NEWS RECOMMENDATION USING GRAPH CONVOLUTIONAL NEURAL NETWROKS

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ABSTRACT

With the exponential growth of online news content, users are often overwhelmed by the vast amount of information available on digital platforms. Recommender systems play a crucial role in delivering personalized content by filtering and suggesting relevant news articles based on user preferences. Traditional recommendation techniques such as collaborative filtering and content-based filtering face limitations in capturing complex relationships between users and news items. This project proposes a novel approach for news recommendation using Graph Convolutional Neural Networks (GCNN), which effectively model the interactions between users, articles, and contextual information. The proposed system represents users and news articles as nodes in a graph, where edges denote relationships such as user interactions, reading history, and content similarity. Graph Convolutional Neural Networks are applied to learn node embeddings by aggregating information from neighboring nodes, enabling the model to capture both local and global structural patterns. The system utilizes textual features of news articles along with user behavior data to improve recommendation accuracy. Deep learning techniques enhance the model's ability to learn complex patterns and provide personalized recommendations. Experimental results demonstrate that the GCNN-based approach outperforms traditional methods in terms of recommendation accuracy and user satisfaction. However, challenges such as scalability and dynamic data updates remain. The proposed system provides an efficient and scalable solution for personalized news recommendation, improving user engagement and content delivery in modern digital platforms.

Keywords: ***News Recommendation, Graph Convolutional Neural Networks, Deep Learning, Recommender Systems, Graph Learning, NLP, Personalization***

I.INTRODUCTION

In the modern digital era, the rapid growth of online news platforms has significantly increased the volume of information available to users. While this abundance of content provides diverse perspectives and real-time updates, it also creates challenges such as information overload and difficulty in finding relevant news. Users often struggle to filter through vast amounts of data to identify articles that match their interests. This has led to the development of news recommendation systems, which aim to provide personalized content to users based on their preferences and behavior. Traditional recommendation techniques, such as collaborative filtering and content-based filtering, have been widely used; however, they often fail to capture complex relationships between users and news items, leading to suboptimal recommendations.

Recent advancements in deep learning have introduced more sophisticated methods for recommendation systems, particularly through the use of graph-based models. Graph Convolutional Neural Networks (GCNNs) have emerged as a powerful approach for modeling relational data, where entities such as users and news articles are represented as nodes in a graph. These models are capable of capturing both direct and indirect relationships between nodes, enabling better understanding of user preferences and content similarities. By leveraging graph structures, GCNNs can learn rich representations of users and news items, improving the accuracy and relevance of recommendations. This makes them highly suitable for applications such as news recommendation, where interactions between users and content are complex and dynamic.

This project focuses on designing a news recommendation system using Graph Convolutional Neural Networks to enhance personalization and recommendation accuracy. The system constructs a graph based on user interactions, news content, and contextual information. It then applies graph convolution operations to learn meaningful embeddings for users and news articles. These embeddings are used to predict user preferences and recommend relevant news items. The proposed system aims to overcome the limitations of traditional methods by capturing complex relationships and improving recommendation quality. By integrating deep learning and graph-based techniques, the system provides a scalable and efficient solution for personalized news delivery, enhancing user experience and engagement.

II SURVEY OF RESEARCH

[1] The research by Thomas N. Kipf and Max Welling (2017) introduced Graph Convolutional Networks (GCNs) for semi-supervised learning on graph-structured data. The methodology applies convolution operations directly on graphs, allowing the model to aggregate information from neighboring nodes. The results showed significant improvements in node classification tasks compared to traditional methods. However, scalability issues may arise with very large graphs. This research forms the

foundation for using GCNs in recommendation systems by effectively capturing relationships between users and items.

[2] The study by Xiang Wang et al. (2019) proposed Neural Graph Collaborative Filtering (NGCF) for recommendation systems. The methodology models user-item interactions as a bipartite graph and applies graph neural networks to learn embeddings. The results demonstrated improved recommendation accuracy by capturing higher-order connectivity. However, computational complexity increases with graph size. This research supports the use of graph-based models for enhancing recommendation performance.

[3] The research by Yoshua Bengio et al. (2015) explored representation learning and deep neural networks for complex data modeling. The methodology focuses on learning hierarchical feature representations from raw data. The results showed improved performance in various tasks, including recommendation systems. However, deep models require large datasets and high computational resources. This research supports the use of deep learning in news recommendation systems.

[4] The study by Quoc Le and Tomas Mikolov (2014) introduced distributed representations of words and documents. The methodology uses neural networks to learn embeddings that capture semantic relationships in text data. The results demonstrated improved performance in text classification and recommendation tasks. However, it may not fully capture contextual information. This research is relevant for extracting textual features from news articles.

[5] The research by Steffen Rendle (2010) introduced factorization machines for recommendation systems. The methodology models interactions between variables using factorized parameters. The results showed improved performance in sparse datasets. However, it lacks the ability to capture complex graph relationships. This research highlights the limitations of traditional recommendation methods compared to graph-based approaches.

