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Comparative Analysis: Machine Learning Usage Across Recommender Systems of OTT Platforms

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Abstract

In today's world, OTT (Over the Top) platforms have become an important factor in terms of entertainment and a major stress reliever for people all around the world. The growth of OTT platforms has been increasing day by day i.e., almost 50 percent. Millennial customers, who grew up in a digital world and don't have the time or the patience for films, television programs, or any other content to broadcast on television, will be the largest audience for streaming television. Netflix, Spotify, Amazon Prime, and Disney+Hotstar are a few entertainment platforms.

This paper aims at performing the comparative study of machine learning implementation across various OTT platform's recommender systems by discussing the benefits of leveraging machine learning potentials to overcome the existing challenges being faced by these platforms. Also, we discuss the scope of improvising the features of OTT platforms through Machine learning approaches that could bring more value to the platform users and owners.

1. **Keywords**: Machine Learning, OTT (over the top), Recommendation System (RS), Collaborative Filtering

INTRODUCTION

Over the top, or OTT is so named because, unlike traditional TV, OTT devices provide end-users with access to video content over the cable box. OTT allows content creators to communicate with their viewers through a website or a smartphone. Various forms of entertaining content can be consumed by viewers through OTT platforms on almost any device connected to the internet, such as mobile phones, iPad, laptop, television, computer. **This makes it possible to view movies and other forms of entertainment at one's convenience** [1]. Netflix, Prime Video, Disney+Hotstar, aha are a few examples of OTT platforms that have gained popularity due to their user-friendly features.

The OTT applications have surpassed social media platforms like Facebook, messaging services like WhatsApp. Hence, online streaming has an overall growth of 50 percent in the entertainment industry from the year 2017 to 2022. In February 2019, around 145 million users spent 363 million hours on an OTT platform. **In which 83 percent of time was spent on a Smartphone and 17 percent on a Computer** [2]. **As per the market research carried out by Brightcove in collaboration with YouGov, 29% of customers prefer watching movies on free internet streaming platforms** [3]. Whereas 23% said that they'd rather pay a smaller cost with fewer advertisements. **As a result, advertising has become the most popular sort of marketing strategy utilized in OTT platforms, and is regarded as a success** [4]. The reason behind the success of these OTTs is the recommendation systems. Recommender systems are data filtering technologies with the primary goal of providing individual recommendations. Recommender systems help both services consumers and suppliers. In a digital environment, they reduce the costs of searching and selecting items. The importance of using accurate and efficient recommendation strategies inside a system that provides customers with relevant and trustworthy recommendations cannot be underestimated. According to the study, 72% of consumers expect businesses to provide personalized interactions. Adding to the pressure on businesses, users now have more options than ever to choose something else if they don't like the experience they're getting. **Companies that thrive at personalisation earn 40% more money from these activities than the ordinary player** [5]. The Indian OTT market has around 40 VoD (Video on Demand) providers, and by 2023, it can rise up to 100. This will help in stating a mark of Rs 237.86 billion by FY25- IBEF. In the present world, the number of users as well as the data is increasing. Eventually, it is posing a challenge. Manually building a personalized recommender system which can filter the relevant information from the large volume of data can be a mountainous task. Hence this implementation can be automated by using machine learning approaches, which help in recommending the user perspective products based on several factors. Similarity algorithms, matrix factorization are few ML approaches leveraged in building the recommendation systems.

In this paper, we will be reviewing and discussing the Machine learning approaches that are considered in building the Recommender systems of top OTT platforms like Netflix, Spotify, Amazon Prime Video and Hotstar.

2. Recommendation Systems

Almost all the OTT platforms make use of recommendation systems to recommend the relevant content to the users [6]. A recommendation system is a mechanism for gathering information that assists users in identifying the products they desire among the huge number of items available. **The main aim of the recommendation system is to predict the rating given by a user for a particular thing** [7]. It contributes to the company's growth. **Even today, it is quite challenging what a specific user wants from the available resources as everyday new people come. Suggestion of movies by Netflix, prime video, hotstar; recommending products by amazon, flipkart; etc., is possible by recommendation system** [8]. These recommendation systems make it simple for users to find what they desire. As a result, creating a successful recommender system is tough due to the fact that user preferences vary over time. A significant number of studies on recommendation systems are being conducted using diverse methodologies with the goal of extracting important information from the huge database. There has been significant development in this domain with the surge of technologies like Machine Learning, Artificial Intelligence, Data Mining, Knowledge Discovery and others.

