Implementing Machine Learning Tools and/or Techniques in Media and Entertainment Recommendation Systems

Introduction

Coballar & Stryker (2024) define Recommendation Systems (RSs) as machine learning systems that suggest content to users based on big data analytics of user behaviour, preferences, contextual data and the patterns within the data. RSs are gaining popularity in entertainment and media platforms such as Netflix, Apple Music and Spotify to name a few. In the current digital age most consumers are faced with content overload, which is why RSs are such an innovative solution for both the consumers and the service providers. Recommendation Systems suggest tailored content to individual users, thereby boosting their engagement with the media platforms and media companies in turn get insight into the sort of content (shows, films, music or games) to produce for optimal consumer satisfaction and increased revenue. Last but not least, through the use of AI and machine learning, Recommendation Systems are constantly evolving and becoming more efficient.

In this Literature Review, the evolution of techniques applied in media and entertainment recommendation systems is examined. The review explores the key approaches to RSs, as well as the literature on the use of Machine Learning algorithms such as Convolutional Neural Networks, Autoencoders and Recurrent Neural Networks in the systems. Finally, gaps in the current research, as well as possible future research directions shall be discussed.

Overview of Recommendation System techniques

There are three main approaches employed in RSs namely: Collaborative Filtering, Content Based Filtering and the Hybrid approach. Kalideen (2025) defines User-based Collaborative Filtering as a technique that determines user preferences by analysing the preferences of other users with similar interests. Item-Based Collaborative Filtering on the other hand, recommends items based on their similarity to other items the user already prefers. While this approach has been effective since its introduction in the 1990s, it can suffer from data sparsity and cold-start problems if there is insufficient data to analyze (Ko, 2022).

Content Based Filtering analyses the content or features of the items that are preferred by the user to recommend new items, and while this approach minimizes the data sparsity issue, a study by Salter (2006) determined that systems relying solely on Content-Based Filtering tend to recommend items that are overly similar to past preferences therefore there is no opportunity for the user to discover new content with different features or of different genres.

A way to mitigate the disadvantages of both Collaborative and Content Based Filtering is to use Hybrid RSs such as the CCAM (Co-clustering with augmented matrices) Hybrid Recommendation System which was proposed by Wu in 2014. The RS incorporated Co-clustering to group similar items in the same co-cluster. When combined with Collaborative and Content-Based Filtering, this technique improves accuracy and handles cold-start and sparsity issues more effectively (Kalideen, 2025). However Wu noted that the proposed CCAM System requires a huge amount of computational or processing power to be scalable to popular Media and Entertainment platforms in China such as Tencent and Sina Weibo.

Strub (2016) presented a hybrid RS combining Collaborative Filtering with an autoencoder-based architecture to predict the rating that a user would give to the recommended item using the MovieLens and Douban datasets of users and their ratings of various movies. This RS is not only easily scalable, but it also adressed the cold-start issue. However Brahmans (2024) argued that while autoencoders capture low-order features well, they often struggle to model complex item relationships. This is particularly a major issue for media and entertainment RSs where variables such as genre, length, and cast significantly impact user preferences.

In a 2020 study, Walek proposed the Predictory Recommender System for movies. This RS was a hybrid of an SVD Collaborative Filtering System, a Content Based Filtering System, as well as a Fuzzy Expert system. The Fuzzy Expert system was incorporated into the Hybrid Predictory RS in order to create an ultimate list of recommended items which are ranked according to level of importance; thereby increasing the accuracy of the RS. However Parikh (2024) state in their conference paper that when Hybrid RS's such as Predictory are made up of multiple algorithms and techniques; their design, implementation and maintenance becomes more complex and requires more processing power and other resources.

Machine learning in Media and Entertainment Recommendations Systems

The use of Machine Learning algorithms assists RS's that deal with enormous amounts of media (content) and user data such as those for Nefflix, YouTube and Spotify. According to Pendey(2019), RS's have two main tasks: to predict the Rating that a user would give to a recommended item, and to provide a Ranking of the finite list of recommended items for a user. In this section, In this section, the ML algorithms that have been researched and applied to RS's in Media and Entertainment shall be explored.

van den Oord (2013) proposed a novel RS which tackles the cold-start issue in Music RS's by using Deep Convolutional Neural Networks (CNN) to predict latent factors directly from Music audios. This is an example of a Collaborative filtering approach whereby the authors firstly trained a weighted matrix factorization model using the Million Song Dataset, and then they trained the CNN to analyze the melo-spectrograms of the audios in the dataset to predict the latent factor of any given music audio. This RS would allow new songs to be accurately recommended to users, even if no users have listened to and rated the song because each song is already classified ;together with other similar songs; by a latent factor. The authors, however also concluded that the model analyses only the audio content and not the lyrics or metadata, which could lead to generalization and a reduced accuracy in the RS.

