JOURNAL OF NORTHEASTERN UNIVERSITY

Volume 25 Issue 04, 2022 ISSN: 1005-3026 https://dbdxxb.cn/ Original Research Paper

A REVIEW ON USER PROFILING USING MACHINE LEARNING ON CONTENT STREAMING PLATFORMS

[1]Nikita Jain Nahar, [2]L.K Vishwamitra and [3]*Deepak Sukheja

[1] Department of Computer Science and Engineering, Oriental University, Indore, India.

1School of computer Science, IPS Academy, Indore, India.

[2]Department of Computer Science and Engineering, Oriental University, Indore,India.

[3]Department of Computer Science and Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India. (*corresponding author)

Abstract. Recommendation systems serve an important role in a variety of areas, including movies, novels, entertainment, including e-business and e- commerce, and they help to improve not only user happiness but also e- business and e-commerce. It recommends various items based on the user's personally identifiable information, interests, and actions. Nevertheless, since it is a multi- user device, the special characteristics of viewing from content streaming platforms platform has a significant impact on the final and effectiveness of recommendation system. As a result, recommender systems cannot effectively use the predictions and computations of a user's profile, interests, and behaviors to provide suggestions to the precise viewer(s) viewing an Internet platform. In the context of content streaming platforms platform viewing situations, this article provides a critical evaluation of current recommender systems. It identifies the problems and difficulties, as well as potential research options for addressing them. It also includes qualitative research to verify the emphasized variables that influence recommendations outcomes on content streaming platforms platform. The study indicates that the current recommendation system needs additional development to deal with problems of suggestions on a customized platform, such as content streaming platforms. Improving the recommender system for content streaming platforms may help to increase both audience happiness and conversion rates.

Keywords: First Keyword, Second Keyword, Third Keyword.

1 Introduction

Many nations implemented social distancing restrictions due to COVID-19 in 2019, forcing theatres to restrict or perhaps even close their doors, encourage individuals to remain at home and driving the growth of content streaming platforms subscriptions. As a result, we decided it was time to investigate other content streaming platforms [1]. The inexorable increase of knowledge and audio-visual material on the Internet makes it harder to locate what you are looking for, resulting in cognitive load. Various methods, such as online directories, online tools, and recommendation systems, have been developed to address this problem [2][3]. The recommender systems are also useful in situations when we want to recommend an item from a large collection of objects [4]-[12]. A recommender system is a software program that suggests appropriate things to a consumer, including such channels, videos, clips, advertisements, applications, games, and so on [12]. They are web-based applications that

Submitted: 21/10/2022 **Accepted**: 30/11/2022

assist users in choosing things of interest [13]-[15]. The recommender system uses several factors as input to recommend things that are intended to be relevant to a user [16]. These parameters include profile information, viewing history, demographics, and geography. However, since Different streaming platforms is a common, multi-users system, the predictions, and calculations for creating a user profile on a Various streaming platforms are not always correct [17].
In heterogeneous network infrastructure, the referral issue may be seen as a link prediction problem, in which the goal is to forecast whenever a connection is built between a subscriber and an undefined item or to determine the likelihood of connection between them [5]. Finding the most informative or predictive routes between user nodes and item nodes is essential for achieving high-quality recommendations.

Interaction

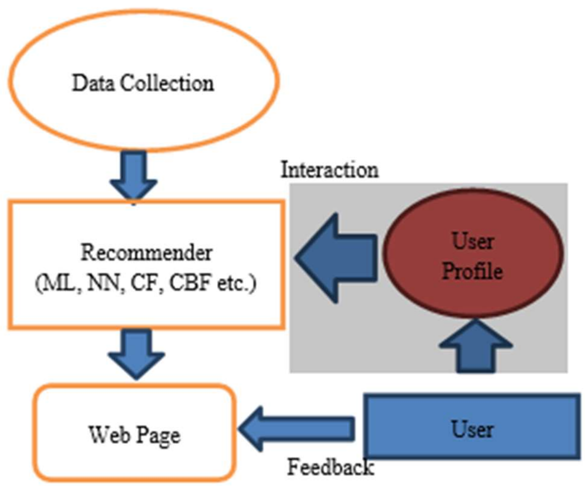

Fig. 1. Basic Flowchart of a Recommender

When we can identify the predicted pathways that lead to a target user's seen things, we will be much more certain that these paths will help us locate the undetected objects in which he or she is interested. In this article, User Profiling is the method of identifying the expected pathways between this kind of a subscriber as well as in unidentified node in this information networks. Information overload has recently become a major problem, making it difficult for users to locate the information they need fast. Since a result, customized recommendation system has grown in popularity, as they assist users in filtering data and discovering new interests [18][19] and [20].
Basic diagram of a recommender system is shown in Fig1. A recommender system is needed to forecast which movies, web series, and platforms a person will watch. A succession of recommendations may be made depending on the various user profiling techniques. A user profile is a representation of a user's preferences, traits, behaviors, and choices, whereas user profiling is a method for gathering, organizing, and insinuating data from user profiles [6].

2 User Profiling System

The user profiling system addresses challenges outlined above by constructing, handling, and demonstrating modified information about each user. A good user profile plan is essential in web-based systems and search engine personalization. Moreover, a user profile is the main component of information systems such as adaptive systems. It has played an active role in various domains such as healthcare sectors, banking sectors, social media, e-commerce, security, access control and social networking [21]-[24].