Some of the benefits of Recommendation Systems are as listed below:

- Higher revenue: There are only a few strategies for increasing sales without increasing marketing efforts. If you set up an efficient recommendation system, you can earn extra money on a regular basis without putting in any effort.
- Greater user gratification: The fastest path to a sale is ideal because it saves time and effort for both you and your customer. Recommendation systems assist you in

shortening your clients' path to a sale by providing an appropriate alternative before they hunt for it.

- Increased loyalty and share of mind: A user-friendly interface keeps the visitor glued to the website thus increasing the probability of buying from the portal.
- Reduced churn: One of the most successful ways to re-engage people is through emails supported by a recommender system. Discounts or vouchers are another cost-effective strategy to re-engage clients, and they can be combined with suggestions to enhance conversion rates.

2.1) Categories Of RS:

The Recommendation System comprises three techniques: Content-based Filtering, Collaborative Filtering and Hybrid Filtering [9]. The content-based filtering revolves around the user's profile. Generally, a user provides data externally or internally. That particular data is stored by the system and recommendation is provided based on his/her previous activities. **Unlike content-based filtering, collaborative filtering identifies the similar users for a new user based on their preferences and recommends according to them as their tastes are similar** [10]. Hybrid filtering is a mixture of both collaborative and content-based filtering.

A. Content Based Filtering

The other name of Content-Based Filtering is cognitive filtering [11]. This technique recommends the things to the user based upon their previous search activities. For instance, if a user/customer wishes to watch only thriller movies, then the system recommends them similar to those thriller movies that are having good ratings. Content-based filtering only deals with the particular user's interest. Before offering cinemas or any other products to users, content-based filtering looks at their interests. It concentrates entirely on the choices of a particular person, drawing conclusions based on user preferences. Therefore, if we speak about the movies, then content-based filtering takes into account the user's rating. It checks which movies the user has given the high ratings by looking at the various genres in the user profile. Behind assessing the users' profile, the approach suggests films to the user based on his preferences.

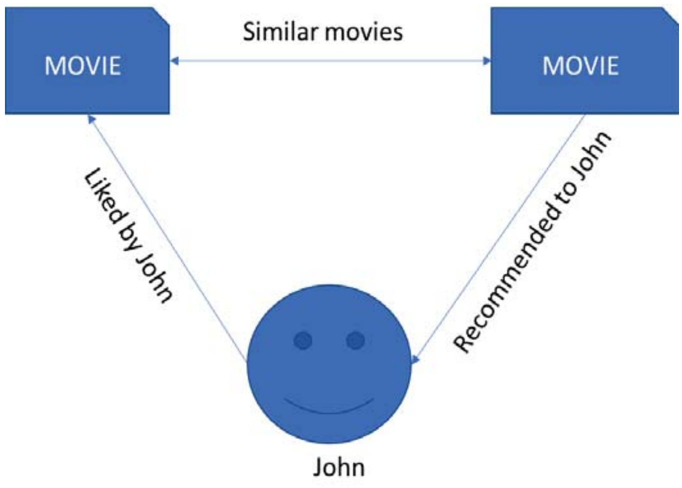

Fig 1: Content-Based Filtering

B. Collaborative Filtering

Goldberg et al., was the first person who proposed the idea of collaborative filtering in 1991 [12]. As there is plenty of data available nowadays, and people don't have time to select and search for the items or products that they require according to their interest. As a result, collaborative filtering is indeed one of the methods for filtering data and providing relevant information to the user. Collaborative Filtering has become one of the most used techniques for suggesting things to the users. Considering the decisions made by the other users, this approach proposes similar things of that user to the current user. This approach initially determines whether the present user and the neighboring user are identical or not, then according to the neighboring user, it anticipates the items. There can be as many users as possible. This method aims to find the similar users from a set of users. The similarity among users, on the other hand, is established by the evaluations that people are giving to a particular product. In this way, the process continues and you will get the desired results. **This technique takes the customer's ratings for any product from a big collection of user ratings** [13]. This huge catalogue is referred to as the user-item matrix.

