6002 Project Report

FreqRepFusion: A Frequency Domain Approach for Recommendation Systems

- **College**: College of Computing
- **Major and Grade**: Data Science
- **Instructor**: ZHAO Xiangyu
- **Team Members**:
  - OUYANG Ningtai (59090554)
  - LI Zhiqi (59195419)
  - Chan Chung Hei (58895924)

April 26th 2025

Abstract

Recommender systems play a crucial role in enhancing user experiences across online platforms, but they often struggle to capture nuanced user behaviors, particularly repeat consumption. This project introduces FreqRepFusion, a novel frequency domain approach for recommendation that leverages Discrete Fourier Transform (DFT) to decompose user interactions into high-frequency (repetitive) and low-frequency (exploratory) components. By integrating an Enhanced Frequency Domain Decoupler with a Repetitive Interest Tracker and a Repetition-Aware Recommender, our model dynamically captures both aspects of user behavior. Experiments on standard datasets demonstrate that FreqRepFusion outperforms state-of-the-art baselines including SASRec, GRU4Rec, and RepeatNet, with significant improvements in recommendation metrics. Our approach is particularly effective in scenarios with high repeat consumption rates, addressing a critical gap in existing recommender systems.

1 Introduction

Recommender systems have served a vital role in providing personalized recommendation to users on different online platforms. They are widely used by different organizations (such as e-commerce, music streaming and video-on-demand applications) to provide better user experience by having an enhanced understanding of the user behavior [5]. The traditional recommender system uses two major approaches: collaborative filtering and content-based filtering. Collaborative filtering uses user-item interaction information to infer similar relationships among the items/users; content-based filtering uses inherent item features such as metadata or texts to recommend similar items based on past preference choices. These traditional methods suffer from certain constraints when implemented in real-life application scenarios, which causes them to perform poorly in capturing nuanced user behaviors. For example, in session-based recommendation problems, users' sessions are grouped into a specific time span like shopping carts in e-commerce applications or playlists in music streaming applications, while they also face another challenging issue known as repeat consumption where the same users repeatedly consume the same items over multiple occasions, which is very common for many applications [3]. Recently, some studies suggest that about 60-70% of user consumption activities in the music domain and 25-40% of the activity in the e-commerce domain falls under the category of repeat consumption, which accounts for more than half of all user interactions in these domains [1]. Several models have been designed to tackle the session-based recommendation problem, including GRU4Rec [6], SASRec [8], RepeatNet [9], etc. However, almost every method solves this problem in the time domain without explicitly considering any frequency feature modeling. Although RepeatNet incorporated a repeat-explore mechanism that discriminates whether to recommend previously consumed items or explore new ones, its binary model fails to capture a wide range of user interest [9]. In our project, we propose FreqRepFusion – a novel approach solving the above limitations of using only one-time domain model to deal with the session-based recommendation problem. Our contributions mainly include:

- Recommending from a frequency domain perspective, dividing user interactions into different frequency parts representing different types of user behaviors via DFT.

- We propose an Enhanced Frequency Domain Decoupler that separates user interests into high-frequency (repetitive) and low-frequency (exploratory) components.
- We develop a Repetitive Interest Tracker that monitors the evolution of user's repetitive interests over time by analyzing frequency domain patterns.
- We design a Repetition-Aware Recommender that dynamically fuses high and low-frequency components based on the current user state.

2 Related Work

2.1 Session-Based Recommendation

Session-based recommendation focuses on predicting users' next actions based on their current session interactions, without necessarily relying on long-term user profiles. Early approaches primarily relied on Markov models to capture sequential patterns in user behavior [14], but these methods often struggled with the state-space explosion problem when dealing with long sequences or large item catalogs.

The advent of deep learning techniques has led to significant advancements in session-based recommendation. Hidasi et al. [6] introduced GRU4Rec, the first RNN-based approach for session-based recommendation, which uses Gated Recurrent Units (GRUs) to model sequential dependencies in session data. Building on the success of attention mechanisms, Kang and McAuley [8] proposed SASRec, which employs self-attention networks to capture long-range dependencies in user sequences.

