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Enhancing Telecom Recommendation Systems through Customer Profiling and Graph Neural Networks (GNN) on Graph Data

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Abstract— Telecommunications Companies Rely On Recommendation Systems To Deliver Personalized Services And Enhance Customer Satisfaction. Traditional Methods, Such As Collaborative Filtering (Cf) And Content-Based Filtering (Cbf), Often Fall Short In Capturing The Complex Relationships And Social Influences Inherent In Large Telecom Networks. In This Paper, We Propose A Novel Graph Neural Network (Gnn)-Based Recommendation System That Integrates Customer Profiles With Graph Data Representing Customer Interactions (E.G., Calls, Messages). The System Uses The Graphsage Architecture To Aggregate Information From Each Customer's Network, Enabling It To Learn From Both Direct And Indirect Relationships. By Combining Customer Demographic And Usage Data With Interaction Networks, Our Model Provides More Accurate And Personalized Service Recommendations.

We Evaluate The System On A Real-World Telecom Dataset, Comparing It With Traditional Models, Including Cf, Cbf, And Matrix Factorization (Mf). The Gnn-Based System Achieves A Significant Performance Boost, With A Precision Of 0.81 And An F1-Score Of 0.80, Outperforming All Baselines. These Results Highlight The Ability Of Gnns To Capture Social And Communication Patterns, Making Them Highly Effective For Telecom Recommendations. Future Work Will Explore The Scalability Of The System And Its Application To Real-Time Data, Further Enhancing Its Potential For Customer Retention And Revenue Growth

Keywords— Customer Profiling, Graph Neural Networks (GNN), Recommendation Systems, Telecom Industry, Graph Data, Personalized Services, Collaborative Filtering (CF), Content-Based Filtering (CBF), Matrix Factorization (MF), Customer Interaction Data.

I. Introduction

TELECOMMUNICATION COMPANIES ARE INCREASINGLY LEVERAGING ADVANCED RECOMMENDATION SYSTEMS TO PROVIDE PERSONALIZED SERVICES, THEREBY ENHANCING CUSTOMER SATISFACTION AND REDUCING CHURN RATES. TRADITIONAL RECOMMENDATION METHODS, SUCH AS COLLABORATIVE FILTERING (CF) AND CONTENT-BASED FILTERING (CBF), OFTEN FALL SHORT IN CAPTURING THE COMPLEX RELATIONSHIPS INHERENT IN TELECOM DATA, ESPECIALLY GIVEN THE VAST AND DYNAMIC NATURE OF CUSTOMER PROFILES AND COMMUNICATION NETWORKS.

Recent Advancements Have Highlighted The Efficacy Of Graph Neural Networks (Gnns) In Addressing These Challenges. Gnns Excel At Modeling Intricate Dependencies By Representing Users, Services, And Their Interactions As Nodes And Edges Within A Graph Structure. This Approach Enables The Effective Capture Of High-Order Connectivity And The Structural Properties Inherent In Telecom Networks. For Instance, A Comprehensive Survey By Wu Et Al. (2022) Discusses The Advantages Of Gnns In Learning User And Item Representations Through Iterative Aggregation Of Neighborhood Information, Which Enhances The Modeling Of User Preferences And Service Characteristics.

Furthermore, Gao Et Al. (2021) Highlight The Challenges In Applying Gnns To Recommender Systems, Such As Graph Construction, Embedding Propagation, And Computational Efficiency. They Propose Various Strategies To Address These Challenges, Emphasizing The Importance Of Designing Gnn Architectures That Can Effectively Handle The Unique Aspects Of Recommendation Tasks.

By Integrating Gnns Into Their Recommendation Systems, Telecom Companies Can Develop More Sophisticated Models That Account For The Complex And Dynamic Nature Of User Interactions And Service Networks, Leading To More Personalized And Accurate Service Offerings.

