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Dedicated to my parents,  
Mr. Shyam Sunder Yadav  
and  
Mrs. Asha Yadav

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# List of Symbols

<b>Symbol</b>	<b>Description</b>
$U$	User Set $i$
$I$	Item Set
$F$	Item Feature Set
$S$	Binary item feature matrix
$R_{m \times n}$	User-Item Interaction Matrix
$G_{m \times n}$	User-feature matrix
$S_{n \times k}$	Item-feature matrix
$C_k$	Number of Clusters
$Div_u$	Individual diversity of user $u$
$ADivClus$	Aggregate diversity of cluster
$R$	Original rating matrix
$U$	User latent factor
$V$	Item latent factor
$\mathcal{G}$	Heterogeneous Graph
$\mathcal{V}$	Set of vertices of heterogeneous graph
$\mathcal{E}$	Set of edges of heterogeneous graph
$\phi$	Vertex mapping function
$T_v$	Set of node types
$T_e$	Set of edge types
$T$	Network schema
$C_g$	Set of group color nodes
$R_c$	Colour relation
$G_u$	User-user homogeneous graph
$R_r$	Rating relation
$E_u$	Similarity edge between user
$\lambda$	Threshold

<b>Symbol</b>	<b>Description</b>
$\mathbf{N}_v$	Neighbour of node $v$
$W_l$	Walk length
$E_U$	Embedding of user node
$E_I$	Embedding of item node
$d$	Embedding dimensions
$R$	Recommendation list
$M$	Model

# Abbreviations

<b>Abbreviation</b>	<b>Description</b>
RS	Recommender Systems
CF	Collaborative Filtering
CBF	Content-based recommendation system
HS	Hybrid recommendation system
DRS	Demographic based recommendation system
DPP	Determinantal point processes
URS	Utility based recommendation system
KBRS	Knowledge based recommendation system
HIN	Heterogenous Information Network
CNN	Convolutional Neural Network
LSTM	Long-short term memory
GAN	Generative Adversarial Network
NN	Neural Network
RNN	Recurrent Neural Network
GRU	Gated Recurrent Unit
MIDI	Musical Instrument Digital Interface
IDS	Individual Diversity Score
IFS	Item Feature Score
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
IL-D	Intralist Diversity
nDCG	Normalized Discounted Cumulative Gain
GNN	Graph Neural Network
ReLU	Rectified Linear Unit
SGD	Stochastic Gradient Descent



# Abstract

The fast development of information technology and ubiquitous computing over the past two decades has led to a huge increase in knowledge being recorded in digital form and archived globally. Such an extensive collection has produced the challenge of information overload. A recommendation system is an application that can be used to deal with the issue of information overload. A recommendation system is a technique for information filtration that makes recommendations to users for items based on their interests, past behaviour, and other pertinent information. Recommendation systems are widely used in various domains, including e-commerce, streaming services, social media platforms, news websites, and more. Recommendation systems use various modalities like audio, video, text, and images for recommendation generation, apart from their past interactions with items.

One application area for recommendation systems that have received a lot of attention is music. In a music recommendation system, music is recommended to users based on their preferences, listening history, and various other factors. These systems are designed to provide personalised music recommendations and help users discover new songs and artists they might enjoy. It is now feasible to readily access all digitized music resources in the music industry because of the internet's rapid development of mobile applications and online music services. Recommendation systems have fulfilled this need in recent years by providing users with a personalized playlist according to their listening habits. This thesis aims at improving two aspects of music recommenda-

tion systems. Besides a general introduction to the content-based music recommender system and an in-depth discussion of various aspects of the music recommendation system, we discuss two different abstraction levels of the music recommendation system or general recommender system.

The first and most prominent way to improve a content-based music recommender system is to focus on the accuracy aspect of the system. State-of-the-art content-based music recommendation algorithms based on machine learning and deep learning are analyzed, and the literature survey discusses their improvements and limitations. Then a novel content-based music recommendation algorithm is introduced, which uses the MIDI (music instrumental digital interface) and lyrics information of the music. We describe a model called MSA-SRec (MIDI Based Self Attentive Sequential Music Recommendation), a latent factor-based self-attentive deep learning model that uses a substantial amount of sequential information as the content information of the song for recommendation generation. We use the MIDI data of a song, which is a piece of under-explored content information, for music recommendations. Deep content-based music recommendation using MIDI and lyrics has been shown to lead to accurate recommendation generation, which is its primary goal.

However, considering only the user's listening behaviour and content information for accurate recommendations is not sufficient nowadays. In this overview, we address the concept of diversity in music recommendation. We review diversity-related methodologies proposed in the literature survey. We focussed mainly on music recommendations, but have also other domains like movies, books, and business. We try to include diversity in recommendation generation. We tried to address this problem by developing an novel machine-learning technique for enhancing diversity in recommender systems. We propose a methodology called Clus-DR (Cluster-based Diversity Recommendation) that uses the individual diversity of users and then uses a pre-trained model for diverse recommendation generation. Instead of relying on a re-ranking approach, we train our

model to generate diverse recommendations for the target user. While exploring these methods, we realized the importance of the accuracy-diversity tradeoff in recommendation generation, where increasing diversity in the model will decrease its accuracy of the model. In the Clus-DR model, we are able to achieve diversity in the recommendation list, but at the same time, model accuracy suffers.

We then tried to address this trade-off. Our research explores how accuracy and diversity collaborate in recommendation systems and we tried to develop new methods for achieving the ideal balance between these two critical factors. We have explored various kinds of systems, including collaborative filtering, content-based filtering, hybrid models, and contextual recommendation, to address the challenges associated with accuracy and diversity trade-offs. By employing advanced machine learning algorithms and incorporating user feedback, the research seeks to enhance recommendation systems' accuracy without compromising diversity, ensuring personalized and engaging recommendations. In order to achieve the accuracy diversity tradeoff, we investigated Graph Neural Networks (GNN). We propose a Diverse Heterogeneous Network Embedding-based Recommendation (Div-HERec) technique that uses metapaths for diverse recommendation generation. The majority of the heterogeneous information networks (HIN) reported in the literature construct a number of metapaths that randomly choose neighbours for the target node (user) and then compute similarity and relevance between nodes to provide recommendations. We use a graph colouring approach to generate similar and dissimilar user pairs in a weighted user-user homogeneous graph instead of randomly choosing neighbours for target users. We develop a joint representation of a series of metapaths in the node representation learning and recommendation generation model. The diverse node embeddings are transformed using various fusion functions and integrated into a matrix factorization model for recommendation generation. The rating prediction task is further optimized for the Div-HERec model. An expanding topic of study, diversity in recommendations, has seen much work proposed to improve

diversity in recommendation systems. However, few works have been proposed for diversity and accuracy enhancement in recommendation systems as a single objective in recommendation generation. We propose some novel approaches for diversifying recommender system that increase accuracy. We will try to incorporate a framework for a conversational recommendation system based on this research in subsequent works.

**Keywords:** *Content-based Music Recommendation, MIDI-Lyrics Information, Sequential Recommendation, Diversity, Accuracy-Diversity Trade-off*