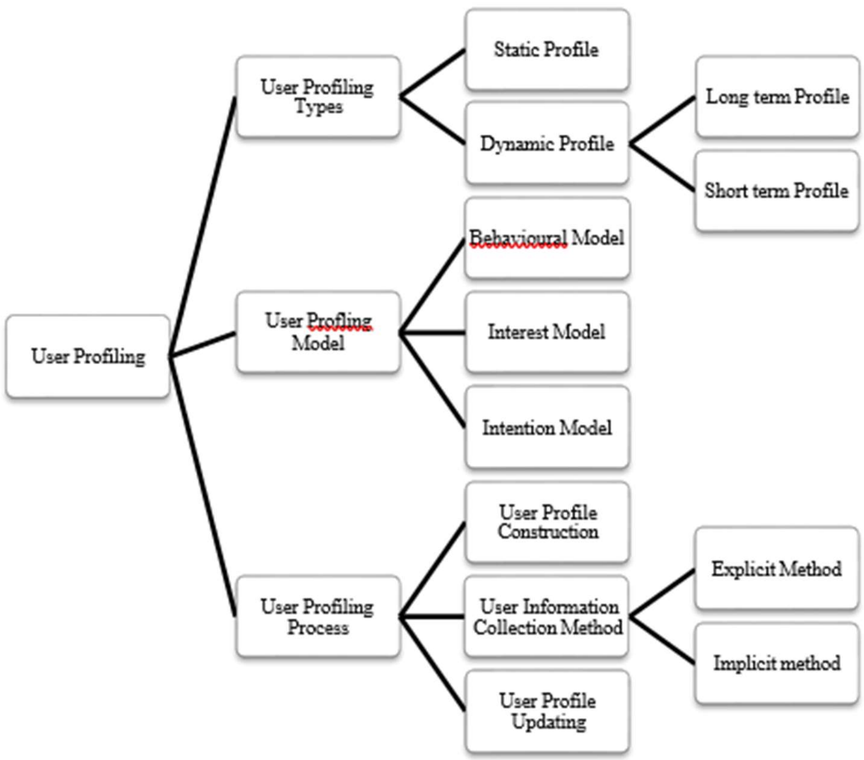

Fig. 2. User Profiling Taxonomy

When dealing with customization, the first step is to create an accurate users' information representations (user preferences and interests), which is generally maintained in the user profile. The correctness of the user data representation is exclusively responsible for a faster retrieving of user results. Therefore, a correct description of the user profile is critical for obtaining optimal retrieval results [25][26]. In a personalized desktop context, user profiling is a visual depiction of unique data relevant to a certain user. User profiling, as defined by Kanoje et al. [25], is a method of identifying a user's interest data based on the user's knowledge and an efficient system's recovery of customer satisfaction. Information about the user and the service is included in the user profile. User information is stored in the user service, including the user's name, ID, personal preferences, and interests. Service information, on the other hand, keeps track of the service name, supplier, context, frequency, and value. etc. [27]. The objective of tailored information retrieval and product recommendations. In general, the goal of user profiling is to collect information about a user's interest or topic, as well as the time span over which they have exhibited interest, to improve the quality of user accessing information and determine the user's purpose. User profiling is important in a variety of fields, including identification of trends, service recommendation, and attribute inference. Fig 2 depicts the taxonomy of user profiling [28].

USER PROFILE TYPES

A user profile may be expressed as a collection of weighted keywords and a rich semantic-based structure (sometimes augmented using ontologies). Nevertheless, when this profile is extracted autonomously from a text or even other resources, the weighed keywords form is usually utilized. User profiles are divided into two categories: static profiles and dynamic profiles [29]. The next sections go through each of these categories in further depth.

Static Profile: In general, the user-profiling task is thought to be supervised learning. The information presentation in this sort of profile is based on a static location, which is achieved by creating aggregated representations across all datasets. "Static profiling technique is a process of assessing user's predictable and static attributes," as according Poo et al. [30]. According to their technique, the information given by the user through the static profile is used to determine the kind of information in which the user is interested. A static profile is one that stores user information for an extended length of time. In other words, no changes or modifications are made to the user information. For instance, the user's age and gender. Furthermore, the information provided by users is used to create a static profile. As a result, the user's characteristic and accessible content are static, meaning they do not alter over time.

Dynamic Profile: The dynamic profile, in contrast to the static profile, is autogenerated by the system, and as a result, the user attribute and contents vary over time. In dynamic profiling, profile information about a user's behavior is used to predict the user's data on future rather than recent data. To put it another way, it's called a behavioral or adaptive profile. In situations when data is sent at a rapid pace, the dynamic profile is always correct. Furthermore, the user ontology is used to lead profile extraction, specify the collection of relationships in issue, and supply the entity dictionary. Some recent efforts have been made to develop dynamic user profiles by analyzing user temporal behavior. On Twitter, Liang et al. [31] investigated the topic of dynamic user profiling. In order to solve the issue, they used the dynamic user and word embedding (DUWE) model and the streaming keyword diversification model (SKDM). DUWE, on the other hand, was used to dynamically monitor the semantic representation of words and users over time, as well as modeling their embedding in similar space to efficiently assess their similarities. A dynamic profile that takes into account time may help differentiate between long-term and short-term goals. While the short-term profile displays the user's current interests, the long-term profile depicts the user's long-term interests.

User Modeling

A user model is a distinguishing feature of the adaptive process. In an adaptive system, it reflects the user's knowledge for successful adaptation. For example, while looking for relevant data, it aids in emphasizing an adaptable selection of crucial elements for the user. However, for the generation and upgrading of a user model, data gathering via the adaptive process for users modelling via various sources (which may include implicit observation, user interaction, or direct recording of user data directly) is required. User modeling [32] is the term used to describe the procedure. The three following categories of user modeling were identified:

Behavioral modeling: A behavioral model is one that is based on the patterns of human behavior. The information obtained during in the interactions here between systems as well as the user is saved in this models, and the planned action is estimated after the prior action is analyzed.