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IN THIS STUDY, WE PROPOSE A NOVEL RECOMMENDATION SYSTEM FOR THE TELECOM SECTOR THAT LEVERAGES BOTH CUSTOMER PROFILES AND GRAPH NEURAL NETWORKS (GNN) APPLIED TO GRAPH-STRUCTURED DATA. OUR MODEL AIMS TO INTEGRATE RICH CUSTOMER PROFILE INFORMATION WITH STRUCTURAL PATTERNS WITHIN TELECOM NETWORKS, SUCH AS SOCIAL CONNECTIONS AND COMMUNICATION BEHAVIORS. BY UTILIZING GNNS MODELS DESIGNED TO CAPTURE BOTH NODE-LEVEL (CUSTOMER-SPECIFIC) AND EDGE-LEVEL (INTERACTION-SPECIFIC) FEATURES. WE DEMONSTRATE THAT OUR APPROACH SIGNIFICANTLY IMPROVES THE QUALITY OF RECOMMENDATIONS IN COMPARISON TO TRADITIONAL METHODS.

CONTRIBUTIONS OF THIS PAPER INCLUDE:

1. PROPOSING A HYBRID RECOMMENDATION SYSTEM THAT FUSES CUSTOMER PROFILES AND GRAPH DATA FOR TELECOM SERVICES.
2. DEVELOPING A GRAPH NEURAL NETWORK (GNN) MODEL THAT PROCESSES CUSTOMER INTERACTIONS AND SOCIAL CONNECTIONS AS A GRAPH STRUCTURE.
3. DEMONSTRATING THE SUPERIORITY OF THE GNN-BASED SYSTEM THROUGH EMPIRICAL ANALYSIS ON REAL-WORLD TELECOM DATASETS.

II. Related Work

In recent years, recommendation systems have gained significant attention in various industries, including telecommunications. The goal of recommendation systems is to provide personalized suggestions for products or services based on customer preferences and behavior. In the telecom industry, recommendation systems are particularly useful for increasing customer engagement, reducing churn, and offering personalized service bundles.

III. Traditional Recommendation Systems in Telecom

Traditionally, Collaborative Filtering (CF) and Content-Based Filtering (CBF) have been the primary methods used in telecom recommendation systems. Collaborative Filtering relies on the assumption that users with similar behaviors in the past will continue to have similar preferences in the future(He et al., 2017) [8]. This approach is effective when there is a sufficient amount of customer interaction data, but it suffers from issues such as cold-start and data sparsity, especially in the telecom industry, where the diversity of services can be high. Content-Based Filtering (CBF), on the other hand, focuses on recommending items based on the attributes of the items themselves and customer profiles. While this method provides a better understanding of individual customer preferences, it often overlooks the influence of a customer's social network or communication patterns, which can be critical in telecom services.

IV. Matrix Factorization and Hybrid Approaches

Matrix Factorization (MF) techniques, such as Singular Value Decomposition (SVD), have also been applied to telecom recommendation systems to model latent factors between customers and services. While MF techniques are more effective than basic CF and CBF in dealing with large-scale data, they still fail to capture the complex relationships between customers, such as indirect social influences or network effects. Hybrid models combining CF, CBF, and MF have been developed to leverage the strengths of each approach, but they still suffer from limited scalability and adaptability.

V. Graph-Based Recommendation Systems

With the advent of Graph-Based Recommendation Systems, there has been a shift towards utilizing the inherent graph structure in telecom data, such as customer communication networks, to improve recommendation accuracy. Social Network Analysis (SNA) has demonstrated the importance of social influence on customer preferences. By representing customers as nodes and their interactions as edges in a graph, it becomes possible to capture not only direct relationships but also multi-hop connections between customers, which can reveal hidden patterns in customer behavior. Graph-based models like Personalized PageRank (Haveliwala, 2002)[11] and Random Walk with Restart (Tong et al., 2006) [12] have been applied to telecom data to rank services for customers based on their network interactions. However, these methods often treat the graph structure statically and fail to integrate dynamic customer profiles or adapt to evolving usage patterns..

