE and DIN algorithms, and the results are shown in Figure 7.

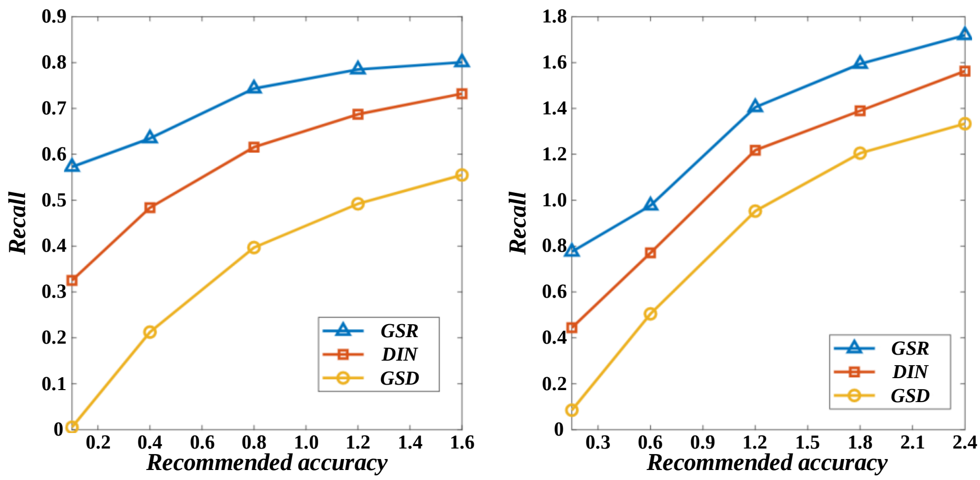

Figure 7: Trade-off between recommendation accuracy and recall rate between GraphSAGE and DIN algorithms

It can be observed in the figure that with the improvement of recommendation accuracy, the recall rate of each algorithm shows an increasing trend, but GraphSAGE (GSR) always shows the best recall rate, especially when the accuracy is 1.6; the recall rate is close to 0.9. In contrast, the recall rates of the DIN algorithm and GSD algorithm under the same accuracy are 0.7 and 0.5, respectively, showing that GraphSAGE can better retain the recall rate while accurately recommending, thus improving the comprehensiveness and effectiveness of the recommendation system.

This paper analyzes the influence of different user behaviors on the recommendation effect of DIN and GraphSAGE algorithms, and the results are shown in Figure 8.

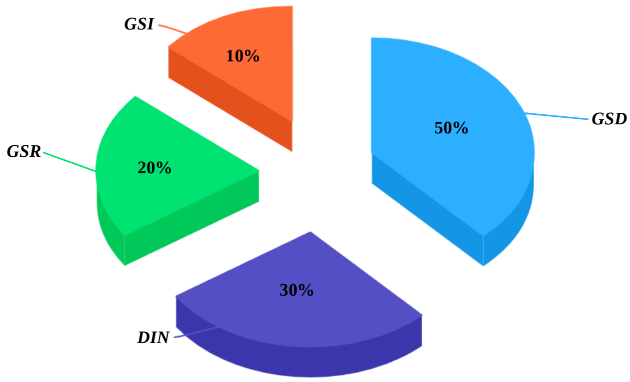

Figure 8: Influence of different user behaviors on the recommendation effect of DIN and GraphSAGE algorithms

According to the data in the figure, the GSD algorithm occupies 50% of the overall recommendation effect, showing its advantages in most user behavior scenarios. In contrast, the contribution of the DIN algorithm to the recommendation effect is 30%, showing a high personalized recommendation ability. GraphSAGE contributes 20%, which can capture more social and graph structure information under specific user behavior patterns. GSI accounts for only 10%, showing its relatively small impact on recommendation effectiveness. This analysis shows that the impact of user behavior on the recommendation system is multifaceted. The algorithm combining GraphSAGE and DIN can better balance recommendation accuracy and personalized needs under different user behaviors, thereby improving the overall recommendation effect.

