Classical Music Recommender for Beginners

——Based on ChatGPT

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1. Introduction: Literature Review

With the advent of the digital age, recommendation systems have become indispensable in multiple application areas, particularly in recommending music, movies, and other multimedia content. The design and implementation of these systems present unique complexities and challenges. The diversity of recommendation systems stems from their various types, such as content-based, collaborative filtering, knowledge-based, and hybrid recommendations [3].

Collaborative filtering, a commonly used method, predicts based on users' past preferences [1]. However, this approach encounters difficulties in handling classical music, especially when dealing with new users or new works, often referred to as the cold start problem. The characteristics of classical music, such as its lack of lyrics, emphasis on melody, rhythm, and emotion, make content-based recommendations more appealing [1]. For example, classical music pieces are often identified by abstract names, composers, or work numbers, rather than descriptive song titles. This increases the challenge of finding new music that audiences might like, especially for those less familiar with classical music. Notably, while the audience for classical music is relatively small, they often possess higher purchasing power and a deeper understanding of music [2]. This presents an excellent opportunity for recommendation systems to meet the specific needs of this niche market through personalized recommendations.

However, with the widespread adoption of recommendation systems in the industry, especially by internet giants, they face a series of challenges such as scalability issues, data sparsity, and the aforementioned cold start problem [4]. These challenges have prompted researchers to seek new methods and technologies to enhance the effectiveness of recommendation systems. Matrix factorization techniques, such as Singular Value Decomposition (SVD), have been proven to effectively address some of these problems in recommendation systems [5].

Recently, many scholars have shown broad interest in the potential application of large language models in multimedia recommendations. In literature [20], authors attempted to use ChatGPT for music recommendations in video editing, successfully demonstrating the capability of large language models in interpreting user needs, capturing video emotions, and matching appropriate music. Further, literature [23] delves into how large language models, by analyzing and understanding textual data, can achieve personalized user experiences in movie recommendations. This recommendation is not merely based on traditional user ratings and preferences but through an in-depth semantic analysis of the text descriptions or comments provided by users, thus recommending more matched movie content. Literature [24], through empirical studies, compared and evaluated different recommendation algorithms. This study highlighted the feasibility and potential advantages of large language models in recommendation systems, especially in handling complex queries, solving cold start problems, and providing depth in recommendation interpretability. Additionally, literature [25] further proposed integrating more specific domain knowledge during the underlying pre-training phase of large language models, to better adapt the model to recommendation system application scenarios. This not only helps to improve the model's accuracy but also enhances the model's interpretability and relevance to recommended content.

Overall, combining large language models with traditional recommendation methods has become a cutting-edge direction in the research of recommendation systems, showing great potential in providing users with more accurate, more interpretable, and more personalized recommendations.

2. Proposed Research

This study is dedicated to exploring how effectively prompt engineering can be applied to improve classical music recommendation systems, especially in solving the "cold start" problem. The cold start issue often arises when a user first uses a recommendation system, where the lack of sufficient user historical data makes it difficult for the system to provide personalized recommendations. Classical music, with its unique attributes and relatively smaller audience, makes the cold start problem particularly prominent in this field. Prompt engineering offers a unique method, utilizing the powerful natural language processing capabilities of large language models, to guide the model in generating more accurate and personalized recommendations by designing specific prompts. By combining traditional recommendation strategies and the advantages of large language models, I aim to provide a more in-depth and satisfactory classical music experience for users.

3. Attempts at ChatGPT Role-Playing

https://chat.openai.com/g/g-GyyOl2c7S-classical-music-recommender-for-beginners

4. References

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