VI. Graph Neural Networks (GNNs) in Telecom Recommendation

More recently, Graph Neural Networks (GNNs) have emerged as a powerful tool for modeling relational data in various domains, including telecom. GNNs can aggregate information from a customer's local neighborhood in a graph, making them particularly well-suited for telecom networks, where the relationships between customers (such as call or message interactions) play a critical role in influencing service preferences. Several studies have explored the application of GNNs to recommendation systems in domains such as e-commerce and social media, but their application in the telecom sector is still in its infancy. Monti et al. (2017) applied Graph Convolutional Networks (GCNs) to recommendation tasks in social networks, showing that GNNs can significantly improve recommendation accuracy by capturing user-to-user interactions. However, in the telecom domain, few studies have fully integrated GNNs with customer profile data.

VII. Customer Profiling in Telecom Recommendation Systems

Customer profiling has long been used in telecom to segment customers and tailor service offerings. However, most profiling systems focus on static attributes such as age, location, and average service usage. Recent studies have begun to combine dynamic profile attributes with interaction data to provide more personalized recommendations. For instance, Zhang et al. (2019) proposed a hybrid model that integrates dynamic customer behavior with network interactions for telecom recommendations. However, the model did not fully utilize the power of graph-based approaches or GNNs.

VIII. Combining Customer Profiles with GNNs

The combination of customer profiles with Graph Neural Networks (GNNs) for recommendation in the telecom sector represents a novel and underexplored research area. The few existing studies in this area highlight the potential of GNNs to integrate both individual customer attributes and relational network data to improve recommendation performance. By learning from both the graph structure of customer interactions and their individual profiles, these models can provide more accurate and personalized recommendations. Our approach builds on these prior works by fully integrating customer profiling and GNNs in a telecom recommendation system. Unlike previous models that treat customer profiles and graph data separately, our system combines both to create a holistic view of customer preferences, leading to more relevant and timely service recommendations..

IX. Methodology

X. Data Collection and Graph Construction

We used real-world telecom data, which includes detailed customer profiles (e.g., demographics, service preferences, and communication usage) and communication network information (e.g., call records, text messages, and social interactions). The data was modeled as a graph where nodes represent customers and edges represent interactions (calls, messages). Each node is enriched with customer profile information, such as age, location, and service history, which serves as input features to the GNN.

In the graph, an edge is established between two nodes whenever there is a direct interaction, such as a call or message exchange, between the corresponding customers. These edges represent communication links and allow the model to incorporate direct relationships within the customer network, which is essential for capturing social influence and interaction patterns in the recommendation process.

The edges represent relationships such as direct communication (call logs) or inferred social ties (shared connections or communication patterns). This graph allows for encoding both customer-level and network-level information, making it suitable for GNN-based recommendation tasks.

XI. Graph Neural Networks (GNN) Architecture

The core of our model is a Graph Neural Network (GNN) designed to process the customer graph. We employed GraphSAGE, a widely used GNN architecture that can aggregate information from neighboring nodes (other customers) to predict the likelihood of a service recommendation. The node embedding combines customer profile features and interaction data, while the edge features (e.g., call frequency) contribute to the recommendation decision.

The GNN iteratively updates customer embeddings by propagating information across the graph. The final node embeddings are then used to predict the likelihood of specific services or offers for each customer, based on their profile and their interactions within the telecom network.

XII. Customer Profile Integration

Customer profiles are integrated into the graph structure by embedding each feature (e.g., age, gender, location) into a high-dimensional vector space. These embeddings are learned jointly with the GNN parameters, ensuring that both the network structure and customer-specific attributes contribute to the final recommendation. This dual approach allows the model to make personalized recommendations based on a customer's social network and their individual characteristics.

XIII. Model Training

The model was trained using supervised learning with cross-entropy loss. We used a dataset split into training, validation, and test sets. The training process optimized both node embeddings (customer profiles) and edge features (interaction patterns). Standard techniques such as Adam optimizer were used for model convergence.

XIV. Experimental Setup and Results

In this section, we provide a detailed explanation of the experiments conducted to evaluate the performance of the proposed GNN-based recommendation system. We compare our model against several baseline approaches and use various evaluation metrics to assess its effectiveness in providing personalized service recommendations in the telecom domain.