Interest modeling: An interest model is created by detailing the methods for assessing the degree of interest in a new item or venue, for example. Interest modeling may take two forms: direct and indirect. Users are openly asked what they appreciate in the direct method of interest modeling. The indirect kind of interest modeling, on the other hand, captures users' interests based on past browsing behavior, such as the time spent reading a book or clicking on hyperlinks.

Intention modeling: A user's intention (expressed as a goal, objective, or purpose) expresses what they want to achieve or why they are looking for information. Customers, for example, may be divided into two groups depending on their purchasing intentions: those who do not intend to purchase and those who do want to buy. This kind of user modeling tries to figure out why the user began engaging with the system in the first place. It is built on a behavioral and interest modeling base.

User Profiling Process

The process of user profiling is described in this section. It covers the full user profiling process, including profile creation, user information collecting techniques (implicit and explicit methods), and user profile updating. Each procedure is described in depth in the subcategories following.

Creating User Profiles: A user profile may be created for an individual by either directly acquiring data from the user or remotely by a system continuously includes the user's activity. Depending on the model used, different learning algorithms/data retrieval methods are used to create user profiles. The semantic network, keyword, and idea profiles are the three types of profile building. A user profile may be manually created by users or experts. Nevertheless, most consumers find this technique difficult and time consuming, thus limits the adoption of tailored services. In contracts, the approach that uses user input to create profiles automatically is the most prevalent. Other techniques, such as probabilistic NN/genetic methods or vector space models, are often utilized and have been proven to be more efficient in a variety of fields. Despite the fact that user profiles are often built based on the user's subject interests, several studies have expanded the profile development process to include additional profile topics that the user is not interested in. In this sense, both strategies are made accessible for the system to detect key papers while simultaneously eliminating irrelevant ones[33].

Methods of collecting user information: User profiling strategies begin with the acquisition of information regarding a particular user. However, it is anticipated that the system just identifies the users, since this is the system's most important need. The data about users could come from the user's input or be acquired automatically by an automated tool. Five typical techniques to obtaining user identity are applicable: login, software agents, upgraded proxy servers, cookies, and session ids. Cookies, on the other hand, are more efficient and commonly used among the strategies since they are transparent to users and allow for cross-section monitoring. Furthermore, the login strategy is favored in terms of consistency and accuracy since it monitors user activity across a session between machines given that users are willing to register and login each time they visit. User information may be gathered deliberately or implicitly to establish a user profile [34].

Updating user profiles: After the user profile has been successfully created, the user profile is generally updated. The term "update" refers to submitting a specific query to the system. As a result, the system obtains the query's particular element (searched for) and keywords, and then verifies the target's presence in the profile. If the validation is affirmative, the query is reinforced based on the user's selection criteria, and the system also delivers beneficial services to users depending on the hybrid model or user - generated content matching and estimates. [35].

Modeling phase of the user profiling

This section summarizes the stages of user profile modelling. It goes through the procedures required in modelling user profile in detail. The evaluation process, also called as the modeling phase, is an important aspect of the user profile implementation process. The goal behind user profiling as a data-mining activity is to create a user profile that can reflect all users' behaviors and interests, which can then be evaluated to forecast the user's future requirements. Data gathering, pre-processing, feature extraction, and analysis are all part of the modeling step (using various profiling techniques) as shown in Fig 3 [36].

Fig. 3. User Profiling Modeling Phase

Data Collection: The datasets needed to enable the thorough deployment of the user profile are gathered in this phase. Furthermore, the gathered data may be in the form of physical context data expressed in regards to time, climate, and humidity, which can help with user profiling in a big way. Recommender systems get their information from different sources. They capture a variety of information, including very basic information (user ratings/evaluations), more knowledge-based information (ontological description), and information about users' social relationships and activities. We recognize three things regardless of the data source: objects, users, and relationships among users or items.

Pre-processing of data: The majority of the profile data gathered has several faults. There is a requirement to clean the collected datasets in this respect so that the real features retrieved for profile modeling offer a higher overall performance. Furthermore, certain extracted features may seem to be duplicated. During in the pre-processing step, duplicate data is deleted. In order to be ready the information for the analysis phase, most researchers used various pre-processing procedures in their user profiling studies. Tokenization, stop word removal, and tagging are some fundamental pre-processing approaches. Tokenization is the procedure of segmenting text information into token and assigning a tagged to each token using a tokenizer [16][37].

Feature Extraction: One of the most important components of profile modeling is feature extraction. Feature extraction is the process of extracting human profile characteristics from several domains. Various researchers in the area to identify these properties have used different

approaches. The feature extraction step is essential to extract the relevant feature for better modeling performance. Content features, pattern features, profile features, term features, and user behavioral characteristics are among the most widely utilized features in newly suggested methodologies reported in literature [38].
Modeling Technique: User profile modeling is the process of creating a computer model that can anticipate user wants or preferences based on the retrieved information. Neighborhood-based approaches [11], machine-learning approaches [39], ontology- based approaches[40], and filtering approaches such as collaborative filtering [41] are examples of modeling methods. Machine learning algorithms may be used to assess user profiles. Machine learning may take the form of either supervised or unsupervised learning [42]. The data is trained and tested using a machine-learning technique. Various categorization methods have been used in the development of the user profile in recent years. The model's accuracy and other profile features increase when the baseline learning classifier is updated on a regular basis. The filtering strategy, on the other hand, includes rule-based, content-based, collaborative, and hybrid filtering [42]. The next paragraph contains an explanation of the modeling methodologies.

