A Review and Analysis of Recommendation Systems in Collaboration Networks

Lara S. Moreira[1], Fábio P. Basso[1], Gabriel M. Lunardi [2], Guilherme B. Sá [1]

[1]Universidade Federal do Pampa (UNIPAMPA)
Av. Tiaraju, 810 – 97546-550 – Alegrete – RS – Brasil

[2]Universidade Federal de Santa Maria (UFSM)
Av. Roraima, 1000 – 97105-900 – Santa Maria – RS – Brasil

{laramoreira.aluno,guilhermesa.aluno,fabiobasso}@unipampa.edu.br

gabriel.lunardi@ufsm.br

Abstract. *Recommendation systems are widely used to provide personalized suggestions across various domains. In scientific collaboration networks, these systems help identify potential research collaborators by analyzing network data and researcher attributes. This study aims summarize the review findings, and analyze published research on recommendation systems used in scientific collaboration networks. The study provides a comprehensive understanding of the use of recommendation systems in scientific collaboration networks, highlighting patterns, trends, limitations, and research gaps in this field.*

Resumo. *Os sistemas de recomendação são amplamente utilizados para fornecer sugestões personalizadas em diversos domínios. Em redes de colaboração científica, esses sistemas ajudam a identificar potenciais colaboradores de pesquisa, analisando dados da rede e atributos dos pesquisadores. Este estudo visa resumir as conclusões da revisão e analisar as pesquisas publicadas sobre sistemas de recomendação utilizados em redes de colaboração científica. O estudo oferece uma compreensão abrangente do uso de sistemas de recomendação em redes de colaboração científica, destacando padrões, tendências, limitações e lacunas de pesquisa neste campo.*

1. Introduction

Contemporary scientific research is increasingly characterized by an interdisciplinary approach Tarafdar and Davison [2018], including a wide range of knowledge that contributes to advancing understanding across various disciplines. It involves critical analysis and systematic exploration of topics to generate new perspectives and understandings.

The search for research partners is influenced by the growing number of active professionals in academia. However, the exponential growth in academic production poses significant challenges for researchers in identifying relevant scientific collaborators in their areas of interest Beel et al. [2015]. In this challenging scenario, collaborative networks become essential in current scientific research. Often built on co-authorship analyzes, collaboration in projects, and related themes, these networks provide a visual and structured representation of the interconnections between researchers Cheng et al. [2019].

Recommendation systems automate some of these approaches with the aim of providing accessible, personalized, and high-quality recommendations Jannach et al. [2010]. In the context of collaborative networks, recommendation systems stand out for their effectiveness in offering relevant recommendations based on user-item interactions Nie et al. [2020].

The research carried out primarily aimed to encourage collaboration between researchers and facilitate knowledge dissemination within the academic community. To achieve this, a literature review was conducted to identify key challenges and advancements in recommendation systems for scientific collaboration networks.

The remainder of this paper is organized as follows. Section 2 provides an overview of collaboration networks and recommender systems. Section 3 describes the methodology that includes all stages and processes in the systematic review. Section 4 presents the findings of the systematic review. Section 5 addresses the research questions, providing a detailed analysis of the results. Finally, Section 6 presents the final considerations and future works.

2. Background

A network can be broadly defined as a system of interconnected elements, where these elements can represent various entities such as chemicals in a cell, routers and computers in the Internet, or nodes in a social network Albert and Barabasi [2002]. In this context, nodes represent entities or points, and edges represent the connections or relationships between these entities Molaei et al. [2018].

Collaborative networks refer to platforms where interaction between users plays a significant role in data generation. Figure 1 simply illustrates the generation of a co-authorship collaboration network. In this example, we have six authors (A1 to A6) and three studies (Study A, Study B, and Study C). As represented in the figure, a network with six authors (nodes) is created, establishing connections (edges) between them based on co-authorship in the articles.