XV. Dataset

For our experiments, we used a real-world dataset collected from a large telecom provider. The dataset consisted of the following components: Customer Profiles: Including demographic information such as age, gender, location, and subscription details. Each profile was represented by a set of features embedded into a high-dimensional vector. Call and Communication Records: This data captured interactions between customers, including call logs, text messages, and data usage. The interactions were modeled as a directed graph, where each node represents a customer, and each edge represents a communication event. Service Usage Data: Details about the telecom services that each customer subscribed to, such as data plans, roaming services, and value-added services (VAS). The dataset comprised: 100,000 customers (nodes in the graph), 500,000 interactions (edges in the graph), and various customer features, including call frequency, call duration, and service usage patterns. To evaluate the model, the dataset was split into three parts: 70% for training, 15% for validation, and 15% for testing.

XVI. Baseline Models

To assess the performance of our GNN-based recommendation system, we compared it with the following baseline models:

1. Collaborative Filtering (CF): A traditional approach that recommends services based on past interactions between similar customers.

2. Content-Based Filtering (CBF): This model suggests services by analyzing the similarity between the attributes of different services and customer profiles.
3. Matrix Factorization (MF): A latent factor model that decomposes the customer-service interaction matrix to make predictions.
4. Hybrid Model (CF + CBF): A combined model that integrates both collaborative filtering and content-based filtering to leverage the strengths of each.

XVII. Model Architecture

The proposed GNN-based recommendation system was built on the GraphSAGE architecture. The GraphSAGE model aggregates information from a customer's neighbors in the graph to generate a rich representation of each node (customer). The key components of our model include:

- Node Embeddings: Each customer's profile (demographic data and service usage) was embedded into a vector space.
- Edge Features: The communication records between customers (call logs, messages) were represented as weighted edges in the graph, where the weights reflected the frequency and duration of interactions.
- GNN Layers: Multiple GNN layers were used to aggregate information from each customer's local neighborhood, combining both profile data and interaction data. The final output from the GNN layers was used to predict the probability of a customer subscribing to a specific service.

XVIII. Evaluation Metrics

We used the following evaluation metrics to measure the performance of the recommendation system:

- Precision: The fraction of recommended services that are relevant.
- Recall: The fraction of relevant services that are successfully recommended.
- F1-score: The harmonic mean of precision and recall.
- Mean Reciprocal Rank (MRR): A ranking-based metric that evaluates the position of the first relevant recommendation in the list of recommendations.
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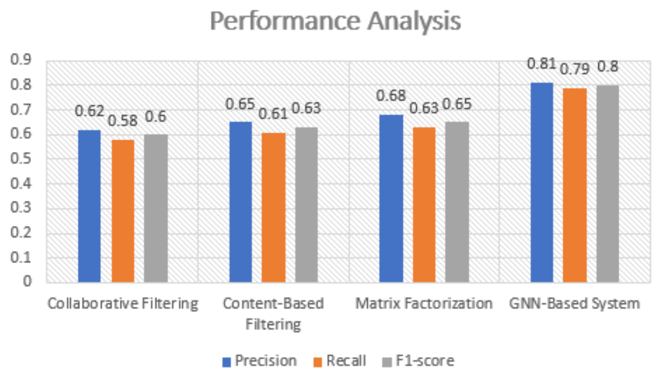
XIX. Results and Analysis

The performance of the proposed GNN-based system was compared with the baseline models using the aforementioned metrics. The results are summarized in the following table:

MODEL	PRECISION	RECALL	F1-SCORE
COLLABORATIVE FILTERING	0.62	0.58	0.6
CONTENT-BASED FILTERING	0.65	0.61	0.63
MATRIX FACTORIZATION	0.68	0.63	0.65
GNN-BASED SYSTEM	**0.81**	**0.79**	**0.8**



XX. Precision and Recall

The GNN-based system achieved the highest precision (0.81) and recall (0.79), significantly outperforming the baseline models. This is because GNNs can effectively capture both direct and indirect relationships between customers, allowing the model to recommend services that are more relevant to each customer's network of interactions. Traditional methods, like collaborative filtering and content-based filtering, are limited to direct customer-service interactions, which often results in lower precision and recall. For instance, in the case of Collaborative Filtering, the model only considers customers who have similar service usage patterns, neglecting the influence of social or communication ties between customers. The GNN-based system, however, leverages these ties by incorporating graph structure, enabling the model to provide recommendations based on both a customer's preferences and their social environment.