Table 4: Analysis of recommendation effect based on user interests and behaviors

User Interest Type	Recommended accuracy	Recommended coverage	User interactions
Music preference type	0.88	0.75	350
Behavioral preference type	0.85	0.70	400
Mixed User Interest Type	0.92	0.80	420

The recommendation effect analysis based on user interests and behaviors is shown in Table 4. The table data shows significant differences in the performance of recommendation systems based on different types of users' interests. For music preference users, the recommendation accuracy rate is 0.88, and the coverage rate is 0.75, which shows a good recommendation effect and high user satisfaction. The recommendation accuracy rate of behavior-preferred users is 0.85. However, it is slightly lower than that of music-preferred users. Still, the number of user interactions reaches 400 times, indicating that behavior data greatly influences the recommendation system. Mixed users have the highest recommendation accuracy rate, reaching 0.92; the recommendation coverage rate is 0.80, and the number of user interactions is also the highest, reaching 420 times. This shows that the hybrid model that combines music preference and behavior data can provide more accurate and comprehensive personalized recommendations, meet diverse user needs, and enhance users' sense of participation and satisfaction.

This paper compares the system response time and performance of GraphSAGE and DIN algorithms under different data volumes and focuses on comparing their operating efficiency under different system loads. See Figure 9 for specific results.

As can be seen from the figure, when the system response time is short, the recommendation accuracy rate of GraphSAGE is maintained at a high level, close to 90%. However, when the system response time increased to around 15 hours, the recommendation accuracy of GraphSAGE decreased somewhat, down to about 75%. In contrast, DIN achieves the highest recommended accuracy at about 80% at a system response time of 10 hours, with little fluctuation in accuracy over subsequent periods. However, GSD and SRP show a relatively stable recommendation accuracy when the system response time is long, which is about 60%, respectively. The GraphSAGE algorithm can provide high recommendation accuracy when the response time is short, while the DIN achieves a better balance at medium response time. Although GSD and SRP have strong stability after prolonged response time, their recommendation accuracy is relatively low, indicating that their recommendation effect under long-term response is inferior to GraphSAGE and DIN.

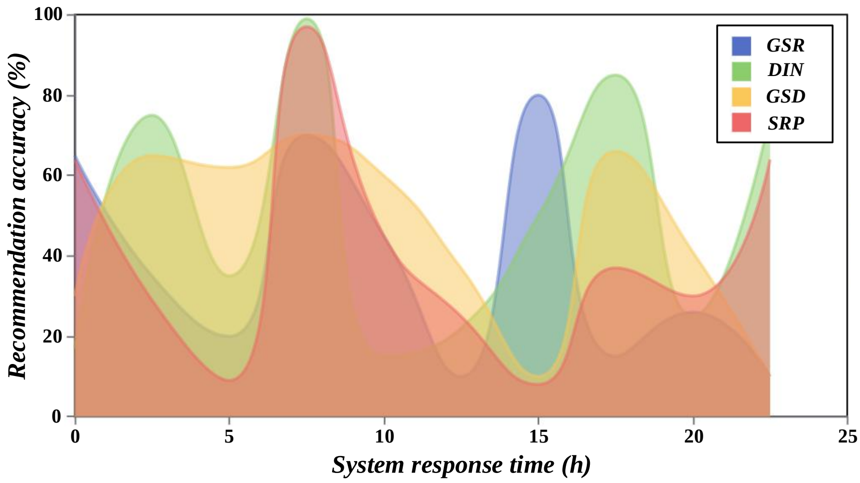

Figure 9: Comparison of system response time and performance combining GraphSAGE and DIN algorithms

5 Conclusion

The proposed music recommendation system combining GraphSAGE and DIN has significant advantages in handling complex large-scale music recommendation scenarios. However, it faces several limitations, including model latency, which may increase with the growth of user groups and interactions, and can be alleviated through optimization such as batch processing or approximate nearest neighbor search. The joint training of GraphSAGE and DIN introduces complexity and potential overfitting, especially for smaller datasets, requiring more robust regularization or alternative fusion methods. In addition, although the system performs well on the current dataset, scalability remains a challenge and requires optimization of memory management and distributed computing in larger environments. Through experimental analysis, we verify the model's superiority on several key indicators and deeply explore the influence of different factors on the recommendation effect.