Recommender System

Recommender systems have gained popularity in recent years as a possible answer to the issue of information overload. Recommender systems are a kind of customized information filtering technology [6] that helps users find things of interest by making suggestions. They've been used to enhance the quality of web services in a variety of applications with great success. Recommender systems employ a variety of profiling approaches to gather data about user interactions, which they then incorporate into user profiles. The information stored in user profiles is viewed as indicative of the users' preferences and interests, and often includes information such as age, gender, birthplace, preferences, requirements, and so on. The latter profiles may be classified as single-faceted or multi-faceted based on the internal type of representation of the user information. The three steps of user profiling are (i) relevance feedback, (ii) feature selection, and (iii) profile updating. Because users are often led by a vague information demand that they cannot readily describe in terms of keywords or link to unseen information items, the feedback cycle is a crucial practice [7]. As a result, the usefulness of relevance evaluations comes in the gradual disambiguation of that demand, which is often accomplished via the use of various feedback approaches. These strategies vary from explicit to implicit, and they aid in determining the relevance of the objects that have been retrieved. Nevertheless, they frequently do so by assessing relevance in terms of cognitive and environmental levels of interaction, ignoring the role of intentions, motivation, and other factors.

3 User Profile Techniques Used in Recommender System

User profile design is the method of creating a digital prototype that really can anticipate user requirements or interests based on the collected characteristics. The basic framework of different techniques discussed is shown in Fig 4. The Database is collected from different sites, processed using any of the mentioned recommender. According to the requirement dynamic user profile is predicted. Neighborhood-based approach, Content Based, Knowledge Based Filtering approach, collaborative filtering method, Deep learning method, K-mean clustering methods, machine-learning approach, ontology-based approach, filtering approach, and statistical modeling approach are some of the modeling approaches available.

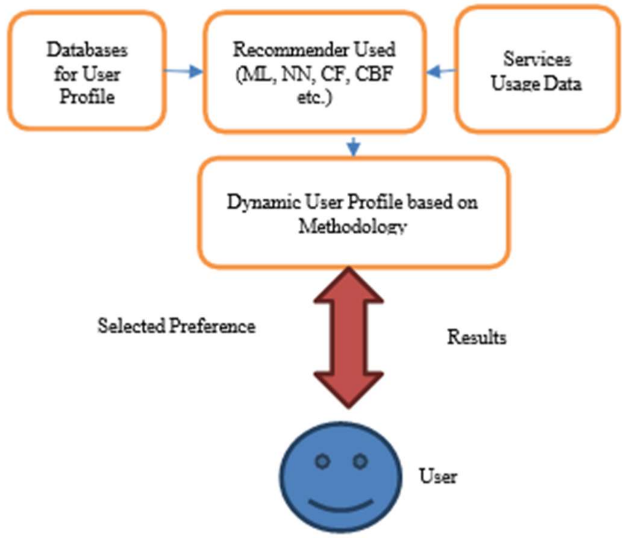

Fig. 4.Architecture for Proposed User Profile

Fig 5 shows the Types of Methodologies used in User Profiling. Machine learning techniques may be used to evaluate user profiles. Machine learning may take the form of either unsupervised or supervised and semi supervised [18]. The data is trained and tested using a machine-learning technique. Various categorization methods have been used in the building of the user profile in recent years. For example, collaborative learning algorithm [19] was used in recent research that included dynamic profile updating. The model's accuracy and other profile characteristics increase when the baseline learning classifier is updated on a regular basis. The filtering method, on the other hand, includes rule-based, content-based, collaborative, and hybrid filtering.

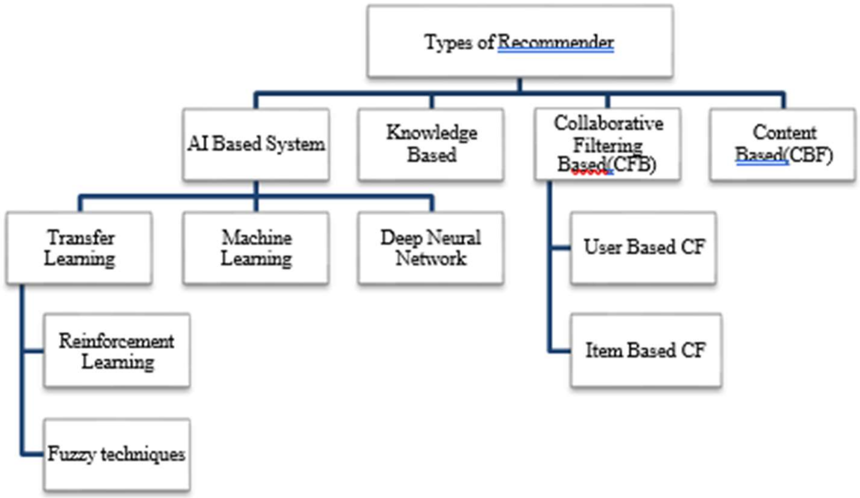

Fig. 5.Types of Methodologies used in User Profiling

Content-Based Filtering

Depending on a user profile (UP), content-based recommendation system is using the information of a product's statement to forecast its usability. CBS are designed to suggest products that are comparable to those that have already sparked a user's behavior. The first objective is to extract various item characteristics from files. A movie, for example, might be represented by genre, director, writer, actors, narrative, and so on. Structured data, such as a table, can provide these attributes directly. Then predict according to the database processed in the algorithm

Collaborative Based Filtering

The usefulness of an item is inferred by CF-based recommender systems based on the evaluations of some of the other subscribers. The CF approach is based on the idea that people with similar preferences would acquire comparable goods, therefore a program that utilizes the CF technique depends on data from members with specific interests to the current user.

AI Based System

Artificial intelligence is a rapidly expanding area with applications that range from games to learning environments to illness diagnosis. AI methods are being developed with the objective of automating intelligent behavior. Rationale methodologies are established to assist machineries in conflict resolution and valid logic; strategic plan aims to assist machineries in setting and achieving a goal; interaction seeks to understand natural speech and interact with humans; perceiving analyses and processes components like pictures or way of speaking; and eventually movement is concerned. In recommendation system, NLP as well as Reinforcement techniques are two main areas where Advanced technologies are used. Types of the AI based Recommender system are such as machine learning, Reinforcement Learning, Fuzzy Algorithms, Neural Network, etc.