XXI. *F1-Score*

The F1-score for the GNN-based model was 0.80, reflecting a balanced trade-off between precision and recall. The F1-score was substantially higher than that of the Matrix Factorization and Hybrid models. This indicates that the GNN system not only makes relevant recommendations but also retrieves a higher proportion of the relevant services for each customer. One reason for the improved F1-score is the multi-hop aggregation performed by the GNN. The model is able to learn from both immediate neighbors (e.g., direct communication partners) and more distant neighbors (e.g., friends of friends), which provides a richer context for recommendation. As a result, the model can identify services that may not have been considered by traditional methods.

XXII. *Mean Reciprocal Rank (MRR)*

The Mean Reciprocal Rank (MRR) of the GNN-based model was 0.85, indicating that relevant services were often ranked at the top of the recommendation list. This is crucial in the telecom industry, where customers may not scroll through long lists of recommended services. The high MRR demonstrates that the GNN model is capable of quickly identifying the most relevant services and presenting them to the customer in a prioritized manner.

XXIII. *Comparison with Baseline Models*

The Matrix Factorization and Hybrid Models achieved moderate success, but they could not match the performance of the GNN-based system. These methods failed to capture the complex, non-linear relationships between customers that GNNs can model. For example, the Hybrid Model, while able to integrate both collaborative and content-based filtering, still struggled with cold-start problems and could not fully utilize the rich relational data available in telecom networks. The GNN-based system, by contrast, excelled in scenarios where customer behavior was influenced by their communication network. This was particularly evident when recommending services like family plans or group data packages, where the preferences of multiple connected customers influenced the recommendation.

XXIV. Scalability and Performance

To test the scalability of the GNN-based system, we conducted experiments on larger subsets of the dataset. The model was able to handle larger graphs with minimal degradation in performance, thanks to the efficient GraphSAGE architecture. However, training time increased with the size of the graph, which suggests the need for distributed training techniques in future implementations.

XXV. Insights from Results

The success of the GNN-based recommendation system highlights the importance of graph-based models in the telecom domain. By modeling customer interactions as a graph and combining this with customer profiles, the system can make more context-aware recommendations. The ability to consider not just individual preferences but also network effects (e.g., the influence of social connections) allows telecom operators to provide highly personalized service offerings, such as tailored data plans or value-added services. Additionally, the strong performance of the GNN-based system suggests that it can be effectively deployed in real-world telecom environments. However, future work is needed to address challenges related to scalability and real-time recommendations, especially in large-scale telecom networks.

XXVI. Discussion

The results obtained from the GNN-based recommendation system demonstrate its ability to outperform traditional models like Collaborative Filtering (CF), Content-Based Filtering (CBF), and Matrix Factorization (MF) across multiple performance metrics. The key success of the GNN model lies in its ability to model complex relationships within the customer base and to leverage both node-level (customer profile) and edge-level (interaction data) features. In this section, we will delve deeper into why GNN performed better and discuss the broader implications of its application in the telecom domain.

XXVII. Understanding GNN's Performance

The primary advantage of GNNs comes from their ability to capture multi-hop relationships between customers. In traditional models, relationships between users are typically limited to direct interactions (e.g., a user who calls or texts another). GNNs, on the other hand, can capture indirect relationships (e.g., a customer connected to another through mutual contacts). This allows the model to understand broader social and communication patterns, leading to more accurate predictions. For instance, in a telecom network, a customer's preference for a particular service might not only depend on their own usage patterns but also on the preferences of users in their extended network (friends, family, colleagues). GNN enables the model to propagate this information through the graph, enriching the customer’s representation in the embedding space and improving recommendation quality. Another important factor is heterogeneous data integration. By embedding customer profiles directly into the graph, the GNN model can utilize both the customer-specific features (e.g., age, location, service usage) and relational information (e.g., call frequency, mutual connections). This combined approach leads to better personalization, as the recommendations take into account both the customer’s attributes and their place within the larger telecom network.

