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Friendship Recommendation Algorithms Based on Machine Learning: A Review

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Abstract: In today's digital world, where online social networks are booming, recommender systems play a crucial role in managing the overwhelming amount of information. This paper focuses on friendship recommendation algorithms and their impact on facilitating social connections within the realm of online platforms. It starts by underscoring the importance of recommender systems in alleviating the information overload problem, then delves into an exploration of recommendation algorithms, specifically friending algorithms. The primary focus of the paper revolves around the integration of machine learning techniques into friendship recommendation algorithms, showcasing the potential of artificial intelligence in enhancing social interactions. By combining current research with practical insights, this paper highlights the harmony between machine learning and friendship recommendation algorithms, with the aim of improving personalized and rewarding social experiences in the digital landscape.

Keywords: *Recommender systems, Friendship recommendation, Neural collaborative filtering*

1. Introduction

For decades, the proliferation of digital information on the World Wide Web has been staggering. This is because more users are joining online every day. According to a report by Statista, the number of online users increased 110.8% during the last 10 years reaching 5.4 billion users (Statista link and internet world link). This data is based on 67% of the entire global population. This increase resulted in exponential growth in the digital information produced online which poses a significant challenge for consumers seeking relevant content, leading to the introduction of recommender systems to aid in information discovery [1][2][3].

Recommender systems function as personalized filtering mechanisms, tailoring content based on various user-specific factors. The nature of these factors depends on the system's objective. For example, an advertising system might analyze browsing histories to deliver pertinent ads, while a social networking recommendation system may consider user interests, preferences, and geographic locations to connect users with similar profiles. Recommender systems make the internet useful by helping users find what they might be interested in from the overloaded information online [1].

Collaborative filtering-based models have been widely used in many applications due to their effectiveness in generating relevant recommendations [4][5][6], which is based on the similarity between users' behavior and their historical records [7]. This approach has been used in many domains such as product recommendations in Amazon and Netflix [3], and relationships in LinkedIn [8].

A Collaborative filtering-based recommender system utilizes the similarity between users' past interactions to generate recommendations [7]. It operates on the premise that if users have previously liked similar items, they are prone to future agreements with each other rather than with randomly selected users [6].

These customization and filtering techniques distinguish CF recommendation systems from traditional information retrieval systems [6]. Information retrieval systems generate results solely based on searched keywords, regardless of user preferences. While effective in specific database contexts, this approach may yield accurate yet irrelevant outcomes when applied to the vastness of the World Wide Web. In contrast, recommender systems refine results based on user preferences such as language, age, and past interactions, thereby presenting more tailored recommendations.

CF algorithms mainly struggle with data sparsity when there is insufficient history between users and items [4] [9][10]. This is common, especially at the start of a system where there are very few interactions between users and items. In addition, CF is also limited by the cold-start problem [5][4][9]. This occurs when the system encounters difficulties with new users and items due to its reliance on prior behavior associated with these entities. When a new user engages with a CF-based system, the system faces challenges in providing recommendations since it lacks prior interactions from the user to base its recommendations

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[5]. Content-based algorithms on the other hand overcome these challenges as it is user independent.

Content-based recommender algorithms, in contrast, leverage users' content such as profiles, preferences, and interests to provide tailored recommendations [11]. Unlike collaborative filtering, this algorithm operates independently of other users' input, recommending items based solely on individual user data [11]. Notably, content-based algorithms excel in recommending new products, as they match product attributes with user preferences without requiring prior ratings from other users. This helps such algorithms to alleviate the the cold-start problem unlike typical collaborative filtering techniques [12][13][14].

Many researchers have implemented collaborative filtering-based Machine learning (ML) algorithms to alleviate the problem of sparsity [15][2] and cold-start problems [14][15]. In this paper, we focus on reviewing state-of-the-art friending algorithms that are machine learning driven.

The subsequent sections of this work are structured as follows: The following section, Section 2, presents the literature review of friendship system. Section 3 introduces a analysed system and results.. Ultimately, this work is concluded in Section 4.

2. Literature Review on the Use of Machine Learning in Friending algorithms

The rapid development of the Internet has led to an exponential increase in information, resulting in the problem of information overload. Collaborative recommendation systems have been widely used to address this issue by providing an effective way to filter information. However, the data sparsity problem associated with interaction data limits the performance of traditional recommendation methods. To alleviate this issue, the authors in paper [2] proposes a graph neural network social recommendation algorithm that integrates the multi-head attention mechanism. This algorithm aims to deeply extract the latent features of users and items based on the user-item interaction and social network graphs. The multi-head attention mechanism is introduced to increase the importance of friends with high influence when learning user embedding vector representations. The proposed method outperforms existing algorithms in terms of both Recall and Normalized Discounted Cumulative Gain, as demonstrated by experimental results on the Epinions dataset.