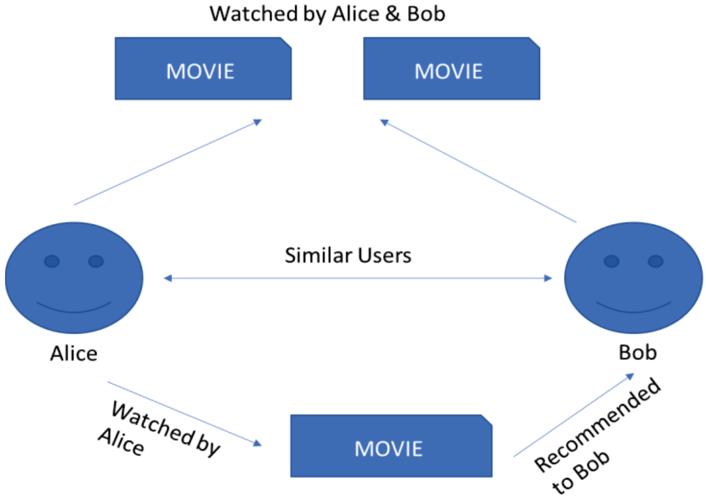

Fig 2: Collaborative Filtering

C. Hybrid Filtering

This method uses ratings and reviews of movies as input and performs collaborative and content-based filtering to provide lists of suggestions. It combines the two strategies, namely collaborative filtering and content-based filtering. Hybrid filtering is effective in case the aforementioned methods don't give the right outcomes. Through this approach we can address many unsolvable issues raised by collaborative filtering and content-based filtering. The cold start problem (sometimes RS has difficulty recommending products to users since there is little data about the user or the item) is a big stumbling block in collaborative filtering or in recommender systems in general. [14] **So, using content-based filtering followed by collaborative filtering may be a viable option**. As a result, making it hybrid may be able to fix the problem.

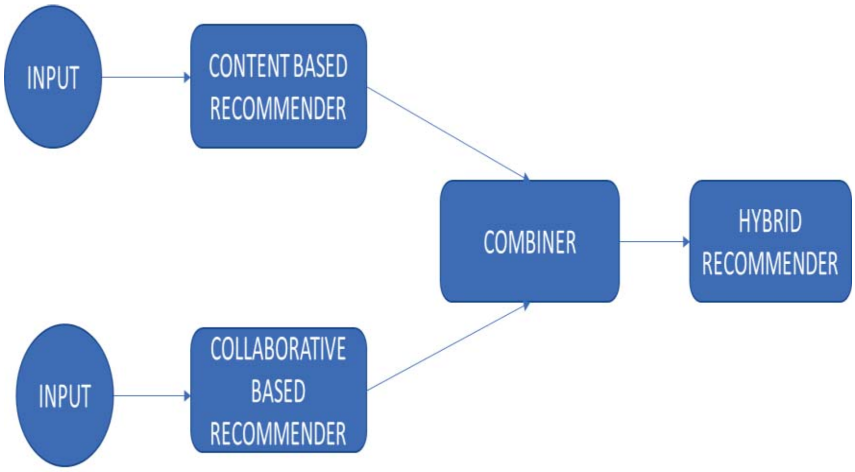

Fig 3: Hybrid Filtering

S. M. Ali et al. suggested a hybrid model that combines movie genomic markers with a content-based filtering idea [15]. It employs Principal Component Analysis with Pearson Correlation to eliminate redundant tags, hence reducing processing complexity.

F. Deng et al. proposed a method for calculating a user's potential preference using hybrid features such as user-generated features, picture visual features, and converting user item evaluations into hybrid feature ratings [16]. The results of the trials reveal that the suggested strategy is more effective on large datasets and gives better results on sparse datasets.

In this paper [17], **C. Yang et al. proposed a hybrid technique based on object attribute and social similarity**. The author employed collaborative filtering techniques in conjunction with social commonalities and movie genres.

As per the study developed by Priscila Valdiviezo and J. Bobadilla [18], **they combined multiple customer reviews and demographic information such as age, identity, and profession into a single matrix model, which showed that collaborative filtering was used in finding the missing ratings**. The key objective of the same is to improve the overall rating prediction of the film. The BPR-MF model was used by the author to solve the sparsity issue.

2.2) Metrics for Evaluating Recommendation Algorithms

The benefits of the recommendation system occur when the accuracy of the system is good. **There are basically three measures to evaluate the accuracy of the recommendation system** [19]. They are MAE, k fold cross validation and RMSD.