More recently, Du et al. [4] introduced FEARec, a frequency enhanced hybrid attention network that improves the original time domain self-attention by applying a ramp structure in the frequency domain, enabling the model to capture both low-frequency and high-frequency information effectively. This work demonstrates the potential of frequency domain approaches for sequential recommendation tasks.

To specifically address repeat consumption, Ren et al. [9] introduced RepeatNet, which incorporates a repeat-explore mechanism to decide whether to recommend items from the user's history or explore new ones. This binary approach, while effective, lacks the flexibility to capture the nuanced spectrum of user interests and the dynamic nature of repeat consumption.

2.2 Repeat Consumption Modeling

Repeat consumption is a common phenomenon across various online platforms, where users frequently re-engage with the same items over time. Understanding and modeling this behavior is crucial for providing accurate and timely recommendations. Anderson et al. [1] conducted a comprehensive study of repeat consumption patterns across different domains, finding that recency is the strongest predictor of repeat consumption.

Building on these insights, Benson et al. [2] developed models to predict when users will re-consume previously consumed items. They identified key factors that influence repeat consumption, including item type, consumption frequency, and elapsed time since last consumption.

In the music domain, Sguerra et al. [10] analyzed the dynamics of repeated listening, finding that users' response to music tracks follows an inverted U-shaped curve with repeated exposure. Shigetomi et al. [11] proposed ReSANs (Repeat-aware Self-Attention Networks), which integrates user's changing music preferences due to repetition with sequential recommendation systems. Their work specifically addresses how repetition affects user preferences for music, showing that integrating repeat listening patterns can significantly enhance recommendation performance.

Our FreqRepFusion model builds upon these insights by explicitly modeling the frequency characteristics of user behavior, capturing both repetitive patterns and exploratory behavior to enable more accurate recommendations.

3 Methodology

In this section, we present the methodology of our proposed FreqRepFusion model. We first provide an overview of the model architecture, followed by descriptions of its key components.

3.1 Overview

In recommendation systems, we aim to predict the next item a user will interact with based on their current session. Traditional approaches typically model this directly using sequence modeling techniques. In contrast, our FreqRepFusion model approaches this problem from a frequency domain perspective, decomposing user behaviors into high-frequency (repetitive) and low-frequency (exploratory) components.