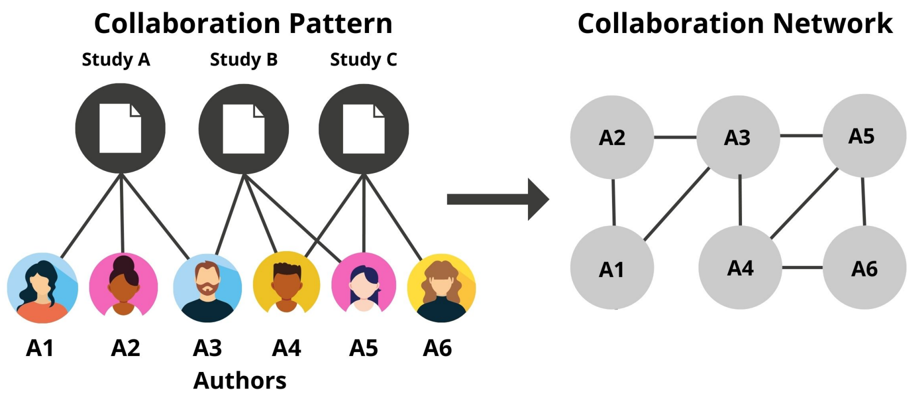

Figure 1. Visualization of a Scientific Collaboration Network

3. Methodology

All data necessary for understanding and replicating this research is available in a folder on Google Drive, accessible via the link https://bit.ly/3y9nGfw. The research protocol and essential bibliography have been provided to ensure transparency and reliability in the research developed. In this study, our goal is to review, evaluate, and provide future directions for the use of network science in the field of software engineering, with a specific focus on collaboration between researchers. Therefore, the first step in conducting this systematic review was to formulate the research questions to be addressed. In this case, the review aims to answer the following questions and sub-questions.

- RQ1: How do recommendation systems customize their suggestions for collaborators within a scientific network?

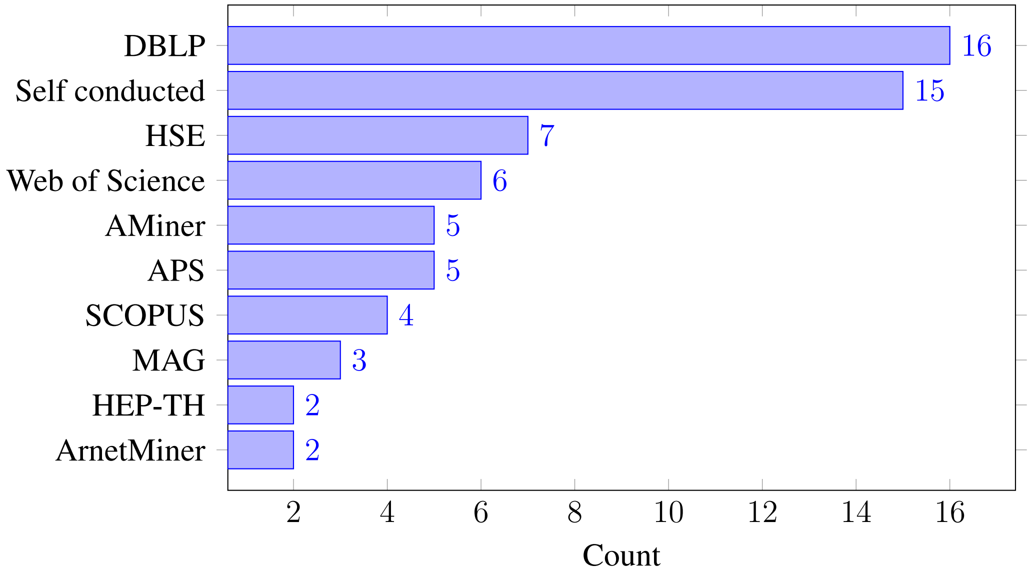

Figure 2. Top ten most used datasets

RQ1.1 How do recommendation systems balance between user preferences and network characteristics in providing recommendations?
RQ1.2: What role do user profiles and historical data play in customizing recommendations for collaborators?
RQ1.3: How do recommendation systems handle interdisciplinary collaborations within scientific networks?