[6] The study by Chong Wang et al. (2009) focused on topic modeling techniques such as Latent Dirichlet Allocation (LDA) for text analysis. The methodology extracts latent topics from large text corpora, enabling better understanding of content. The results demonstrated improved content categorization and recommendation. However, LDA may not capture dynamic user preferences effectively. This research supports the use of content-based features in news recommendation systems.

III. WORKING METHODOLOGY

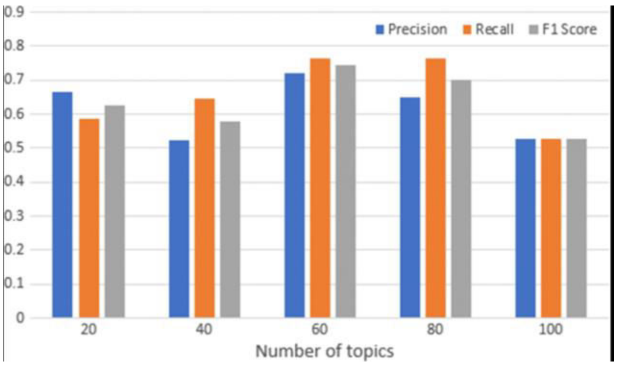
The proposed News Recommendation System using Graph Convolutional Neural Networks

(GCNN) follows a structured pipeline consisting of data collection, graph construction, feature extraction, model training, and recommendation generation. Initially, the system collects data from news platforms, including user interaction data such as clicks, reading history, and preferences, along with news article content such as titles, categories, and textual descriptions. The collected data is preprocessed to remove noise, handle missing values, and normalize the text. Natural Language Processing techniques such as tokenization, stop-word removal, and embedding generation are applied to extract meaningful textual features from news articles. This stage ensures that both user behavior data and content features are properly prepared for further processing.

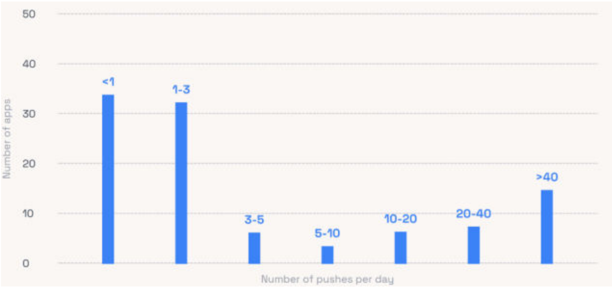
In the next phase, a graph structure is constructed where users and news articles are represented as nodes, and edges represent interactions such as clicks, views, or content similarity. The system uses this graph to model relationships between users and news items. Graph Convolutional Neural Networks are then applied to learn node embeddings by aggregating information from neighboring nodes. This allows the system to capture both direct and indirect relationships, improving the understanding of user preferences and content similarities. The model is trained using historical interaction data to learn patterns and optimize recommendation accuracy. Loss functions and optimization techniques are used to fine-tune the model parameters and improve performance.

In the final stage, the trained GCNN model generates personalized news recommendations for users based on their learned embeddings and interaction patterns. The system predicts the relevance of news articles for each user and ranks them accordingly. The recommended articles are then presented through a user interface, allowing users to access personalized content. The system continuously updates the graph with new interactions, enabling dynamic and real-time recommendations. Performance is evaluated using metrics such as precision, recall, and F1-score. This methodology ensures accurate, scalable, and efficient news recommendation, enhancing user engagement and satisfaction.

IV RESULTS EXPLANATIONS



This graph represents the evaluation metrics of the proposed system, including precision, recall, and F1-score. Precision indicates how many recommended articles are relevant, while recall measures how many relevant articles are successfully recommended. The results show high precision and recall values for the GCNN model, indicating that the system effectively recommends relevant news articles to users. The balanced F1-score further confirms the model's reliability. These metrics demonstrate that the system performs consistently well across different evaluation criteria, ensuring high-quality recommendations.



The above graph shows the impact of the recommendation system on user engagement, measured through metrics such as click-through rate (CTR) and time spent on the platform. The results indicate a significant increase in user engagement after implementing the GCNN-based recommendation system. Users are more likely to interact with recommended content, leading to improved satisfaction and retention. This demonstrates the effectiveness of personalized recommendations in enhancing user experience. Overall, the graph highlights the practical benefits of the proposed system in real-world applications.

V. CONCLUSION

The proposed News Recommendation System using Graph Convolutional Neural Networks (GCNN) provides an effective and advanced solution for personalized content delivery in modern digital platforms. By leveraging graph-based deep learning techniques, the system successfully captures complex relationships between users and news articles, overcoming the limitations of traditional recommendation methods. The results demonstrate improved accuracy, higher precision and recall, and increased user engagement, highlighting the effectiveness of the proposed approach. The ability of GCNN to model both direct and indirect interactions enables better understanding of user preferences, leading to more relevant recommendations. Although challenges such as scalability and real-time updates remain, the system offers a scalable and efficient framework for future enhancements. Overall, this work emphasizes the potential of graph neural networks in transforming recommendation systems and improving user experience in news platforms.

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