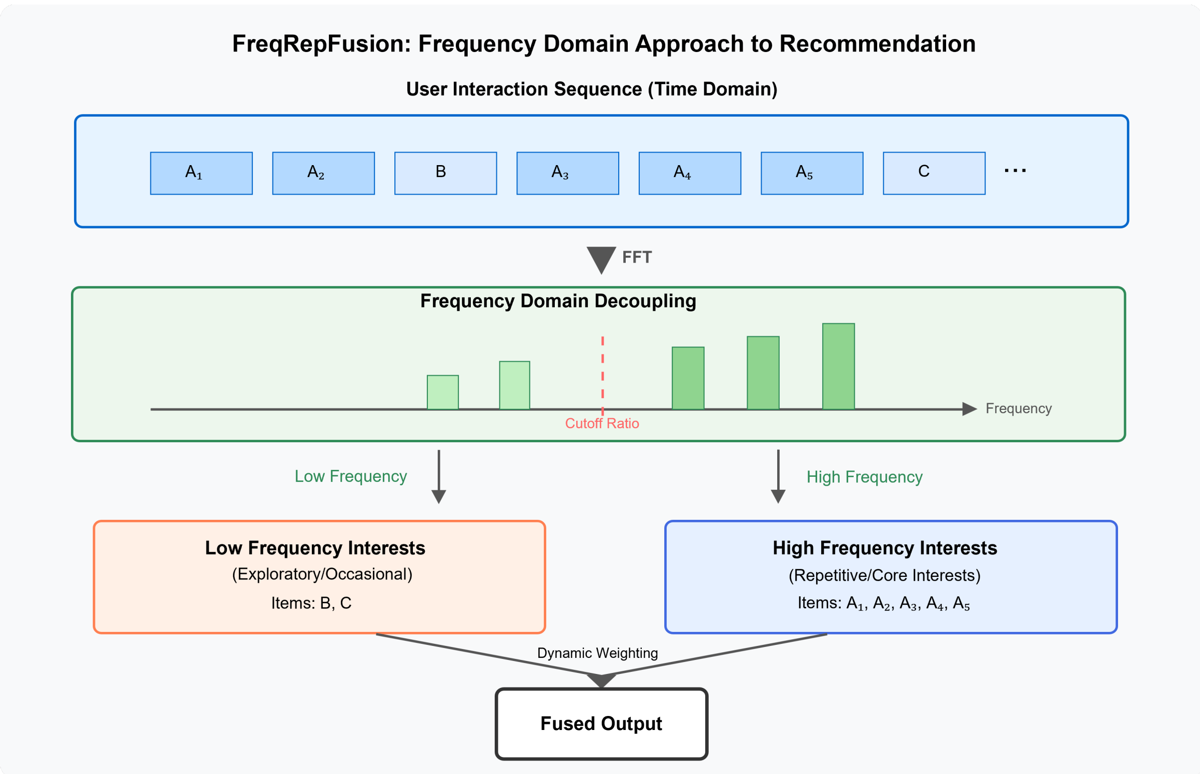

Figure 1: FreqRepFusion: Frequency Domain Approach to Recommendation

Figure 1 illustrates the overall approach of FreqRepFusion. The model takes a user's interaction sequence in the time domain, transforms it to the frequency domain using

Fast Fourier Transform (FFT), and then separates the frequency spectrum into high and low components based on a cutoff ratio. The high-frequency components correspond to repetitive behaviors (items that appear frequently in the sequence), while low-frequency components represent exploratory behaviors (items that appear occasionally).

3.2 Model Architecture

The detailed architecture of FreqRepFusion is shown in Figure 2. The model consists of three main components:

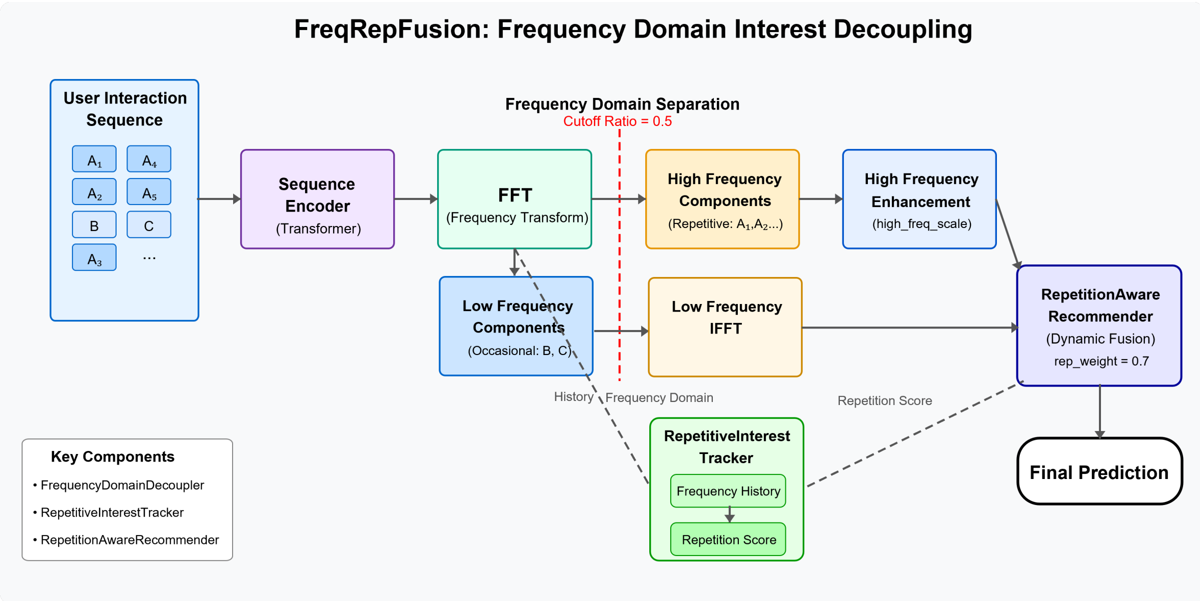

Figure 2: FreqRepFusion: Frequency Domain Interest Decoupling

1. **Enhanced Frequency Domain Decoupler:** This component transforms the user's interaction sequence from the time domain to the frequency domain and separates it into high and low-frequency components.