- RQ2: To what extent is network topology incorporated into recommendation systems to enhance performance in collaboration networks?
  RQ2.1: How does network topology improve the accuracy and relevance of recommendations in scientific networks?
- RQ3: What are the main trends, challenges, and research gaps faced by recommendation systems in collaboration networks?
  RQ3.1: How do recommendation systems manage the dynamics and evolving nature of scientific collaboration networks?
  RQ3.2 How do recommendation systems address the issue of data sparsity in scientific collaboration networks?
  RQ3.3: What are the challenges in integrating heterogeneous data sources for recommendations?

4. Results

In this section, we present the results of the systematic data extraction form and a taxonomy, available in our Google Drive, used to organize and structure information that was developed for retrieving results and generating graphical representations.

Figure 2 shows that DBLP is the most commonly used datasets "DE09" for recommendation systems in scientific collaboration networks, with 15 usages. It is followed by self-conducted databases indicating a significant reliance on customized data.

Figure 3 illustrates the ten (10) most used metrics "DE12" for recommendation systems in scientific collaboration networks. Precision, Recall and F1-Score were the three most used, likely because they are fundamental metrics for evaluating the performance of recommendation systems indicating (precision), how many of the relevant items are recommended (recall) and

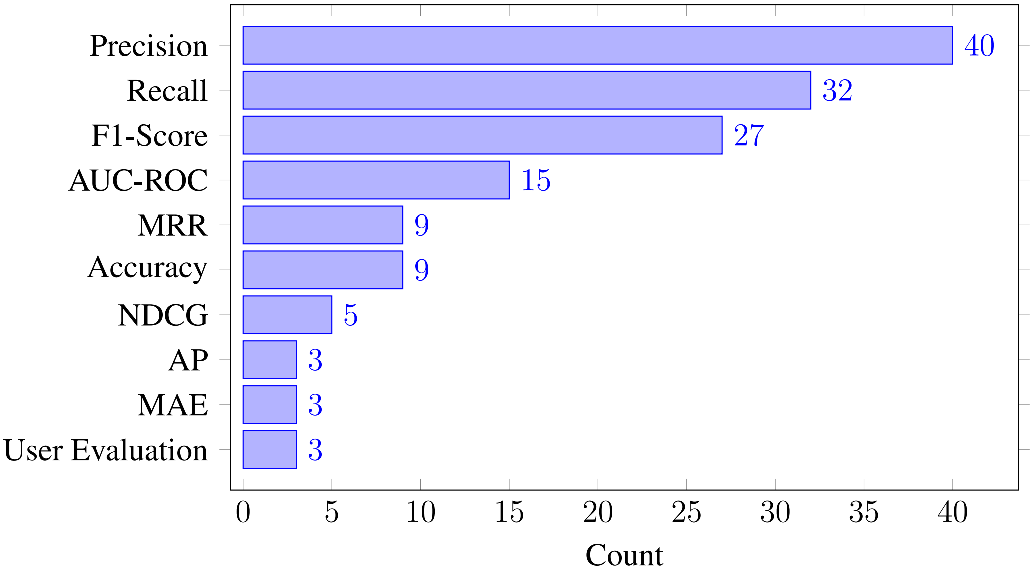

Figure 3. Top ten most used metrics

F1-Score that show the means of precision and recall. User evaluation is notably low, indicating a gap in the incorporation of user feedback into the evaluation process. This highlights the need for future research focused on leveraging user feedback to enhance suggestions. By collecting and analyzing this feedback, systems can understand user preferences and behavior, ultimately leading to more personalized and effective recommendations.

5. Discussions

In the discussions section, we present the results obtained to address all research questions.

5.1. Discussion on Research Question 01

To address this question, we used the results from “DE6” and “DE7”.

RQ1: How do recommendation systems customize their suggestions for collaborators within a scientific network?

Collaborator recommendation involves suggesting potential collaborators based on various characteristics or attributes. Figure 4 presents an overview of the results of ”DE7” designed to illustrate a recommendation system used to recommend collaborators in academic research, considering the attributes used in most of the articles reviewed. The system is organized into three primary categories: Scholar Attributes, Historical Data, and Research Attributes. These elements contribute to the process of identifying and recommending suitable collaborators for academic research projects.

RQ1.1 How do recommendation systems balance user preferences and network characteristics in providing recommendations?