MAE (Mean Absolute Error)

The mean absolute error (MAE) is a statistic that analyzes the errors of observations by measuring the magnitude of difference between actual values and predicted values of observations. The MAE can be calculated as shown below:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n}$$

MAE = mean absolute error
y_i = prediction
x_i = true value
n = total number of data points

- Lower Value of MAE, the better performance
- It ensures a much more robust estimation
- The range of MAE is from 0 to infinity

B. K fold cross validation

A validation strategy known as K-Fold divides the data into k-subsets. It uses the holdout method k times, wherein each of the k subsets acts as a test set while the remaining k-1 subsets acts as the training set. In order to perform k fold validation, MSE (Mean Squared Error) is used.

MSE = (1/n)*Σ(yi – f(xi))2

Where,

n = Total Observations

yi = The ith observation's response value

f(xi) = The ith observation's predicted response value

There are a few steps to perform k fold cross validation.

Step 1: Begin with the division of the dataset into k similar-sized groups/folds.

Step 2: Then select one group among others and fit the model to remaining k-1 folds. Compute MSE for the groups.

Step 3: Repeat this process until al, the folds are calculated.

Step 4: Now calculate the average of MSE of all folds by using the formula,

Test MSE = (1/k)*ΣMSEi

Where,

k = Number of folds

MSEi = Test MSE on the ith iteration

C. RMSD (Root Mean Square Deviation)

$$\mathrm{RMSD} = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \hat{x}_i)^2}{N}}$$

RMSD = root-mean-square deviation
i = variable i
N = number of non-missing data points
x_i = actual observations time series
$\hat{x}_i$ = estimated time series

- Lower the RMSD, better the performance
- RMSE is most useful when large errors are particularly undesirable
- The range of RMSD is from 0 to infinity

3. Implementation Of Machine Learning By Ott Platforms

Machine learning is the most important technology in today's world. It empowers the computer to improvise without relying on explicit programs. The objective of this technology is to create data-driven computer systems that can learn on their own.

OTTs like Netflix, Spotify, amazon use recommendation systems. Recommendation systems are a sort of machine learning algorithm that ranks and rates products as well as users. A recommender system is a software system that tries to predict how users will review a specific product or a good. These predictions will then be assessed and given to the user,

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increasing user involvement on the platform by boosting product quality and user decision-making processes. The algorithms like decision tree, random forest, XGboost, etc., help in the decision-making process.

The general implementation steps of recommendation system in machine learning are [20]:

Step 1: Load the dataset of users and products

Step 2: Convert data frames to graph lab sframe

Step 3: Make comparisons based on users & products

Step 3: Train the model

Step 4: Provide recommendations

There are three types of approaches in recommendation systems - user-user interaction, item-item interaction, user-item interaction. The problem with user-user interaction & item-item interaction is that users' preferences change over time. So to solve this problem, user-item interaction is implemented in which a matrix factorization technique is applied. The basic principle behind matrix factorization is to decompose a single matrix into the product of multiple matrices. Now, let us see in detail how ML is used by the OTT platforms.

3.1) Usage of ML In Netflix's RS

The success of Netflix can be attributed to the application of machine learning algorithms named the Netflix Recommendation Engine or NRE. It categorizes the information fetched from the user's profile. Depending on the user's preferences, the system uses 1300 recommendation clusters to filter over 3,000 titles in one go. It's so effective that customized recommendations from the algorithm contribute for 80% of Netflix's audience participation. The NRE is assumed to save Netflix somewhere around $1 billion per year. With a 93 % retention rate, Netflix is chosen by 47 % of North Americans.

Data Points tracked by Netflix using Machine Learning are:

- User's information like gender, mobile number, location, etc
- The time he watched the content

- Videos or scenes he watched frequently
- The exact date and time, the user watched
- User's search history, etc

3.1.1) Algorithms Used By Netflix RS:

Netflix uses algorithms such as KNN (k- Nearest Neighbour), deep learning. They also used two algorithms named Restricted Boltzmann Machines (RBM) and Singular Value Decomposition (SVD). RBM is used to enhance the collaborative filtering model's capabilities and SVD is used to provide users with the best dimensional embedding. Using a sequential combination of these two algorithms, SVD and RBM, in ensemble, the best results were obtained.

