A Review Paper on Recommendation Systems

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Abstract* - Recommender systems have grown to be a critical research subject after the emergence of the first paper on collaborative filtering in the 1990s. Despite the fact that educational studies on recommender systems, has extended extensively over the last 10 years, there are deficiencies in the complete literature evaluation and classification of that research. This paper represents an overview of the techniques generated in recommendation systems. The articles are categorized into three techniques of recommender system, i.e.; collaborative filtering (CF), content based and context based. To classify research done by authors in this field, this paper shows different approaches of recommender with the help of tables. Furthermore, this paper will give practitioners and researchers the perception and destiny route on the recommender system. I hope that this paper enables anyone who is interested in recommender systems research with insight for destiny.

Keywords: Recommender Systems, Collaborative filtering, Content based, Context based, Review

I. Introduction

Recommender systems is a part of daily life where people rely on knowledge for making decisions of their personal interest. The number of people around the world who use the internet has witnessed an increase of approximately 40% since 1995 and reached a count of 3.2 billion. The increased information flow has opened more avenues, but it has also lead to added confusion for the user. Amidst this huge amount of data, the task of making certain decisions becomes difficult. Thus, in order to save a user from this confusion, recommender systems were introduced. Recommendation system is a subclass of information filtering to predict preferences to the items used by or for users. It is a sharp system that provides idea about item to users that might interest them. Francesco Ricci, LiorRokach and BrachaShapira define the recommender systems as software tools that make relevant suggestions to a user [1], [2]. Depending upon the user profile and the product profile, which are formed using various techniques and algorithms, suggestions are made. More than 32% of consumers rate a product online, over 33% write reviews and nearly 88% trust online reviews.

Sentiment analysis helps in determining the attitude of the writer by computationally dividing opinions in a piece of text into positive, negative or neutral. Extracting the sentiments in reviews can largely contribute to the quality of the recommender system by incorporating in it valuable information present in the reviews and also help in the understanding that how a particular review affects the consumer. The usage of the process of sentiment analysis paves the way for the development of personalized recommender system. Extensive research has been done in this field of recommendation systems. A variety of approaches has been used to provide recommendation that may use rating or content information. Recommendation systems have been broadly divided into three categories. These categories are collaborative filtering, content based and context based recommendation systems. The rest of the paper is organized as follows: Section 2 gives a brief overview of various types of Recommender systems. Section 3, 4 and 5 gives a detailed overview about the types of recommender systems with related work carried out by researchers in tabular form. Section 6 talks about extension and section 7 concludes the paper.

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II. Types of Recommender Systems

Over the years, recommender systems have been studied widely and are divided into different categories according to the approach being used. The categories are collaborative filtering (CF), content based and context based.

A. Collaborative filtering

Collaborative filtering (CF) uses the numerical reviews given by the user and is mainly based upon the historical data of the user available to the system. The historical data available helps to build the user profile and the data available about the item is used to make the item profile. Both the user profile and the item profile are used to make a recommendation system. For example, in movie recommendation system, collaborative filtering tries to find other like-minded users and then recommends the movies that are most liked by them. Collaborative filtering is considered the most basic and the easiest method to find recommendations. It does have some disadvantages which has led to the development of new methods and techniques. Collaborative filtering can be categorized as three types [3]:

- Memory-based approaches
- Model-based approaches
- Hybrid approaches

B. Content-based recommender system

Content based systems [4] focus on the features of the products and aim at creating a user profile depending on the previous reviews and also a profile of the item in accordance with the features it provides and the reviews it has received. It is observed that reviews usually contain product feature and user opinion in pairs. It is observed that users' reviews contain a feature of the product followed by his/her opinion about the product. Content based recommendation systems help overcome sparsity problem that is faced in collaborative filtering based recommendation system.

C. Context-based recommender system

Extending the user/item convention to the circumstances of the user to incorporate the contextual information is what is achieved in context-based recommender systems [5]. This helps to abandon the cumbersome process of making the user fill a huge number of personal details.