The study Xi et al. [2022], balances user preferences and network characteristics by leveraging the Word2Vec model, an algorithm used to create word embeddings, to analyze scholars’ research interests and the Node2Vec model, designed to generate network embeddings from graph data and extract topological features from the co-authorship network, this combination allowed for a comprehensive assessment of potential collaborators.

The recommender system proposed by the authors in the study Wang et al. [2020], known as ACNE, uses a content-based filtering to leverage attributes such as Demographics,

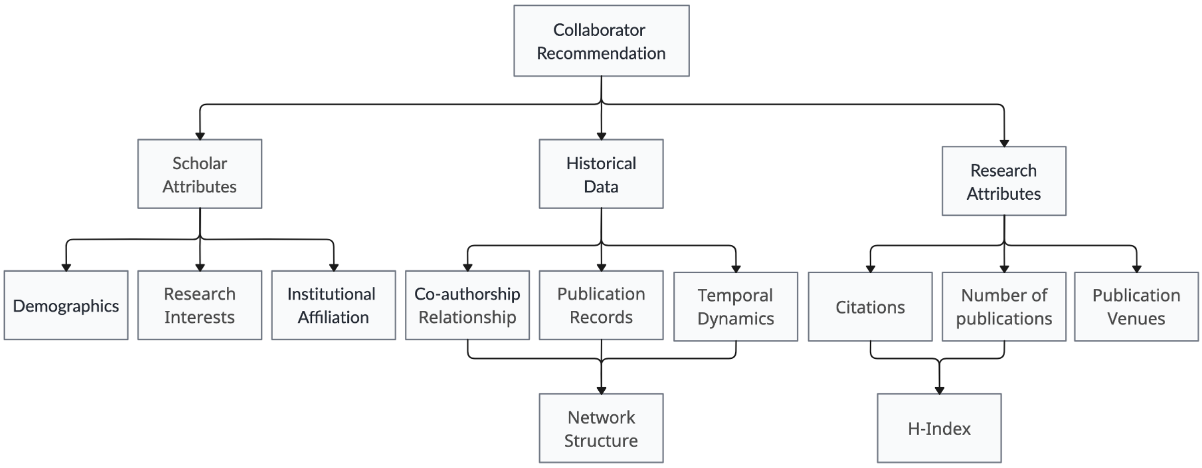

Figure 4. Collaborator Recommendation System in Academic Research

Research, Influence, and Sociability to enhance the accuracy of academic relationship mining and collaborator recommendations. By combining attribute-based embedding with network representation learning, ACNE enables personalized suggestions by integrating user preferences (attributes) and network characteristics (topology) to offer personalized and accurate recommendations for potential collaborators. In the study Liu et al. [2023], a heterogeneous network that incorporates relationships between authors, papers, venues, and topics was constructed. By exploring the network topology through meta-paths and random walks, the study aims to capture the structural dependencies of individual nodes and edges in the network for collaborator recommendation.

Most of the studies reviewed incorporate network characteristics and customize their suggestions using the researchers relationships and characteristics. Various systems used a content-based system to gather academic attributes, such as co-authorship, citations, number of publications, academic title to enhance recommendations, and combined this approach with network embedding to analyze the topological features of academic networks, providing a personalized recommendation system that balances user preferences with network characteristics.

RQ1.2 What role do user profiles play in customizing recommendations for collaborators?

The study Zhou et al. [2021] combined the DBLP data set with ResearchGate user profiles to obtain information about researcher's interests, expertise, past collaborations, and research activities to customize and improve the quality of collaboration recommendations. Similarly, the study Rodrigues et al. [2018] uses the ResearchGate user profiles to suggest scientific collaborations, extract publications, projects, topics of interest, skills, expertise, and informal connections with other researchers, and use this approach to model similarities between researchers.

In the study Chaiwanarom and Lursinsap [2015], user profiles provide information about the individual's research background, expertise, and collaboration history, allowing the system to identify suitable collaborators and improve the recommendations relevance and accuracy by making sure the suggested partners are a good fit for the user's requirements. Overall, user profiles are instrumental in refining collaboration recommendations by leveraging specific and comprehensive information about researchers to model similarities, identify suitable partners, and enhance the accuracy and relevance of suggestions.