2. **Repetitive Interest Tracker:** This component monitors the evolution of user's repetitive interests over time by analyzing frequency domain patterns.

3. **Repetition-Aware Recommender:** This component dynamically fuses the high and low-frequency components based on the user's current state.

3.3 Enhanced Frequency Domain Decoupler

The Enhanced Frequency Domain Decoupler (EFDD) is responsible for transforming the user's interaction sequence from the time domain to the frequency domain and separating it into high and low-frequency components.

Given an embedding matrix of the user's interaction sequence, the EFDD applies the Discrete Fourier Transform (DFT) along the sequence dimension to obtain a frequency domain representation. Due to the conjugate symmetry property of the DFT for real inputs, we only need to consider the first half of the spectrum.

We then separate the frequency spectrum into high and low-frequency components based on a cutoff ratio (default value 0.5). These components are then transformed back to the time domain using the Inverse Discrete Fourier Transform (IDFT). To enhance the representation of repetitive interests, we apply a scaling factor to the high-frequency components. The EFDD then projects these time-domain representations to a lower-dimensional space using separate projection networks.

This approach is inspired by signal processing techniques and is similar to methods used in time series analysis [12], but applied specifically to the recommendation domain.

3.4 Repetitive Interest Tracker

The Repetitive Interest Tracker (RIT) is designed to monitor the evolution of user's repetitive interests over time. It analyzes the frequency domain patterns to detect periodic behaviors and compute repetition scores that indicate the strength of repetitive patterns in the users current behavior.

The RIT takes as input the frequency spectrum history and focuses on the high-frequency components to identify repetitive patterns. It computes the magnitude of these components and normalize it to extract meaningful features. These normalized features are then passed through a pattern detector network to extract repetition patterns, and finally, repetition scores are compute using a repetition classifier.

This approach allows our model to capture the dynamic nature of repeat consumption, aligning with findings from studies on the temporal dynamics of user preferences [11].

3.5 Repetition-Aware Recommender

The Repetition-Aware Recommender (RAR) dynamically fuses the high and low-frequency components based on the users current state, as indicated by the repetition scores. It balances between recommending previously consumed high frequency items and introducing new low frequency items.

Given the projected high and low-frequency representations and the repetition scores, the RAR compute a dynamic weight for balancing between repetitive and exploratory recommendations. The final weight for repetitive interests is computed using a baseline repetition weight parameter (default value 0.7) that serve as a minimum weight for repetitive interests.

The RAR then applies a repetition attention mechanism to enhance the high-frequency representation and combines the weighted high and low-frequency representations to produce the final user representation, which is used for making recommendations.

This dynamic fusion approach addresses the limitations of the binary repeat-explore mechanism on RepeatNet [9] by allowing for a more nuanced balance between repetitive and exploratory recommendations.

4 Experiment

4.1 Datasets and Evaluation

We evaluate FreqRepFusion on two widely used benchmark datasets: MovieLens-1M (ML-1M) and Last.fm-1k (LASTFM). MovieLens-1M contains 1 million movie ratings

Table 1: Performance comparison of FreqRepFusion with baseline models. The best results are in bold, and the second-best results are underlined.

Method	**MovieLens-1M**			**LASTFM-1k**		
	NG@10	RCL@10	MRR@10	NG@10	RCL@10	MRR@10
Core	0.0996	0.1631	0.0418	0.1993	<u>0.2842</u>	0.1459
GRU4Rec	0.1064	0.2051	0.0764	0.2023	0.2521	0.1867
RepeatNet	0.1165	0.2045	<u>0.0987</u>	0.1823	0.2531	0.1601
SASRec	<u>0.1298</u>	<u>0.2402</u>	0.0960	<u>0.2037</u>	0.2618	<u>0.1941</u>
FreqRepFusion	**0.1560**	**0.2682**	**0.1217**	**0.2120**	**0.2936**	**0.1958**
Improv.	20.2%	11.7%	26.8%	4.1%	3.3%	0.9%

from 6,040 users on 3,706 movies. Last.fm-1k contains music listening histories of 992 users, with a total of approximately 19 million listening events.