4 User Profiling Using Machine Learning

H. Liang et al. [7] proposed a deep learning based prediction system for recommendation systems in heterogeneous information data networks, this article suggested a deep learning based on reinforcement technique for recommendation. To teach an RL a multi-iteration training method is suggested. It develops a prediction framework to help it determine which steps to perform in order to locate potentially interesting item nodes. To enhance training efficiency, the reward functions take into account both global exactness and effectiveness. During each cycle, To learn a policy network, the training procedure includes expert knowledge and data-specific information. It took approximately 3 hours to train one part, according to the results. For RN, GA, and DR, the average predicting time for one test user is 0.940s, 0.010s, and 0.850s, correspondingly. There are several limits to this work. The learning process is practiced and evaluated in a non-dynamic offline environment rather than in a real- time online one.

Y. Xiu et al. [8] utilized semantic information to profile similarity between users and propose a user cluster-based collaborative point-of-interest recommender system to address the data sparsity issue. Because the number of users is so large, utilize a clustering technique to profile related individuals before making recommendations. The findings show that our suggested model outperforms the two baseline models. The experiments showed that our suggested model, which includes two types of semantic information, outperforms two baselines. Instead of using the basic min, max, mean pooling method, Researchers will use a more efficient approach to represent POI names in future development. Furthermore, investigate several methods for discovering comparable users for the current user. train word vectors with various dimensions in our system, such as 50, 100, 200, and 300.

S. Tanuwijaya et al. [9] proposed a machine learning predictive analytic methodology using Netflix data for user profiling. The goal of this research is to profile and forecast future Netflix consumers in order to personalize marketing objectives for one of the VOD channels. Subscriber data and performance data are split into three kind of clusters using algorithm based on K-Means model before being evaluated with various using machine learning predictive analytic technique. To provide marketing intelligence to every target-prospective client, feature significance analysis is performed. The number of possible Netflix customers is exactly determined by the number of main factors affecting Netflix purchasers and already subscribed, which are divided into three separate groups. The results show that a mobile carrier may be using the technique to target potential customers with strong marketing or product opportunities using a customized marketing strategy based on the psychological trends and customer needs. When compared to the traditional approach, it is anticipated that using this methodology would improve the efficacy and precision of marketing activities.

Based on prior research, Fathima Shanaz et al. [10] believed that using Twitter data for user profile in news recommendation has promise. Twitter is one of many social media platforms with a lot of publicly available user-generated material. People use Twitter as a means of disseminating real-time information. In addition, for many readers, it serves as an entrance point to news. As a result, watching a user on Twitter may reveal a lot about their area of interest. However, only a small amount of study has been done using Twitter data to characterize individuals' news interests. This article will examine the possibility of utilizing Twitter as a data source for user profiling in news recommendation, as well as various techniques for creating user profiles using Twitter data to offer customized news recommendations.

Pradeep Kumar et al. [11] proposed Apioro algorithm for user ease to find the type of movie they want to see. The suggested method employs the Apriori algorithm to create user profiles based on the ratings and category characteristics of the objects. The apriori algorithm is used to create the user profile. The likes and dislikes of categorical features of items by users make up each user's profile. The efficiency of the suggested recommendation method is evaluated using the MovieLens dataset. On the MovieLens datasets, the comparison findings indicate that the proposed new method outperforms existing famous collaborative filtering techniques in terms of rating prediction accuracy. The estimated precision ranges from 0.4 to 0.699. For many characteristics, the F1 value is approximately 0.4. The range of recall is 0.2 to 0.699. Consequently, the proposed CF-based RS outperforms existing conventional CF-algorithms employing Jaccard in terms of precision–recall, F1-measure, and accuracy.

Qin X et al. [12] initiated a unique definition of neighborhood high dependency on recommender systems based on CF, that uses a set of individuals' shared rankings to assess the relevance for every set of item set using Bhattacharyya similarity. The accuracy of the suggested model was further evaluated using precision, recall value, and F1 parameters. As per results, while some memory levels will be reduced, precision would be greatly improved. Overall, it yielded favorable results.

Duc-Vinh et al. [13] In this article, the Dempster–Shafer theory is applied to the user profiling for evidentiary argumentation. Dempster's rule of combining with decision - making process is used to construct the recommendation system. Whenever incoming information comes from a variety of channels, as well as numerous sites on the internet, the proposed architecture is adaptable enough then to scale. For textual data, highest a Bayesian estimation is used to determine mass functions. Furthermore, the resultant profiles may be interpreted, visualized, and used in actual applications. Experiments using datasets crawled from Twitter and Facebook have verified the efficacy of the suggested approach.

Reddy S et al. [14] proposed a system that is based on the user's preferred genres of entertainment. Content-based filtering with genre association was utilized to accomplish this. The Movie Lens dataset is the platform's database. The collected data were analyzed with R. A recommendation system is a system that, depending on a data collection, makes recommendations to users for specific resources such as books, movies, music, and so on. Typically, movie recommendation algorithms estimate what movies a user would like based on the characteristics of previously enjoyed movies. Such recommendation systems are useful for businesses that gather data from a big number of consumers and want to provide the best recommendations possible. Many variables may be taken into account while creating a movie recommendation system, including the movie's genre, performers, and even the director. The systems may provide recommendations based on a single characteristic or a combination of two or more.