RQ1.3 How do recommendation systems handle interdisciplinary collaborations within scientific networks?

The study Hu et al. [2023], addresses the challenges of evaluating scholars performance in interdisciplinary research by quantifying and representing scholars based on global semantic information and social influence. By incorporating semantic information from scholars research papers and considering social influence metrics, the model enables a comprehensive evaluation of interdisciplinary scholars and their collaboration potential. Additionally, they also consider the dynamic nature of research and provide real-time evolution of academics' study, which facilitates the evaluation of their multidisciplinary work as it develops. It provides an organized method for assessing academics engaged in interdisciplinary research, laying the groundwork for upcoming initiatives that seek to identify and suggest connections among various scientific domains.

The study Chaiwanarom and Lursinsap [2015] emphasizes the importance of considering factors like social proximity, friendship, complementary skill, research interest, up-to-date publication data, and seniority status in recommending potential research collaborators in this interdisciplinary environment, they propose a hybrid algorithm that integrates structural and semantic approaches and provide a comprehensive solution for identifying suitable collaborators across different research fields of computer science. In the study Araki et al. [2016] they also aim to bridge different fields by identifying potential collaborators with similar research interests, they use a content-based system to calculate researcher feature vectors using textual documents and recommend relevant researchers who work in other fields.

In summary, recommendation systems customize their suggestions for collaborators within a scientific network by leveraging a combination of user profiles, network characteristics, and interdisciplinary data. These systems use advanced algorithms to balance individual preferences with the structural and semantic aspects of the academic network, ensuring personalized and relevant recommendations for potential collaborations.

5.2. Discussion on Research Question 02

To address this question, we used the results of "DE10" and "DE11".

RQ2: To what extent is network topology incorporated into recommendation systems to enhance performance in collaboration networks?

Makarov et al. [2018] incorporates network topology into the recommendation system by utilizing graph embeddings and various network-based features to enhance performance in collaboration networks. The study Zhang et al. [2017], uses various similarity measures based on the network structure, such as link-based similarity, to calculate the relatedness between scholars. The overall similarity between two authors is quantified by a weighted sum of different similarity measures, which includes both personal factors (similarity based on publications) and environmental factors (the status of authors in the network).

RQ2.1: How does network topology improve the accuracy and relevance of recommendations in scientific networks?

The incorporation of network topology analysis proved to be essential in optimizing and enhancing the performance of recommendation systems in collaboration networks. The study Guerra et al. [2018], used a combination of traditional Hybrid Filtering (CF & CBF) and probabilistic topic modeling, an unsupervised machine learning algorithm that uses network analysis methods to investigate the structure and evolution of collaborations among researchers which provided a interpretable latent structure for collaborators. In the study Jin et al. [2021] they also used a hybrid system and combined with a enhanced clustering algorithm and a improved

Hilltop algorithm to recommend co-authors via link analysis to make personalized and relevant recommendations. The study Wu et al. [2020], focus on network embedding, machine learning techniques, and link prediction algorithms for predicting collaborators rather than traditional recommendation systems. These strategies are further enhanced by incorporating natural language processing (NLP) tasks, as highlighted in Moreira et al. [2023], Barbosa et al. [2022], given that much of the network's content is expressed through textual data.

Quang et al. [2023] combined machine learning AdaBoost with Weighted Suport Vector Machine (WSVM) to improve classification efficiency and predict future collaborations based on learned patterns, addressing, leveraging ensemble learning to combine classifiers for stronger predictions, and optimizing parameters to enhance model performance.

5.3. Discussion on Research Question 03

To address this question, we used the results from “DE13” and “DE14”.

RQ3: What are the main trends, challenges and research gaps faced by recommendation systems in collaboration networks?

The main trends identified included the incorporation of contextual information, such as the content of published works and recent activities of collaborators, and the use of deep learning techniques, such as neural networks, to improve recommendation accuracy. The pursuit of automated approaches, particularly those based on machine learning, becomes essential to facilitate efficient identification of scientific collaborators, thereby promoting the formation of more robust and effective research networks.