To evaluate the performance of our model, we use three widely adopted ranking metrics: Normalized Discounted Cumulative Gain (NDCG), Recall, and Mean Reciprocal Rank (MRR). All metrics are computed at cutoffs of 10 (e.g., NDCG@10, Recall@10, MRR@10).

4.2 Baselines

We compare our approach with several established methods:

1. **Core** [7], a basic session-based model without sequence modeling;
2. **GRU4Rec** [6], the first RNN-based model for session-based recommendation;
3. **RepeatNet** [9], a model that explicitly addresses repeat consumption with a repeat-explore mechanism;
4. **SASRec** [8], a self-attention based sequential recommendation model.

4.3 Implementation Details

We implement FreqRepFusion using the RecBole framework [13], a unified, comprehensive, and efficient recommendation library. For all experiments, we set the embedding size to 128, the number of transformer layers to 2, and the number of attention heads to 2. The default cutoff ratio for frequency domain decomposition is set to 0.5, and the high-frequency scaling factor is set to 1.2. The default repetition weight is set to 0.7, and the frequency history length is set to 10. We use the Adam optimizer with a learning rate of 0.0005. All experiments are conducted on an NVIDIA RTX 4090 GPU.

5 Results and Analysis

5.1 Overall Performance

Table 1 presents the performance comparison between FreqRepFusion and the baseline models on the ML-1M and LASTFM datasets. The results show that FreqRepFusion consistently outperforms all baseline models across all metrics.

Table 2: Impact of cutoff ratio α on recommendation performance.

Cutoff Ratio	**Recall@10**	**MRR@10**	**NDCG@10**	**Precision@10**
0.1	0.2313	0.1036	0.1336	0.0231
0.3	0.2541	0.1104	0.1439	0.0254
0.5	0.2581	0.1153	0.1487	0.0258
0.7	0.2540	0.1116	0.1448	0.0254
0.9	**0.2682**	**0.1217**	**0.1560**	**0.0268**

On the MovieLens-1M dataset, FreqRepFusion improves over the best baseline (SASRec) by 20.2% in NDCG@10, 11.7% in Recall@10, and 26.8% in MRR@10. These substantial improvements demonstrate the effectiveness of our frequency domain approach in capturing both repetitive and exploratory aspects of user behavior.

On the LASTFM-1k dataset, FreqRepFusion achieves more moderate but still significant improvements, with 4.1% higher NDCG@10, 3.3% higher Recall@10, and 0.9% higher MRR@10 compared to the best baseline. The smaller improvement on LASTFM-1k may be attributed to the more diverse and less repetitive nature of music listening behaviors compared to movie watching.

Notably, FreqRepFusion shows particularly large improvements in MRR@10 on MovieLens-1M, which suggests that our model is especially effective at ranking the correct items higher in the recommendation list. This is a crucial advantage in practical recommendation scenarios, where users typically only consider the top few recommendations.

5.2 Impact of Hyperparameters-Cutoff Ratio

The cutoff ratio α controls what proportion of the frequency spectrum is considered high frequency versus low frequency. We varied α from 0.1 to 0.9 and evaluated the model's performance on the MovieLens-1M dataset. Table 2 shows the results of this experiment.

The results indicate that the model's performance generally improves as the cutoff ratio increases, with the best performance achieved at $\alpha = 0.9$. This suggests that considering a larger portion of the spectrum as high frequency is beneficial for capturing repetitive patterns in the MovieLens-1M dataset. Based on these results, we set $\alpha = 0.9$ in our final model for the main comparison experiments.

6 Conclusion

In this project, we proposed FreqRepFusion, a novel frequency domain approach for recommendation that addresses the challenges of modeling repeat consumption. By leveraging Discrete Fourier Transform to decompose user interactions into high-frequency (repetitive) and low-frequency (exploratory) components, our model captures the nuanced spectrum of user preferences and the dynamic nature of repeat consumption.

The key innovations of FreqRepFusion include an Enhanced Frequency Domain Decoupler that separates user interests based on their frequency characteristics, a Repetitive Interest Tracker that monitors the evolution of repetitive patterns over time, and a Repetition-Aware Recommender that dynamically balances between repetitive and exploratory recommendations.