J. Zhang et al. [15] proposed a basic yet effective recommendation system, which takes use of users' profile characteristics to divide them into various groups. For every group, a virtualized attitude leader is constructed to encapsulate the entire group, thereby decreasing the size of the image consumer matrices. The virtualized influencers matrix is then subjected to a Weighted Slope method, which yields suggestion outcomes. In comparison to traditional clustering-based CF recommendation algorithms, our methodology has the potential to significantly decrease computational complexity yet keeping equivalent recommendation accuracy. Researchers also created MovieWatch, a real-world customized web-movie recommender system, opened this to the community, collected user feedback on ideas, and evaluated the practicality and accuracy of our framework utilizing actual information. MovieWatch recommendations have a customer approval rating of 90.2 percent (i.e., 203/225).

Ian Wei et al. [16] presented two recommendation models depends on deep learning NN and CF method. The content characteristics of the objects are extracted using a deep neural network called SADE. Extensive tests on a large Netflix rating dataset of movies demonstrate that our suggested recommendation models beat baseline methods for rating prediction of cold start items by a significant margin. For cold start item recommendation, the CF technique with such a deep convolutional NN would be both feasible and accurate. The architecture is generic and may be used in a variety of different online commerce and social networking recommender systems. The solution to the issue of cold start items may greatly enhance user experience and recommender system confidence, as well as successfully promote cold start goods. For cold start items, two recommendation models were suggested. The models integrate deep learning and time-aware collaborative filtering. An experiment using the Netflix dataset revealed significant improvements over current methods.

M. Heidari et al. [17] proposed to utilize a collaborative filtering algorithm to anticipate users' movie reviews to learn about their movie preferences. Create a user profile that includes all favorable and unfavorable characteristics. As a result, the system will give movies to individuals based on how similar they are and the optimistic profile and how different they are from their unfavorable profile. Ultimately, experiments show that prpoded strategy increases the MAE index by 12.540 %, the MAPE index by 17.680 percent, and the F1 index by 10.160 percent when compared to the traditional CF method.

Table 1 represents some contributions of machine learning for user profiling in content streaming platform.

Table 1. Contributions of Machine Learning For User Profiling

Ref.	Method Used	Data-Set used	Result	Advantage

[7]	Deep Reinforcement User Profilin gApproach	Different Heterogen ous Informatio n Networks	Predicting time for one test user is 0.940s, 0.010s, and 0.850s	Accuracy and efficiency
[8]	Clustering Algorithm+ CF	Semantic Informatio n Based Data Set	Achieve the best performance with train word vectors with different dimensions, i.e. 50, 100, 200, and 300.	Proposed model outperforms the two baselines.
[9]	Machine Learning Predictive Analytic Methodology	Netflix	For marketing purposes model is effective and accurate	Target potential customers
[10]	Implicit And Explicit User Profiling Methods	Twitter Data	Different methods to build user profiles using information were discussed	Personalized news recommendatio n
[11]	Apriori Algorithm to Form Users 'Profiles	Movie Lens Dataset	The recommended suggestion approach's efficacy has been evaluated and validated. Precision–recall, F1-measure, and reliability have all increased.	Outperforms other prominent collaborative filtering algorithms
[12]	Bhattacharyy a Coefficient Based O nCollaborative Filtering(CF)	Users Common Ratings	It achieved good results.	The precision is greatly improved
[13]	Dempster's Rule of Combination and Decision	From Twitter and Facebook.	Effectiveness of the proposed framework is validated	Proposed work is flexible resulting profiles are interpretable
[14]	Genre Correlation CBF	Movie Lens	Improved parameters in recommend movies	Efficient and time saving

[15]	Collaborative Filtering	Movielens And Netflix	The user satisfaction level of MovieWatch recommendations is 90.2% (i.e., 203/225)	Reduce the time complexity
[16]	Collaborative Filtering And Deep Learning	Netflix Movie Recommendation	Feasible and very effective for cold start item	Recommendation models largely outperform the baseline models for rating prediction of cold start items
[17]	collaborative filtering algorithm	movie ratings	Enhance the MAPE. Index by 17.680 %, and the F.1 index by 10.160 %	Improves the standard collaborative filtering method's
[44]	knowledge-based design recommender system (IKDRS	fashion product design	lower standard deviation around 0.0914, rate of satisfaction is 91%	performance of the proposed system is better, classify body shapes and model
[45]	collaborative Filtering	Times of India" news paper tweets	From 1000 tweetes overall 88% accuracy is obtained	better performance, efficient way

5 Challenges and Future Scope

The ways we watch videos has changed dramatically. We now have numerous content streaming platforms to watch TV programs and movies online, such as Netflix, Prime Video, and Disney Plus. Users are finding it more challenging to discover the best match for their preferences due to an excess of information and numerous criteria to evaluate various content streaming platforms. We examined various content streaming platforms in order to offer consumers with insights into each platform and suggest their preferred content on different platforms.

In recommender systems, modifying learning models to make them more scalable is still a difficulty. Furthermore, when the size of data rises, solutions for optimizing exponential expansion of parameters are still needed. Additional information needs to be added into user-item preferences in order to increase accuracy and handle sparsity issues in recommender systems. Contextual data, tags, and the growth of user preferences, as well as the user-item preference matrix, can be used to provide good e- commerce recommendations. As a result, learning approaches can be combined to extract meaningful information from a variety of data sources and integrate it into the suggestion generating process. Specialized recommender systems can help solve the problem of sparsity and provide more accurate recommendations. But research in this field is limited, especially for cross-domain, geographically aware recommender systems that are also group-based and trust-based.