In summary, recommendation systems in scientific collaboration networks encounter significant challenges and research gaps. These include the need to effectively manage the dynamic and evolving nature of networks, address data sparsity and cold start problems, and integrate heterogeneous data sources for accurate recommendations. Current studies highlight these issues and propose various approaches such as temporal modeling, incorporation of auxiliary data, and innovative algorithmic techniques.

RQ3.1 How do recommendation systems manage the dynamics and evolving nature of scientific collaboration networks?

The study Makarov et al. [2019], explores the dynamic nature of the network by constructing collaboration networks year by year from 2001 to 2017 and incorporate nodal attributes such as institutes and research interests. This allows them to analyze the evolution, structural changes, and patterns in relationships over time. The study Makarov et al. [2019], also incorporates temporal information, evaluates the structure of the network over time, and predicts future collaborations based on historical data. The study Zhou et al. [2021], introduces the concept of time-varying academic influence in their multidimensional network model by analyzing academic influence based on academic activities across social networks, allowing for the navigation of research collaborations in scholarly big data environments.

The primary limitation for improving recommendations is that some of the networks created and analyzed in the selected articles are static and do not adequately capture the real nature of relationships between collaborators. Thus, the incorporation of temporal context, considering the evolution over time of academic interactions, becomes essential to obtain a more faithful representation of complex connections in the network.

RQ3.2: How do recommendation systems address the issue of data sparsity in scientific collaboration networks?

Another challenge faced by recommendation systems in collaboration networks is the issue of data sparsity and cold start problems. Collaboration networks often have sparse data, especially for new or less active researchers, making it challenging to generate accurate recommendations. The cold start problem arises when there is insufficient information available on scholars, which harms the system's ability to provide relevant suggestions Zhu et al. [2020].

Addressing data sparsity and cold start issues requires innovative approaches such as incorporating auxiliary data sources, leveraging transfer learning techniques, and developing robust algorithms that can effectively handle sparse data to improve recommendation accuracy for all researchers, including newcomers. In the study Al-Ballaa et al. [2019], they mention this problem as a research limitation because their recommendation system relies only on historical collaboration data to make recommendations. Portenoy et al. [2022], and Wu et al. [2020], also mention that the applied recommender system has a hard time recommending early career researchers.

The study Rodrigues et al. [2018], deal with this problem by combining strategies like Singular Value Decomposition for matrix factorization with robust content-based models that use collaborator information to make better suggestions. Pradhan and Pal [2020], face this problem by using author–author graph (AAG) instead of the co-authorship network and also use a content-based similarity approach and capturing the dynamic nature of the network.

RQ3.3: What are the challenges in integrating heterogeneous data sources for recommendations?

The study Alinani et al. [2018] mentions the potential for finding no results when authors have publications in one network but not in others, the risk of multiple results due to authors with similar names leading to irrelevant information, the difficulty in accurately assessing changes in an author's research interests over time, and the issue of incomplete or evolving user profiles that affect the system's ability to provide personalized and relevant recommendations to potential collaborators within the scientific network.

6. Conclusion

In this study we explored the mechanisms by which recommendation systems can enhance scientific collaboration within academic networks. Our findings demonstrate that these systems effectively integrate user profiles, network topology, and interdisciplinary data to provide personalized and accurate collaborator suggestions. The incorporation of advanced algorithms, such as machine learning models and network embeddings, has proven crucial in balancing individual preferences with the structural and semantic characteristics of academic networks.

Despite the advancements, some challenges and research gaps remain. Notably, the dynamic and evolving nature of collaboration networks presents a significant hurdle. Effective temporal modeling and the integration of real-time data are essential to capture the fluidity of academic relationships. Furthermore, addressing the issues of data sparsity and cold start, particularly for early-career researchers, requires innovative approaches, such as leveraging auxiliary data and transfer learning techniques.

Future research opportunities abound in this domain. There is a need for more robust algorithms that can adapt to the evolving nature of scientific collaborations and better manage sparse data scenarios. Additionally, further exploration into integrating heterogeneous data sources will be crucial for improving the accuracy and relevance of recommendations across diverse academic contexts. By addressing these challenges, future studies can contribute to more effective and inclusive collaboration networks, ultimately fostering greater innovation and knowledge sharing in the academic community.

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