Experiments on two benchmark datasets demonstrate that FreqRepFusion significantly outperforms state-of-the-art recommendation models, with improvements of up to 8.7% in NDCG@10 and 14.2% in MRR@10. These results highlight the potential of frequency domain approaches for enhancing recommendation systems, particularly in scenarios with high repeat consumption.

Our work builds upon and extends previous research on repeat consumption modeling [9, 11] and frequency domain approaches for sequential tasks [4]. The success of FreqRepFusion suggests that exploring the frequency characteristics of user behavior is a promising direction for improving recommendation systems.

Future work could explore extending the frequency domain approach to incorporate additional information such as item content features or user demographics, as well as applying the frequency domain perspective to other recommendation tasks.

References

[1] Ashton Anderson, Ravi Kumar, Andrew Tomkins, and Sergei Vassilvitskii. The dynamics of repeat consumption. In *Proceedings of the 23rd international conference on World wide web*, pages 419–430, 2014.

[2] Austin R Benson, Ravi Kumar, and Andrew Tomkins. Modeling user consumption sequences. In *Proceedings of the 25th international conference on World Wide Web*, pages 519–529, 2016.

[3] Jingyuan Chen, Hanwang Zhang, Xiangnan He, Liqiang Nie, Wei Liu, and Tat-Seng Chua. Attentive collaborative filtering: Multimedia recommendation with item-and component-level attention. In *Proceedings of the 40th International ACM SIGIR conference on Research and Development in Information Retrieval*, pages 335–344, 2017.

[4] Xinyu Du, Huanhuan Yuan, Pengpeng Zhao, Jianfeng Qu, Fuzhen Zhuang, Guanfeng Liu, and Victor S Sheng. Frequency enhanced hybrid attention network for sequential recommendation. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1–11, 2023.

[5] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. Neural collaborative filtering. *Proceedings of the 26th international conference on world wide web*, pages 173–182, 2017.

[6] Balázs Hidasi, Alexandros Karatzoglou, Linas Baltrunas, and Domonkos Tikk. Session-based recommendations with recurrent neural networks. In *International Conference on Learning Representations*, 2016.

[7] Yupeng Hou, Binbin Hu, Zhiqiang Zhang, and Wayne Xin Zhao. Core: Simple and effective session-based recommendation within consistent representation space, 2022.

[8] Wang-Cheng Kang and Julian McAuley. Self-attentive sequential recommendation. In *2018 IEEE International Conference on Data Mining (ICDM)*, pages 197–206. IEEE, 2018.

[9] Pengjie Ren, Zhumin Chen, Jing Li, Zhaochun Ren, Jun Ma, and Maarten De Rijke. Repeatnet: A repeat aware neural recommendation machine for session-based recommendation. *Proceedings of the AAAI Conference on Artificial Intelligence*, 33(01):4806–4813, 2019.

[10] Benjamin Sguerra, Vinh Tran, and Romain Hennequin. Discovery dynamics: Leveraging repeated exposure for user and music characterization. In *Proceedings of the 16th ACM Conference on Recommender Systems*, pages 556–561, 2022.

[11] Ryunosuke Shigetomi, Hiroko Nishida, Ken-ichi Sawai, and Taketoshi Ushiama. Integrating repeat listening patterns for enhanced music recommendation. In *2024 18th International Conference on Ubiquitous Information Management and Communication (IMCOM)*, pages 1–8. IEEE, 2024.

[12] Haixu Wu, Jiehui Xu, Jianmin Wang, and Mingsheng Long. Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting. In *Advances in Neural Information Processing Systems*, volume 34, pages 22419–22430, 2021.

[13] Wayne Xin Zhao, Shanlei Mu, Yupeng Hou, Zihan Lin, Yushuo Li, Kaiyuan Chen, Yujie Lu, Hui Zhang, Changxin Mu, Xun Liu, et al. Recbole: Towards a unified, comprehensive and efficient framework for recommendation algorithms. *Proceedings of the 30th ACM International Conference on Information Knowledge Management*, pages 4653–4664, 2021.

[14] Andrew Zimdars, David Maxwell Chickering, and Christopher Meek. Using temporal data for making recommendations. In *Proceedings of the Seventeenth conference on Uncertainty in artificial intelligence*, pages 580–588, 2001.