Previously [21], **Netflix used A/B testing to select the best algorithms**. This testing was not accurate as it is a traditional method. So, to improve the selection of algorithms, efficiency; Netflix used the interleaving techniques. Interleaving is a learning strategy that involves combining different topics or types of practice to make learning easier.

3.1.2) Interleaving In Machine Learning:

Similar to the notion of interleaving in cognitive behaviour [22], Netflix uses interleaving to speed up algorithm growth by enhancing the volume of learning, resulting in even more personalized and hence better suggestions. So, Netflix employs a variety of ranking algorithms, each customized for a certain purpose. The 'Trending now' row, for example, combines recent popularity patterns, but the Top choices row, which appears on the homepage, offers suggestions based on individual video rankings. These algorithms are used with others to create personalized homepages for millions of subscribers.

Netflix uses the interleaving technique to accelerate learning by rapidly testing a wide range of concepts. They created a two-stage online experimental procedure. The first stage entails a quick trimming process in which we select the most promising ranking algorithms from a vast collection of initial concepts. The second stage involves running a standard A/B test on the reduced set of algorithms to see how they affect long-term member behaviour.

3.1.3) Improvable Approaches In Netflix's RS

Netflix's RS can be improved by making use of reinforcement learning. The latter works by rewarding good behaviour while penalizing bad conduct. In general, [23] **a reinforcement learning agent can observe and grasp its environment, act, and learn through trial and error technique**. When a Netflix user hits shuffle play, this is an action that is delivered to Environment (Netflix APP), which starts the Internal State. This suggests a result to the user, and the amount of time spent watching the movie is used to calculate the reward. The purpose of the algorithm is to maximize the reward, or how much time the user invests on watching the suggested films or series. The "Markov Decision Process" is used by RL algorithms to identify and preserve internal state. It is a mathematical framework that finds application in decision-making, wherein the results are impacted partly random and they are partially affected by the decision maker. Based on it, the algorithm determines the Next Recommended. For example, if the reward is relatively low, like if the user is frequently changing movies, then the previous path that the model adopted was incorrect, and so it needs to switch to an alternative genre, wherein it can figure out the path to find movies that were most viewed by the user. If the user watches the movie for a fair amount of time (a few minutes, for example), the path is partially correct, and you have the next probable option with you. It can be concluded that the genre may be correct, but the selection's sub nature is incorrect. And so, the user can find the perfect movie via continual learning process.

3.2) ML Used By Spotify's RS

Spotify has been emerging as the most popular music platform in the present world. **This application uses the concepts of Machine learning as it is being utilized to assist listeners in finding content that is relevant to them and recommend the music according to the users' interest** [24]. **Reinforcement learning, deep learning, causal inference, approximate inference, meta-model learning, graphical models, and time series modeling are the machine learning techniques used by Spotify** [25]. Reinforcement learning (RL) is the main concept used in Spotify's RS. The RL model identifies the user's satisfaction as the customer's happiness is a very important criterion. Collaborative filtering, Natural Language Processing, audio model are the three models used by Spotify.

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3.2.1) Improvable Approaches In Spotify's RS

KNN (k-Nearest Neighbour), the supervised machine learning algorithm, can be used to improve Spotify. KNN is used to classify the different songs. Random Forest is also the best algorithm that can be used in improving spotify's RS as it makes use of ensemble techniques i.e., combining multiple models and obtaining a single model from them improves the accuracy.

3.3) ML Used By Amazon Prime Video's RS

Similar to Netflix, Amazon prime Video also uses a recommendation system to recommend the movies to its users. The elemental concept of machine learning used in prime video is graph convolutional networks. This technique works by integrating the data from films most viewed by the user and viewers from different sources, and processing large data sets. Thus making it easier for Amazon Prime to find the area of interest of the user and make recommendations accordingly. **NLP (Natural Language Processing) is used in developing Alexa which is also used to recommend the relevant products to the user** [26]. Linear Regression, Random Forest are used to check the most popular video among all the available videos.

3.3.1) Improvable Approaches In Amazon Prime Video's RS

Active learning is a part of supervised learning. **This method is used to develop a high-performance classifier while minimizing the size of the training dataset to a minimum by actively selecting the accurate data points** [27]. The dataset related to users is very huge as millions of people come every day. So, it is significant to classify the users based on their personal formation as well as their preferences. The next thing is classifying the movies. This may be small data or large data depending on the releasing of the movies. We can perform query synthesis when the data is small and sampling when the data is large. Therefore, by utilizing the concept of active learning, the recommendation system of Amazon Prime video can be improved.