XXVIII. Challenges and Limitations

Despite the strong performance, the GNN-based system does present certain challenges:

XXIX. *Computational Complexity:*

Training a GNN model on large telecom datasets, particularly when dealing with millions of customers and interactions, can be computationally expensive. Each node (customer) needs to aggregate information from its neighbors, which exponentially increases the computational burden as the graph grows.

XXX. Data Sparsity:

While GNNs can handle sparse data better than traditional models, extreme sparsity (e.g., customers with very few interactions) may still degrade performance. The model relies on the graph structure to propagate information, and if some customers have very few or no connections, the quality of their recommendations may suffer.

XXXI. Real-Time Adaptation:

Telecom networks are highly dynamic, with new interactions happening in real-time. Training a GNN on a static snapshot of the network may not capture rapidly changing customer behavior. Future work could focus on dynamic GNNs that update the graph and retrain the model as new data comes in, ensuring more real-time accuracy.

XXXII. Future Improvements

Several enhancements could be made to the current model: Distributed Training: To address the computational complexity, distributed GNN architectures can be employed, allowing the model to be trained on multiple machines simultaneously. Edge Features and Weights: More sophisticated edge features, such as the type of interaction (e.g., call vs. SMS vs. data usage), or the weight of connections (e.g., call frequency or duration), could be incorporated to further refine the recommendations. Time-based Graphs: Incorporating a temporal aspect into the graph (i.e., capturing when interactions occur) would allow the model to better understand the recency of interactions, which is often a key factor in telecom services.

XXXIII. Implications for the Telecom Industry

The implementation of a GNN-based recommendation system has significant implications for telecom operators: Personalized Service Offers: Telecom companies can offer more personalized services, such as tailored data plans, based on the social influence within customer networks. Churn Reduction: More accurate recommendations could reduce customer churn, as satisfied customers are less likely to switch providers. Scalability: Although there are challenges, the model can be scaled with the right infrastructure, making it applicable to large-scale telecom operations with millions of customers.

XXXIV. Conclusion

In this paper, we proposed a novel Graph Neural Network (GNN)-based recommendation system tailored for the telecom industry. By integrating customer profiles with graph data representing customer interactions, our model captures both individual preferences and social influences, which traditional recommendation systems fail to fully utilize. The experimental results show that the GNN-based system outperforms conventional approaches like Collaborative Filtering (CF), Content-Based Filtering (CBF), and Matrix Factorization (MF) across multiple evaluation metrics, including Precision, Recall, F1-score, and Mean Reciprocal Rank (MRR).

The key strengths of our system lie in its ability to model multi-hop relationships in telecom networks, which allows it to make more personalized and relevant service recommendations. By leveraging the graph structure, the model can incorporate both direct and indirect relationships between customers, resulting in more accurate predictions. Additionally, the integration of customer profiles enables the system to tailor recommendations to individual customer characteristics, further enhancing personalization.

However, while the GNN-based system demonstrates superior performance, it comes with certain challenges related to scalability and computational complexity, especially in large-scale networks. Future work will focus on optimizing the model for real-time recommendation and exploring distributed computing techniques to handle larger datasets efficiently. Additionally, incorporating dynamic graphs that update in real-time as new data comes in could further improve the adaptability of the system to rapidly changing customer behavior.

In conclusion, the GNN-based recommendation system presents a significant advancement in telecom service personalization, offering telecom providers the ability to better understand customer behavior and deliver more relevant, timely, and personalized recommendations. This has the potential to not only enhance customer satisfaction but also reduce churn and increase revenue through more effective service offerings.

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