III. COLLABORATIVE FILTERING

Collaborative filtering is a technique for predicting unknown preferences of people by using already known preferences from many users [6]. It computes similarity on two bases: one is user and the other is the item. The main challenges that Collaborative Filtering deals with are data sparsity, scalability and cold start problem. CF introduces three main algorithms: memory-based, model-based, and hybrid CF, which are used to combine CF with other recommendation techniques and their power to deal with the challenges. The most important first step in memory-based CF is similarity evaluation. The system evaluates the similarity between the target user and other users for common rating items. The similarity is used as a weight for predicting the preference score. Various similarity measures have been proposed in previous studies:

Cosine similarity

The Cosine similarity is known as the vector similarity. This metric assumes that common rating items of two users are two points in a vector space, and then calculates cos(θ) between the two points. The magnitude of similarity is given as [7]:

$$similarity = \cos(\theta) = \frac{A.B}{\parallel A \parallel \parallel B \parallel} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n}(A_i)^2} \times \sqrt{\sum_{i=1}^{n}(B_i)^2}}$$

Pearson's correlation

The Pearson's correlation measures the strength of the linear relationship between two variables. It has values in the range [-1.0, 1.0], where -1.0 is a perfect negative correlation, 0.0 is no correlation and 1.0 is perfect positive correlation. The denominator in the following equation shows the standard deviations of two data objects x and y where N is the total number of attributes [7]:

$$Pearson(x,y) = \frac{\sum xy - \frac{\sum x \sum y}{N}}{\sqrt{\left(\sum x^2 - \frac{(\sum x)^2}{N}\right)\left(\sum y^2 - \frac{(\sum y)^2}{N}\right)}}$$

Tanimoto coefficient

This similarity is a ratio of intersections. This metric doesn't consider the user rating but the case of a very sparse data set is efficient. The Tanimoto coefficient between two points a and b is given:

$$T(a,b) = \frac{\sum_{j=1}^{k} a_j \times b_j}{\left(\sum_{j=1}^{k} a_j{}^2 + \sum_{j=1}^{k} b_j{}^2 - \sum_{j=1}^{k} a_j \times b_j\right)}$$

A. Memory-based CF

People with similar interests are combined to form a group and every user is a part of that group [36]. User –based CF and Item-based CF are used to represent memory-based CF. It is easy to implement and scales well with correlated items. There is no need of considering the content of items being recommended. There are many limitations of memory-based CF like cold start problem, sparsity and their dependencies on human ratings.

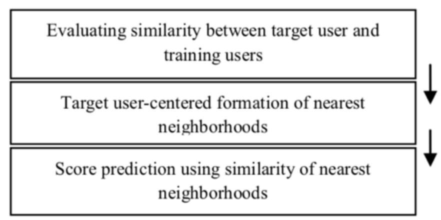

Fig 1. Block diagram of memory-based CF

The prediction process in memory-based CF contains three steps. They are similarity evaluation, generation of nearest neighbors and score prediction. For evaluation of performance, the CF system considers the mean absolute error, precision and recall.

B. Model-based CF

Complex patterns which are based on training data, are recognized by designing and developing the models (such as data mining algorithms, machine learning) and then intelligent predictions are made for CF tasks for the real-world data which are based on learnt models [8]. Rather than using the raw data directly in making predictions, instead the model parameters are estimated from the available rating data and the model is used for making predictions. It gives an intuitive rationale for recommendations. Model-building is an expensive procedure. Other disadvantage of model-based CF is that it loses useful information for dimensionality reduction techniques.

C. Hybrid CF

In hybrid recommender system, different techniques of collaborative approaches and other recommender techniques are combined to get better results. Various problems like cold-start, data sparsity and scalability can be avoided by using hybrid approach [9]. There are different ways of combining CF with other recommender techniques which are following:

- Hybrid Recommenders Incorporating CF and Content-Based Features
- Hybrid Recommenders Combining CF and Other Recommender Systems
- Hybrid Recommenders Combining CF Algorithms.

Fig 2. illustrates the flow chart of Collaborative Filtering Recommender System. It shows how collaborative filtering considers only numerical reviews given by different users and then gives recommended products as result. The user reviews are stored in a database to make further references and predictions.

In the figure User 1 and User 6 show similar behavior and thus their profiles lie in the same neighborhood which indicates similar interests. Using this similarity, review about a product not rated by User 6 can be predicted using the reviews of User 1 that are available. Thus, a prediction regarding product C's review by User 6 is made using the available data. From these predictions, recommendations are extracted and suggested to the user.

