Chapter 6

Conclusions and Future Work

The main contributions of this thesis are summarized below, followed by possible directions for future work.

6.1 Conclusion

In this thesis, we proposed some novel approaches to address two problems in recommendation systems. The cold-start issue was addressed as we started the thesis by primarily concentrating on the accuracy perspective. We observed that diversity in recommendation systems plays a significant role in improving user experience while investigating the accuracy perspective in recommendation systems, which leads to an accuracy-diversity trade-off. To address these issues in recommendation systems, we developed three models. To address the cold-start problem, we looked into using the MIDI data from the music datasets, which is not often looked into in the literature. The proposed algorithms have been developed using machine learning, deep learning, and network-based graph neural techniques. The overview of the models we proposed for the problems addressed in this thesis is shown in Table 6.1.

Our first model, MSA-SRec, is for the accurate and effective recommendation for music recommender systems. In this model, we address the problem of cold-start rec-

Table 6.1: Overview of our proposed chapters

Chapter	Proposed Model	Problem	Features	Dataset
3	MSA-SRec	Cold-start Problem	MIDI+implicit feedback	Million Song Dataset
4	Clus-DR	Diversity	Explicit + Implicit Feedback	MovieLens, LastFM, Goodbooks
5	Div-HERec	Diversity	Implicit Feedback	MovieLens, LastFM, Douban Book, Yelp

ommendation generation using deep attentive sequential model. To do this, we added MIDI data as additional content information. This model is a hybrid approach that draws on both user listening history and information about the music's content that was extracted from MIDI files. MIDI files are an encoded representation of music according to a well-known and widely used standard and the corresponding format. Given the recent development of MIDI 2.0, the inclusion of MIDI in the future is likely to strengthen this kind of model. We can use much more information about the content of the music for processing in the future. As we know, more and better data is required for better learning with a deep learning model.

Our experiments (6.2) have shown that our model performs noticeably better than baseline recommendation systems. Moreover, we validated the effectiveness of combining the content data for addressing the item cold-start problem, an important limitation of collaborative filtering techniques. We plan to extend the model by using more content, such as from the MIDI data itself, rather than relying more on personalization.

Table 6.2: Summarization of chapter 3

Model	Features	Cold-start	Sparsity	Conclusion
MF	Implicit Feedback	✗	✓	Our suggested model performed more effectively than these baseline models by a mean average precision increase of 19.02%.
NeuMF	Implicit Feedback	✗	✓	
BPR+MF	Implicit Feedback	✗	✓	
ItemPop	Implicit Feedback	✗	✓	
MSA-Srec	MIDI+implicit feedback	✓	✗	

Another aspect of our research lies in the issue of diversity in recommendation systems. We only attempted to overcome the model's accuracy for accurate recommendation generation in the first model. In Chapter 4, we suggested a model for the recommendation system's diversification. The main goal of the recommender system is to give users better recommendations based on their interests and relevance, which may change over time. The diversification in the recommendation system is addressed in this chapter by proposing a model based on user clustering that includes accurate and diverse recommendations. Additionally, we got better coverage and diversity outcomes with the Clus-DR model than we did with other recommendation algorithms, albeit with noticeably lower accuracy. The summary of our proposed solution is discussed in Table 6.3.

Table 6.3: Summarization of chapter 4

Model	Accuracy-centric	Diversity-Centric	Approach	Conclusion
NCF	✓	✗	Deep learning	Our proposed model outperformed all accuracy and diversity-centric methods with regard to diversity by including 31.25% more diverse items inclusion recommendation list. But our model's accuracy dropped by 2.09% compared to the baseline model.
NeuMF	✓	✗	Deep learning	
TPGR	✓	✗	Reinforcement learning	
SlateQ	✓	✗	Reinforcement learning	
xQuAD	✗	✓	Re-Ranking	
MMR	✗	✓	Re-Ranking	
Greedy	✗	✓	Re-Ranking	
Clus-DR	✗	✓	Machine learning	