6 Conclusion

This article takes a close look at existing recommender systems, techniques, and algorithms in the context of different streaming platforms. Qualitative research was conducted to confirm the factors that may affect the result of recommendations. Finally, the results and analysis of the qualitative research are detailed. We want to create a recommender system for content streaming platforms users that is based mostly on implicit rather than explicit input. We examined various algorithms used in suggested systems to build a positive or negative user profile in this review article. This article may aid practitioners in the development of recommender systems, such as customized group recommender systems, for platforms

References

1. Kuai H, Wang H, Yan J, et al (2017) A knowledge-driven approach for personalized literature recommendation based on deep semantic discrimination. Proc - 2017 IEEE/WIC/ACM Int Conf Web Intell WI 2017 1253–1259. https://doi.org/10.1145/3106426.3109439
2. Li H, Ge Y, Hong R, Zhu H (2016) Point-of-interest recommendations: Learning potential check-ins from friends. Proc ACM SIGKDD Int Conf KnowlDiscov Data Min 13-17- August-2016:975–984. https://doi.org/10.1145/2939672.2939767
3. Zhang JD, Chow CY (2015) GeoSoCa: Exploiting geographical, social and categorical correlations for point-of-interest recommendations. SIGIR 2015 - Proc 38th Int ACM SIGIR Conf Res Dev Inf Retr 443–452. https://doi.org/10.1145/2766462.2767711
4. Chen T, Hong L, Shi Y, Sun Y (2017) Joint Text Embedding for Personalized Content-based Recommendation. https://doi.org/10.48550/arxiv.1706.01084
5. Miura Y, Taniguchi T, Taniguchi M, Ohkuma T (2017) Unifying Text, Metadata, and User Network Representations with a Neural Network for Geolocation Prediction. ACL 2017 - 55th Annu Meet Assoc Comput Linguist Proc Conf (Long Pap 1:1260–1272. https://doi.org/10.18653/V1/P17-1116
6. Eke CI, Norman AA, Shuib L, Nweke HF (2019) A Survey of User Profiling: State-of-the- Art, Challenges, and Solutions. IEEE Access 7:144907–144924. https://doi.org/10.1109/ACCESS.2019.2944243

7. Liang H DRprofiling: deep reinforcement user profiling for recommendations in heterogenous information networks. Trans Knowl Data Eng 34:1723–1734. https://doi.org/10.1109/TKDE.2020.2998695
8. Xiu Y, Lan M, Wu Y, Lang J (2018) Exploring semantic content to user profiling for user cluster-based collaborative point-of-interest recommender system. Proc 2017 Int Conf Asian Lang Process IALP 2017 2018-January:268–271. https://doi.org/10.1109/IALP.2017.8300595
9. Tanuwijaya S, Alamsyah A, Ariyanti M (2021) Mobile Customer Behaviour Predictive Analysis for Targeting Netflix Potential Customer. 2021 9th Int Conf Inf Commun Technol ICoICT 2021 348–352. https://doi.org/10.1109/ICOICT52021.2021.9527487
10. Shanaz F (2020) The Potential of using Twitter as a Data Source for User Profiling in News Recommendation. Int J Innov Res ComputCommun Eng. IJIRCCE 8(4).
11. Singh PK, Othman E, Ahmed R, et al (2021) Optimized recommendations by user profiling using apriori algorithm. Appl Soft Comput 106:107272. https://doi.org/10.1016/J.ASOC.2021.107272
12. Qin X, Tan W, Tang A (2019) A New Trust-Based Collaborative Filtering Measure Using Bhattacharyya Coefficient. CommunComput Inf Sci 1042 CCIS:399–407. https://doi.org/10.1007/978-981-15-1377-0_31/COVER
13. Vo DV, Karnjana J, Huynh VN (2021) An integrated framework of learning and evidential reasoning for user profiling using short texts. Inf Fusion 70:27–42. https://doi.org/10.1016/J.INFFUS.2020.12.004
14. Reddy S, Nalluri S, Kunisetti S, et al (2019) Content-based movie recommendation system using genre correlation. Smart Innov Syst Technol 105:391–397. https://doi.org/10.1007/978-981-13-1927-3_42/COVER
15. Zhang J, Wang Y, Yuan Z, Jin Q (2020) Personalized real-time movie recommendation system: Practical prototype and evaluation. Tsinghua Sci Technol 25:180–191. https://doi.org/10.26599/TST.2018.9010118
16. Wei J, He J, Chen K, et al (2017) Collaborative filtering and deep learning based recommendation system for cold start items. Expert Syst Appl 69:29–39. https://doi.org/10.1016/J.ESWA.2016.09.040
17. Chen YL, Yeh YH, Ma MR (2021) A movie recommendation method based on users' positive and negative profiles. Inf Process Manag 58:102531. https://doi.org/10.1016/J.IPM.2021.102531
18. Heidari M, Jones JH, Uzuner O (2020) Deep Contextualized Word Embedding for Text- based Online User Profiling to Detect Social Bots on Twitter. IEEE Int Conf Data Min Work ICDMW 2020-November:480–487. https://doi.org/10.1109/ICDMW51313.2020.00071
19. Amara S, Subramanian RR (2020) Collaborating personalized recommender system and content-based recommender system using TextCorpus. 2020 6th Int Conf Adv ComputCommun Syst ICACCS 2020 105–109. https://doi.org/10.1109/ICACCS48705.2020.9074360.