In [16] the authors developed a hybrid collaborative filtering algorithm for friend recommendations. The algorithm incorporates the social similarities between users by calculating the size of the similar social links between the users. The proposed research enhances a recommendation system by combining collaborative, semantic, and social filtering techniques. Results from analyzing the Yelp social network indicate that integrating semantic and social data with collaborative filtering algorithm enhances recommendation accuracy. This approach also overcomes the cold start problem since it generates recommendations based on users' semantic and social information. The study demonstrates the value of incorporating credibility information into the recommendation system.

In Paper [17] the authors propose clustering-based interaction driven friending (CIDF) algorithm that overcomes the limitations of current friending algorithms by identifying interactive connections based on the intensity of interactions exchanged between common friends of the target user and the recommended connections. It utilizes a k-means clustering approach to identify and recommend connections with a higher probability of forming interactive relationships. Experimental results demonstrate that the CIDF algorithm outperforms existing friending algorithms, including Facebook's friends-of-friends (FoF), by recommending a higher percentage of interactive connections while reducing the recommendation of weak relationships. The CIDF algorithm is shown to be effective in promoting meaningful relationships and increasing the level of social interactions in online social networks. The authors Facebook's explains that Facebooks approach excels in acceptance rate of its recommendations but has low interactions rate between declared friends. Figure 1 shows a social network's sub-graph example to explain Facebook's FoF algorithm. User x is an FoF of user y which should be recommended to one another since they have sufficient number of commonFriends(x, y).

The low of interaction rate problem among declared friends within social media has been addressed by a few research. In paper [18] the authors' research aims to tackle the problem of low interactivity among connected users in online social networks caused by existing friending algorithms. They compare the accuracy and effectiveness of their IDF algorithm with Facebook's FoF approach. The IDF algorithm is designed to recommend connections that not only are easily accepted but also have a higher likelihood of leading to interactions. Through experiments on a dataset containing 25 subgraphs with 10,500 publicly available user profiles, the authors demonstrate that the IDF algorithm significantly outperforms Facebook's FoF algorithm in recommending interactive friendships. The experimental results show that the IDF algorithm recommended about two times more interactive friendships than the FoF algorithm. Additionally, the IDF algorithm effectively reduced the number of weak connections recommended by the FoF algorithm, leading to a higher percentage of interactive connections. The document provides a detailed breakdown of the experimental results for each subgraph, highlighting the impact and effectiveness of the IDF algorithm in identifying and recommending interactive connections.

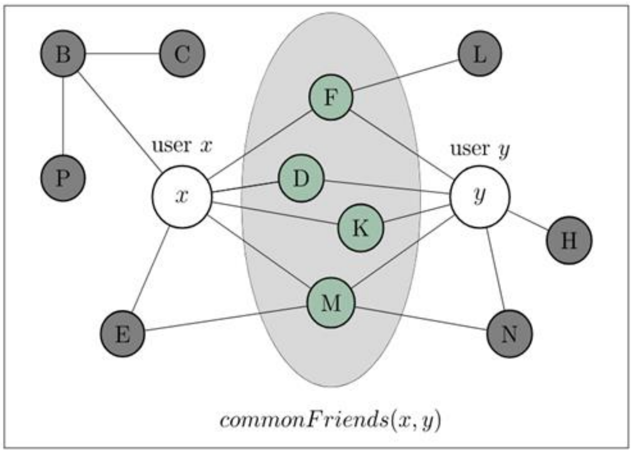

Fig 1: A Sub-graph example for the Friends-of-Friends algorithm

paper [19] presents DFRec++ model which incorporates a broader range of user information, encompassing both static information (topics, geographical location and common friends) as well as dynamic behaviour (likes, comments and mentions). Then, instead of manual processing, it employs a convolutional neural network (CNN) to learn feature representations. Finally, it utilizes an attention model that ensures thorough and comprehensive feature extraction, while the embedding of the social network structure maintains the integrity of these features. The experimental findings indicate that DFRec++ surpasses similar approaches in terms of precision (P@k), recall, and F1-measure.

Paper [13] describes a friend recommendation system using the KNN algorithm in the context of social networking. It emphasizes the growing importance of social networks for communication and the challenges of accurately recommending friends to users. Existing systems often rely on common factors such as mutual friends, age groups, and location, which may not always align with the interests and habits of the target users. To address this, the paper proposes a recommendation system based on semantic and lifestyle similarities between users, using the KNN algorithm to identify users with similar interests. The system also incorporates a similarity metric to measure lifestyle similarities and evaluate user recommendations based on the books they have read. The experimental results demonstrate a high accuracy rate of 90% for the model.