The accuracy-diversity trade-off explains the decline in accuracy in the Clus-DR model. Achieving diversity in recommendation systems is difficult because it necessitates striking a balance between relevance, accuracy, and user satisfaction. The right balance between personalized recommendations and diversity is essential for ensuring that users are exposed to new and interesting items while still receiving relevant suggestions. To address the accuracy-diversity tradeoff, we proposed our next model, Div-HERec. We suggested that the Div-HERec model described in Chapter 5 improves diversity in the recommendation system. This model puts forth a graph colouring algorithm-based model for diversified recommendations. In order to find the closest similar user and the farthest dissimilar user in one metapath, we adopted the graph colouring algorithm to select diverse users. The obtained results (Table 6.4) demonstrate the effectiveness of our suggested model, and we concluded that with minimal metapath selection, we achieved a good model for accuracy and diversity.

Table 6.4: Summarization of chapter 5

Model	Accuracy-centric	Diversity-Centric	Conclusion
NMF	✓	✗	Our proposed model outperformed all accuracy and diversity-centric methods concerning diversity by including 9.04% more diverse items, as well as subsequent accuracy improvement by 1.08%
BPR+MF	✓	✗	
Div2vec	✓	✓	
Div-HeteRec	✓	✓	
DivRank	✓	✓	
Div-HERec	✓	✓	

Table 6.5: Chapters mapping with their associated research questions

Question	Chapter
RG1: How to handle the cold-start problem for an accurate music recommendation system using MIDI data?	Chapter 3
RG2: How to handle cold start problem with limited use of personalized data in the music recommendation system?	Chapter 3
RG3: How to handle the sparsity issue in music recommendation system?	Chapter 3, 4,5
RG4: Explore various applications of theories and methodologies from IR (Information Retrieval) to include diversity in the recommendation system.	Chapter 2, 4
RG5: How to maintain accuracy-diversity trade-off in the recommendation system?	Chapter 5

6.2 Possible research directions

This thesis is part of general recommendation system research where we try to improve the model based on two limitations of the recommendation system. There can be several other directions to follow up, as well as some other limitations that we can try to overcome in our future work.

The Table 6.5, that associates the research questions that we tried to address with the corresponding chapters, is used to illustrate the significance of the research objectives in this thesis. The accuracy of the recommendation system, which refers to how many relevant items are generated for the target user, is the main focus of the proposed music recommendation system. Because of the system's emphasis on accuracy, recommendations are repetitive and less suited to the target user. Diversity is added to the recommendation system to address these issues. We discuss possible future work for music recommendation systems and diversity in the section below.

6.2.1 Music Recommendation System

- We intend to use a variety of heterogeneous graph-based methods to improve the models' accuracy and diversity using various pieces of music content data.
- We also intend to develop real-time music recommendation applications using the Internet of Things. The target user will receive a recommendation from this technology based on their current requirements. Additionally, this will restrict the way recommendations are made based on their past profile information.
- In content-based music recommendations, content information is a significant concern for recommendation generation. In our MSA-SRec model, It can be challenging to choose which MIDI data to use for the recommendation generation when choosing the MIDI data for our proposed MSA-SRec method because using all the data will result in a sparsity problem in the model. Therefore, to reduce the sparsity problem and increase the model's accuracy, we intend to incorporate

a feature selection algorithm into it in the future.

6.2.2 Diversity in Recommendation System

- The accuracy and diversity tradeoff is the anticipated direction for future recommendation systems to incorporate diversification. In future, we will include other methodologies to retain accuracy and diversity tradeoffs in recommendation systems.
- When using a graph neural network to include diversity in the recommendation system, the problem of over-smoothing arises. The over-smoothing problem in GNN arises because more layers are added to the model to include more neighbour information in the node embedding representation. The likelihood of repeatedly adding similar node information will also arise. This may compromise the model's expressivity in terms of node embedding generation.
- In order to diversify the recommendation system, we primarily focused on diverse user exploration. In our proposed model, Div-HERec, which uses a user-user homogeneous graph for diverse pairs, we will explore item diversity in more detail in upcoming work. This can be investigated in the context of an item-item interaction graph.
- Another possible direction for work in diversity and recommendation is dynamicity. We all know that users' tastes vary, especially in music. So, including dynamicity in recommendation diversity will improve the model's relevance and accuracy.