20. Chirgaiya, Sachin et al. 'Analysis of Sentiment Based Movie Reviews Using Machine Learning Techniques'. 1 Jan. 2021 : 5449 – 5456.
21. Middleton SE, Shadbolt NR, De Roure DC (2004) Ontological user profiling in recommender systems. ACM Trans Inf Syst 22:54–88. https://doi.org/10.1145/963770.963773
22. Papatheodorou C (2001) Machine learning in user modeling. Lect Notes Comput Sci (including SubserLect Notes ArtifIntellLect Notes Bioinformatics) 2049 LNAI:286–294. https://doi.org/10.1007/3-540-44673-7_17
23. Chikhaoui B, Wang S, Xiong T, Pigot H (2014) Pattern-based causal relationships discovery from event sequences for modeling behavioral user profile in ubiquitous environments. Inf Sci Comput Sci Intell Syst Appl An Int J 285:204–222. https://doi.org/10.1016/J.INS.2014.06.026
24. Farnadi G, Tang J, De Cock M, Leuven KU (2018) User Profiling through Deep Multimodal Fusion Marie-Francine Moens. https://doi.org/10.1145/3159652.3159691
25. Kanoje S, Girase S, Mukhopadhyay D (2014) User Profiling Trends, Techniques and Applications. Int J Adv Found Res Comput 1:
26. Jang C, Chang H, Ahn H, et al (2011) Profile for effective service management on mobile cloud computing. CommunComput Inf Sci 199 CCIS:139–145. https://doi.org/10.1007/978- 3-642-23312-8_17/COVER
27. Yang Y (2010) Web user behavioral profiling for user identification. Decis Support Syst 49:261–271. https://doi.org/10.1016/J.DSS.2010.03.001
28. FarseevAleksandr, AkbariMohammad, SamborskiiIvan, ChuaTat-Seng (2016) "360 user profiling: past, future, and applications" by Aleksandr Farseev, Mohammad Akbari, Ivan Samborskii and Tat-Seng Chua with Martin Vesely as coordinator. ACM SIGWEB Newsl 1–11. https://doi.org/10.1145/2956573.2956577
29. Mizgajski J, Morzy M (2019) Affective recommender systems in online news industry: how emotions influence reading choices. User Model User-adapt Interact 29:345–379. https://doi.org/10.1007/S11257-018-9213-X/TABLES/5
30. Poo D, Chng B, Goh JM (2003) A hybrid approach for user profiling. Proc 36th Annu Hawaii Int Conf Syst Sci HICSS 2003. https://doi.org/10.1109/HICSS.2003.1174242
31. Liang S, Ren Z, Zhang X, Kanoulas E (2018) Dynamic embeddings for user profiling in twitter. Proc ACM SIGKDD Int Conf KnowlDiscov Data Min 1764–1773. https://doi.org/10.1145/3219819.3220043
32. Farid M, Elgohary R, Moawad I, Roushdy M (2018) User Profiling Approaches, Modeling, and Personalization. SSRN Electron J. https://doi.org/10.2139/SSRN.3389811
33. Gao Q, Xi SM, Cho YI (2013) A multi-agent personalized ontology profile based user preference profile construction method. 2013 44th Int Symp Robot ISR 2013. https://doi.org/10.1109/ISR.2013.6695695

34. Boulaalam O, Aghoutane B, El Ouadghiri D, et al (2020) Design of a Tourism Recommendation System Based on User's Profile. Adv Intell Syst Comput 1104 AISC:217– 223. https://doi.org/10.1007/978-3-030-36671-1_19/COVER
35. Soares M, Viana P (2017) The semantics of movie metadata: Enhancing user profiling for hybrid recommendation. Adv Intell Syst Comput 569:328–338. https://doi.org/10.1007/978- 3-319-56535-4_33/COVER
36. Zhao S, Li S, Ramos J, et al (2019) User profiling from their use of smartphone applications: A survey. Pervasive Mob Comput 59:101052. https://doi.org/10.1016/J.PMCJ.2019.101052
37. Liang H, Xu Y, Li Y, Nayak R (2008) Collaborative filtering recommender systems using tag information. Proc - 2008 IEEE/WIC/ACM Int Conf Web IntellIntell Agent Technol - Work WI-IAT Work 2008 59–62. https://doi.org/10.1109/WIIAT.2008.97
38. Daoudi M, Lebkiri N, Oumaira I (2020) Determining the learner's profile and context profile in order to propose adaptive mobile interfaces based on machine learning. 2020 IEEE 2nd Int Conf Electron Control OptimComput Sci ICECOCS 2020. https://doi.org/10.1109/ICECOCS50124.2020.9314518
39. Khanal SS, Prasad PWC, Alsadoon A, Maag A (2019) A systematic review: machine learning based recommendation systems for e-learning. Educ Inf Technol 2019 254 25:2635–2664. https://doi.org/10.1007/S10639-019-10063-9
40. Ibrahim ME, Yang Y, Ndzi DL, et al (2019) Ontology-Based Personalized Course Recommendation Framework. IEEE Access 7:5180–5199. https://doi.org/10.1109/ACCESS.2018.2889635
41. Sharma R, Gopalani D, Meena Y (2017) Collaborative filtering-based recommender system: Approaches and research challenges. 3rd IEEE Int Conf . https://doi.org/10.1109/CIACT.2017.7977363
42. Hasan A, Moin S, Karim A, Shamshirband S (2018) Machine Learning-Based Sentiment Analysis for Twitter Accounts. Math Comput Appl 2018, Vol 23, Page 11 23:11. https://doi.org/10.3390/MCA23010011
43. Najafabadi MK, Mohamed AH, Mahrin MN (2017) A survey on data mining techniques in recommender systems. Soft Comput 2017 232 23:627–654. https://doi.org/10.1007/S00500- 017-2918-7
44. Dong M, Zeng X, Koehl L, Zhang J (2020) An interactive knowledge-based recommender system for fashion product design in the big data environment. Inf Sci (Ny) 540:469–488. https://doi.org/10.1016/J.INS.2020.05.094
45. Pal A, Pal AR (2021) User profiling based on tweeter data using wordnet and news paper archive. Proc 2021 1st Int Conf Adv ElectrComputCommun Sustain Technol ICAECT 2021. https://doi.org/10.1109/ICAECT49130.2021.9392398