3.4) ML Used By Disney + Hotstar's RS

While heavy traffic is one of the main concerns of OTT platforms such as Hotstar, customer experience is also a major issue [28]. Hotstar, which has over 100 million downloads, is developing machine learning algorithms to extract user insight from the gigabytes of data they collect every day. **The recommendation engine then uses the user's viewing history to create algorithms personalized to the user and the content he or she wants to see** [29]. They also utilize machine learning techniques to deal with user variation among geographies. Whether it's through the latent semantic index, clustering, or deep learning, they are always refining their modeling tactics and creating better features.

3.4.1) Improvable Approaches In Disney+Hotstar's RS

By using the clustering techniques, it becomes easy to group the similar data. **There is a lot of content available in various languages and also different categories such as sports, live channels, movies, shows, etc** [30]. Therefore, by using k-means clustering, it becomes even more simple to recommend the relevant things to the users as everything is grouped together.

4. Conclusion

This study presented the ways of leveraging machine learning techniques in various OTT platform's Recommendation systems that adds value to the platform's users' experience. Also, this study aimed at explaining types of RS and notices that collaborative filtering is better than content-based filtering and any recommender system's accuracy can be improved by including more movies/any content forms features. Through our literature study, we can conclude that Hybrid Filtering is more effective in finding user's preference across the different OTT platforms. It aids the construction of an effective and efficient recommendation system combining the capabilities of other two approaches. Thus, we realized the scope of the OTT platform's recommendation systems to improve their efficiency through various Machine Learning techniques.

References

1. Ganuza, J.J. and Viecens, M.F., 2014. **Over-the-top (OTT) content: implications and best response strategies of traditional telecom operators.** Evidence from Latin America. *info*.

2. Sundaravel, E. and Elangovan, N., 2020. **Emergence and future of Over-the-top (OTT) video services in India: analytical research.** *International Journal of Business, vol. Management and Social Research*, *8*(2), pp.489-499.

3. Brightcove (2018). **Releases Asia OTT TV Research on OTT Adoption Preferences in Partnership with YouGov** (Press release). Retrieved 12 December 2019, from https://www.brightcove.com/en/company/press/brightcove-releases-asia-ott-tv-research-ott-adoption-preferences-partnership-yougov

4. Palop, J.J., Mucke, L. and Roberson, E.D., 2010. **Quantifying biomarkers of cognitive dysfunction and neuronal network hyperexcitability in mouse models of Alzheimer's disease: depletion of calcium-dependent proteins and inhibitory hippocampal remodeling**. In *Alzheimer's Disease and Frontotemporal Dementia* (pp. 245-262). Humana Press, Totowa, NJ.

5. statistics, o., 2022. ***OTT Platform Statistics In India Reveals Promising Growth***. [online] Selectra.in. Available at: <https://selectra.in/blog/ott-streaming-statistics#ott-platforms-at-a-glance> [Accessed 2 June 2022].

6. Rohrer, D. and Taylor, K., 2007. **The shuffling of mathematics problems improves learning.** *Instructional Science*, *35*(6), pp.481-498.

7. Katarya, R. and Verma, O.P., 2017. **An effective collaborative movie recommender system with cuckoo search.** *Egyptian Informatics Journal*, *18*(2), pp.105-112.

8. Wattal, S., Hong, Y., Mandviwalla, M. and Jain, A., 2011, January. **Technology diffusion in the society: Analyzing digital divide in the context of social class**. In *2011 44th Hawaii International Conference on System Sciences* (pp. 1-10). IEEE.

9. Things Solver. 2022. ***Introduction to recommender systems***. [online] Available at: <https://thingsolver.com/introduction-to-recommender-systems/> [Accessed 3 June 2022].

10. Salter, J. and Antonopoulos, N., 2006. **CinemaScreen recommender agent: combining collaborative and content-based filtering.** *IEEE Intelligent Systems*, *21*(1), pp.35-41.

11. Li, H., Cai, F. and Liao, Z., 2012, August. **Content-based filtering recommendation algorithm using HMM.** In *2012 Fourth International Conference on Computational and Information Sciences* (pp. 275-277). IEEE.