Another instance of the application of ML in Entertainment RS’s is the Dynamic Attention Deep Model, a Neural Network Model proposed by Wang (2017) to capture temporal trends in the popularity of news article and predict which news articles to recommend and feature on a news feed. The proposed RS resulted in a higher click-through rate by the users; that is how often the users clicked on the recommended news articles. However since the RS is trained based on the way that human news editors select news articles to be featured, the accuracy of the RS may be lowered if the article selection behaviour of the editors evolve or if there is a shift in news trends. The model also does not take into consideration metadata such as article images; which may affect the selection criteria.

In 2015, Li proposed a Deep Collaborative Filtering Model (DCF) where Matrix Factorization and an autoencoder called a Marginalized Denoising Autoencoder (mDA) were combined to predict user ratings of items in the Book-Crossing and MovieLens datasets. This model outperformed traditional Collaborative Filtering frameworks; however the only drawback is the high computational demand of the algorithm.

Devooght and Bersini (2017) developed a Long Short-term Memory (LSTM) Recurrent Neural Network(RNN) model which learns the sequence in which a user consumed content using the MovieLens 1M and Netflix datasets; allowing the model to predict which item to recommend to the user next. It outperformed other models such as KNN's and Matrix Factorization in terms of accuracy and variety of recommended items. According to Devooght, given 10 trials, the RNN was able to predict the next movie watched by 40% of Netflix users, while other methods which are not based on the sequence achieve below 15%.

Challenges and Limitations

Some of the major challenges of RSs which utilize ML algorithms in Media and Entertainment are the scalability issue and high computational complexity. This is due to the rapid increase in the volume of user data and content across entertainment platforms. Handling such massive datasets requires distributed data analytics systems such as Apache Sparks (Cheedella, 2024). The Netflix RS utilises the same framework for real-time processing of user generated data.

Another major issue is the challenge of data privacy and ethics. RSs rely on collecting and analyzing personal data to build user profiles, and this raises concerns around consent, transparency, and surveillance. Recommendation algorithms do not only reflect preferences; they also shape them, influencing what users see and consume. This becomes a problem when people are not fully aware of how their data is used or how certain patterns might be reinforced. In Europe, laws like the GDPR aim to address this by requiring clear consent and transparency in algorithmic decisions.

There's also the issue of bias as an ethical concern. For example, if the data the system is trained on is already skewed or limited, then the recommendations will reflect the biases. So instead of recommending a wide range of content, the system could mostly recommend items that are already popular or familiar. That leaves less mainstream content such as Indie Films in the shadows. It can also reinforce stereotypes, for example by repeatedly associating certain genres or themes with specific groups of people. To reduce this, developers are working on ways to make these RSs fairer, like by adding some randomness or novelty, and auditing the results regularly to check for patterns that shouldn't be there (Chatterjee, 2023)

Conclusion and Future Research Directions

In this literature review, the progression of recommendation system techniques in media and entertainment, from foundational approaches like collaborative and content-based filtering to complex hybrid models that combine deep learning and fuzzy logic were explored. The use of machine learning algorithms such as CNNs, RNNs, and autoencoders has led to significant advancements in accuracy, scalability, and personalization in Recommendation Systems.

However, several key challenges remain, for example most models struggle with cold-start problems, high computational demands, and difficulties in modelling complex content relationships. In addition, as RSs become more influential in shaping user preferences, concerns around ethics, bias, and data privacy must be addressed. Regulatory frameworks like GDPR are a step in the right direction, but technical measures such as fairness-aware ML, interpretable models, and user-centric design need continued development.

Future research should also explore more ways to reduce computational demands without compromising accuracy especially in the real-time RSs used by major streaming platforms. Incorporating more metadata (like social data, or user intent signals) could help models better understand user preferences. Lastly, further study is needed on how to incorporate fairness and transparency directly into model design

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