Paper [14] discusses the issue of social inconsistency in social recommendation systems and proposes a novel framework, ConsisRec, to address this problem. The main motivation for ConsisRec is to empower graph neural networks (GNNs) to tackle the social inconsistency problem by sampling consistent neighbors and employing relation attention to assign importance factors for aggregation. The study highlights the significance of distinguishing consistent neighbors based on context-level and relation-level social inconsistency. ConsisRec is built upon a GNN model, and it first generates a query embedding for selecting consistent neighbors and then employs a neighbor sampling strategy based on consistency scores. Furthermore, it uses relation attention to handle relation-level inconsistency. The document also provides experimental results on two real-world datasets, demonstrating the effectiveness of ConsisRec in addressing the social inconsistency problem, along with a comparison with baseline methods, an ablation study, and a parameter sensitivity analysis.

Paper [20] discusses the development of a Bayesian Personalized Ranking Deep Neural Network (BayDNN) model for friend recommendation in online social networks. The paper introduces the significance of friend recommendation in social networks and the motivation to design a high-accuracy method that is general enough to be applied to different social networks. The proposed BayDNN model leverages a novel Bayesian personalized ranking (BPR) idea and a CNN to extract latent deep structural feature representations of the complicated network data. The authors present a fine-tuned pre-training strategy for the proposed BayDNN model based on Poisson and Bernoulli probabilistic models to avoid poor parameter estimation for the neural network. The document also details the comparison of BayDNN with other state-of-theart methods for friend recommendation, demonstrating significant performance improvement on two public datasets: Epinions and Slashdot. The proposed BayDNN model achieves a 5% improvement on Normalized Discounted Cumulative Gain (NDCG) over the best baseline and shows a substantial advantage over the baseline algorithms, showcasing its effectiveness in friend recommendation tasks.

In [21] the authors present a novel approach for making explainable friend recommendations based on concept similarity measurements using a knowledge graph. It introduces the shortest path-guide reasoning path to provide explicit reasoning for friend recommendations and proposes the Weighted Euclidean-Shortest Path (WESP) method to address the issue of structural imbalance affecting the accuracy of semantic similarity measurements. The experimental results demonstrate the effectiveness of the proposed method in making friend recommendations on microblogging platforms, outperforming baseline methods and achieving better performance in terms of accuracy and precision. The study contributes to the field of recommendation systems by leveraging the semantic information and structural characteristics of knowledge graphs for more accurate and precise friend recommendations.

Paper [23] highlights the importance of academic social networks in facilitating scientific and educational cooperation and maintaining the academic circles of scholars. It emphasizes the challenges related to data sparseness and the difficulty in recommending valuable suggestions for lazy learners and cold-start learners. The proposed method addresses these challenges by leveraging learners' inter- action behavior, trust degrees, research interest similarities, and geographic distance to recommend implicit friends and provide personalized collaborative recommendations. The experimental analysis compares the PELIRM algorithm with other recommendation methods and demonstrates its higher performance in terms of precision, recall, and F1-measure. Additionally, the document provides insights into the impact of various parameters and the combination of different recommendation models on the effectiveness of the PELIRM algorithm.

Paper [24] presents a comprehensive framework for friend recommendation (FR) in social networks, addressing the limitations of existing solutions by integrating multiple sources of information. The proposed framework is based on the D-S evidence theory, categorizing information sources into personal features, network structure features, and social features. The study emphasizes the significance of user profiles, location, interests, network structure, and social influence in determining friend recommendations. The authors also propose an improved D-S evidence theory that considers the reliability and importance of evidence, providing a more accurate and comprehensive approach to information fusion. The study highlights the importance of user profile similarity, location proximity, and interests in determining friend recommendations. It also emphasizes the influence of network structure, such as the degree of connectivity and common friends, in predicting potential friendships. The proposed methodology integrates these diverse sources of information using a weighted fusion approach, ensuring that each factor is considered in proportion to its importance and reliability. The framework aims to optimize the recommendation performance by providing a scalable and comprehensive strategy for fusing multiple key factors.