(1) Through experimental comparison, the hybrid model combining GraphSAGE and DIN shows the best recommendation accuracy and user satisfaction results. In the recommendation task, the accuracy rate of the hybrid model is 92%, which is about 7% and 4% higher than GraphSAGE's 85% and DIN's 88%, respectively. In addition, regarding user satisfaction, the mixed model scored 4.5 points, significantly higher than GraphSAGE's 4.1 points and DIN's 4.3 points. Combining GraphSAGE's graph structure modeling capabilities with DIN's interest dynamic modeling capabilities, the hybrid model can more accurately capture users' long-term and immediate interests, thereby effectively improving the personalized accuracy of the recommendation system and meeting users' needs.

(2) By analyzing the relationship between the number of user interactions and the recommendation accuracy, the experimental results show that with the increase in the number of user interactions, the recommendation accuracy of the hybrid model continues to improve. When the number of user interactions reaches 12 times, the recommendation accuracy is close to 70%. In contrast, when GraphSAGE and DIN were used alone, their recommended accuracy was 50% and 45%, respectively. This result shows that the hybrid model can better utilize rich behavioral data and improve the accuracy of recommendations when dealing with highly active users. This also verifies the advantages of the hybrid model in dynamic interest modeling and user behavior modeling, especially in the case of high user participation, which can better capture users' immediate needs.

(3) GraphSAGE shows stronger advantages in recommendation coverage capabilities in the analysis of different music types. Especially when the recommended number reaches 150 songs, GraphSAGE's coverage rate is 75%, which is significantly higher than DIN's 65%. This shows that GraphSAGE can provide a wider range of recommendations and enhance the diversity of recommendations when dealing with large-scale music recommendations, especially for scenarios dealing with many songs and complex user behaviors. In addition, the fusion model also shows higher adaptability in the recommendation accuracy of various types of music, especially in the recommendation tasks of popular music and rock music, with accuracy rates of 91% and 89%, respectively, which are better than GraphSAGE and DIN separate algorithms.

The hybrid GraphSAGE + DIN model outperforms both standalone models in music recommendation tasks, achieving 92% accuracy, 80% coverage, and a user satisfaction score of 4.5. It surpasses GraphSAGE (85%) and DIN (88%) in accuracy due to the combination of GraphSAGE's long-term structural relationship modeling and DIN's context-aware, dynamic interest modeling. The hybrid model also provides broader coverage, making it more robust in diverse user scenarios, and excels in cold-start handling by leveraging both long-term preferences and short-term interests.

This study indicates that combining GraphSAGE and DIN for music recommendation has strong practical relevance. The performance of the hybrid model in different user behavior scenarios demonstrates its deployment potential in real-world music recommendation platforms. By integrating structured and dynamic user preferences, the model presented in this article is capable of handling large-scale, personalized recommendation tasks. This provides an innovative solution for music platforms that need to address long-term user interests and short-term behavioral changes, improving user satisfaction and system adaptability.

The music recommendation system combining GraphSAGE and DIN algorithms has significant advantages in multiple dimensions. By combining graph neural networks with deep interest networks, this study improves recommendation accuracy and user satisfaction and effectively solves challenges such as cold start problems, interest charges, and recommendation accuracy. Future research can further optimize the model, improve its response speed and accuracy to complex user behaviors, and provide more powerful technical support for developing a personalized recommendation system.

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