12. Nichols, D., Oki, B.M. and Terry, D., 1992. **Using collaborative filtering to weave an information tapestry**, Comm. *Assoc. Comput. Mach*, *35*, pp.51-60.

13. Jain, K.N., Kumar, V., Kumar, P. and Choudhury, T., 2018. **Movie recommendation system: hybrid information filtering system**. In *Intelligent Computing and Information and Communication* (pp. 677-686). Springer, Singapore.

14. Valdiviezo-Díaz, P. and Bobadilla, J., 2018, August. **A hybrid approach of recommendation via extended matrix based on collaborative filtering with demographics information.** In *International Conference on Technology Trends* (pp. 384-398). Springer, Cham.

15. Ali, S.M., Nayak, G.K., Lenka, R.K. and Barik, R.K., 2018. **Movie recommendation system using genome tags and content-based filtering.** In *Advances in Data and Information Sciences* (pp. 85-94). Springer, Singapore.

16. Deng, F., Ren, P., Qin, Z., Huang, G. and Qin, Z., 2018. **Leveraging Image Visual Features in Content-Based Recommender System.** *Scientific Programming, 2018.*

17. Yang, C., Chen, X., Liu, L., Liu, T. and Geng, S., 2018, June. **A hybrid movie recommendation method based on social similarity and item attributes.** In *International Conference on Swarm Intelligence* (pp. 275-285). Springer, Cham.

18. Jajoo, M., Chakraborty, N., Mollah, A.F., Basu, S. and Sarkar, R., 2019. **Script identification from camera-captured multi-script scene text components.** In

Recent developments in machine learning and data analytics (pp. 159-166). Springer, Singapore.

19. 2022. [ebook] Available at: <**https://www.sciencedirect.com/science/article/-pii/S1110866515000341**> [Accessed 3 June 2022].

20. Klipfolio.com. 2022. ***5 steps to setting up a recommender system.*** [online] Available at: <https://www.klipfolio.com/blog/recommender-system> [Accessed 3 June 2022].

21. Medium. 2022. ***A/B Testing and Beyond: Improving the Netflix Streaming Experience with Experimentation and Data***…. [online] Available at: <https://netflixtechblog.com/a-b-testing-and-beyond-improving-the-netflix-streaming-experience-with-experimentation-and-data-5b0ae9295bdf> [Accessed 3 June 2022].

22. Rohrer, D., 2012. **Interleaving helps students distinguish among similar concepts**. *Educational Psychology Review*, *24*(3), pp.355-367.

23. Medium. 2022. ***Netflix Shuffle Play: One of the Best examples of Reinforcement Learning.*** [online] Available at: <https://medium.com/analytics-vidhya/netflix-shuffle-play-one-of-the-best-example-of-reinforcement-learning-b8e69129ad3d> [Accessed 3 June 2022].

24. Mehrotra, R., 2021, October. **Algorithmic Balancing of Familiarity, Similarity, & Discovery in Music Recommendations**. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management* (pp. 3996-4005).

25. Goldmann, M. and Kreitz, G., 2011, September. **Measurements on the spotify peer-assisted music-on-demand streaming system.** In *2011 IEEE International Conference on Peer-to-Peer Computing* (pp. 206-211). IEEE.

26. Variety.com. 2022. ***Amazon Prime Video Recommendation Technology: Behind the Scenes - Variety.*** [online] Available at: <https://variety.com/2019/digital/news/-amazonprimevideoalgorithms1203233844/> [Accessed 3 June 2022].

27. Elahi, M., Ricci, F. and Rubens, N., 2016. **A survey of active learning in collaborative filtering recommender systems**. *Computer Science Review*, 20, pp.29-50.

28. En.wikipedia.org. 2022. ***Disney+ Hotstar - Wikipedia.*** [online] Available at: <https://en.wikipedia.org/wiki/Disney%2B_Hotstar> [Accessed 3 June 2022].

29. Linkedin.com. 2022. ***How Disney+Hotstar is using Machine Learning and Aritificial Inteligence.*** [online] Available at: <https://www.linkedin.com/pulse/how-disneyhotstar-using-machine-learning-aritificial-patel> [Accessed 3 June 2022].

30. Zheng, L., 2020. **Improved K-Means Clustering Algorithm Based on Dynamic Clustering.** *International Journal of Advanced Research in Big Data Management System*, 4(1), pp.17-26.