Paper [25] introduces the self-rescaling network (SSNet) as a mechanism to bridge the normalization process with the node embedding learning, enabling the model to determine an appropriate scaling factor adaptively. It outlines the theoretical analysis, methodology, and optimization strategies for training the SSNet. Offline experiments conducted on real-world social network datasets demonstrate the significant improvement in accuracy across various GNN models, particularly in candidate retrieval and friend ranking tasks. The findings highlight the impact of SSNet in enhancing the representation quality of GNNs, emphasizing its problem-locating, method-proposing, experience-sharing, and result-verifying contributions. the paper offers a comprehensive exploration of the challenges and advancements in friend recommendations using GNNs, emphasizing the significance of SSNet in addressing the scale distortion issue and improving the effectiveness of GNN models in social link predictions. The findings provide valuable insights for future applications and research in social link predictions and highlight the potential for SSNet to enhance the accuracy and performance of GNNs in online social networks.

In [26] the authors designed and implemented a probabilistic matrix factorization (PMF) model to address the challenge of generating meaningful friend recommendations on social media platforms, specifically Facebook. Meaningful friendship recommendations that are most likely to transform into interactive relationships. The authors used Root Mean Square Error (RMSE) metric to measure the accuracy of the predictions and they suggest that the model is capable of predicting strong interactive connections between users, leading to more accurate friend recommendations.

3. ANALYSIS OF RESULT

In this section, we present a comprehensive analysis of the results obtained from the papers reviewed above. The analysis is summarized in Table 1, which provides a comparative overview of the key contributions, algorithms or models used, datasets employed for validation, accuracy metrics applied, and the primary findings of each study. This table serves as a concise reference to understand the diverse approaches taken by researchers to address the challenges in

Table 1. Summary of Machine Learning-based Friending Algorithms.

Paper	*Key Contribution*	*Method*	*Dataset*	*Performance Metrics*	*Findings*
[2]	Addresses data sparsity in recommendation systems	Graph Neural Network with Multi-Head Attention	Epinions	Recall, NDCG	Outperforms existing algorithms
[16]	Hybrid collaborative filtering for friend recommendations	Combines collaborative, semantic, and social filtering	Yelp	-	Enhances recommendation accuracy, overcomes cold-start problem
[17]	Identifies interactive connections based on interaction intensity	IDF algorithm with k-means clustering	Real real-world Facebook dataset	Interactive connections percentage	Outperforms Facebook's FoF, promotes interactive relationships
[18]	Tackles low interactivity among connected users	IDF algorithm	Real real-world Facebook dataset	Interactive connections percentage	IDF outperforms Facebook's FoF, reduces weak connections
[19]	Deep learning model for friend recommendation	DFRec++ with CNN and attention model	-	Precision, Recall, F1-measure	Surpasses similar approaches
[13]	Friend recommendation system using semantic and lifestyle similarities	KNN algorithm	-	-	High accuracy rate
[20]	Bayesian Personalized Ranking Deep Neural Network for friend recommendation	BayDNN with BPR and CNN	Epinions, Slashdot	NDCG	5% improvement over best baseline
[14]	Addresses social inconsistency in social recommendation	ConsisRec framework with GNN	Two real-world datasets	-	Effective in addressing social inconsistency
[21]	Explainable friend recommendations using concept similarity and knowledge graph	Shortest path-guide reasoning, WESP method	-	-	Outperforms baseline methods
[23]	Friend recommendation in academic social networks	PELIRM algorithm leveraging interaction behavior, trust degrees, research interest similarities, and geographic distance	-	Precision, Recall, F1-measure	Better performance compared to other methods
[24]	Multi-source information fusion for friend recommendation	D-S evidence theory, network structure, and social features	-	-	Improved D-S evidence theory for information fusion
[25]	SSNet for bridging normalization with node embedding learning	SSNet	Real-world social network datasets	-	Significant improvement in accuracy across various GNN models
[26]	Probabilistic matrix factorization for meaningful friend recommendations	PMF model	Real real-world Facebook dataset	RMSE	Capable of predicting strong interactive connections and eliminates most of weak connections

friend recommendation systems, the methodologies they adopted, and the outcomes of their experiments.

4. Conclusion

The exploration of machine learning-based friending algorithms presented in this paper reveals a rich landscape of innovative approaches designed to enhance the quality and relevance of friend recommendations in social networks. Through our review of state-of-the-art papers, we have observed a trend towards more sophisticated algorithms that leverage deep learning, graph neural networks, attention mechanisms, and hybrid recommendation strategies to address the challenges of data sparsity, cold start, and

social inconsistency. The findings summarized in Table 1 highlight the progress made in this field, with researchers developing algorithms that not only predict potential friendships with higher accuracy but also focus on the likelihood of these connections leading to meaningful interactions.

5. References and Footnotes

Author contributions

Aadil Alshammari: Conceptualization, Methodology, Paper writing, Paper formatting

Conflicts of interest

The authors declare no conflicts of interest.

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