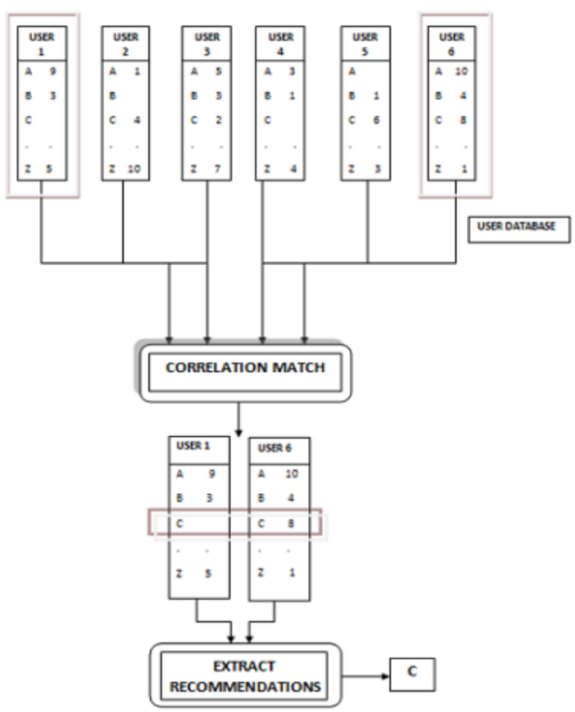

Fig 2. Collaborative Filtering Recommender System

Table 1 shows different collaborative filtering methods based on sentimental analysis for recommendation system. These methods are based on a variety of different models. Over the years, different models are combined with collaborative filtering technique of recommender systems in order to increase the accuracy of the predictions given by the results. J. Wang et. Al. developed the unified relevance model based recommendation system while Parlov et. Al. used maximum entropy approach and both these models helped reduce data sparsity problem, one of the commonly faced problem in collaborative filtering based recommendation systems.

METHOD	DESCRIPTION	RESEARCHERS
Unified relevance model	It is a probabilistic item-to-user relevance framework which uses Parzen-window method for density estimation. This approach reduces data sparsity problem.	J. Wang, A. P. de Vries, and M. J. T. Reinders
Hybrid CF model	It introduces effective recommender system using sequential mixture CF and joint mixture CF. It also implements advanced Bayes belief networks.	X. Su, R. Greiner, T. M. Khoshgoftaar
Fuzzy Association Rules and Multilevel Similarity (FARAMS)	It uses fuzzy association rule mining to extend the existing techniques. FARAMS achieved the task of generating more qualitative predictions.	C. W. K. Leung, S. C. F. Chan, and F. L. Chung
Flexible mixture model (FMM)	Simultaneous creation of user and item clusters. It introduces preference nodes to study a dramatic variation of the rating among users with similar tastes.	L. Si and R. Jin
Maximum entropy approach	Clustering of items based on user access path in order to reduce the apriori probability. This helps in addressing sparsity and dimensionality reduction.	D. Y. Pavlov and D. M. Pennock

Table 1. Collaborative Filtering Methods

The main advantages of this technique are they use information that is provided bottom-up by user ratings, they are domain independent and require no content analysis, and the quality of recommendation increases over time. A disadvantage is the so-called "cold start" problem is due to the fact that CF techniques depend on sufficient user performance from the past. Even when such systems have been running for a while, this problem emerges when new users or items are added.

New users first have to give a sufficient number of ratings for items in order to get accurate recommendations. New items have to be rated by a sufficient number of users if they are to be recommended. Another disadvantage is the sparsity of the past user actions on the network. Since these techniques deal with community-driven information, they support well-liked tastes more strongly than unpopular tastes. The learners with unusual taste may get less qualitative recommendations. Another problem is scalability. Systems which deal with large amount of data like amazon.com, have to be able to provide recommendations in real time, with number of both users and items exceeding millions [10].

IV. CONTENT-BASED RECOMMENDER SYSTEM

Any system implementing content-based recommendation approach analyzes a set of documents and/or descriptions of items previously rated by a user, and build a model or profile of user interests based on the features of the objects rated by that user. The recommendation process basically consists of matching up the attributes of the user profile against the attributes of a content object. It enhances the user's interest and predicts whether the user would be interested in eating at any particular restaurant or interested in seeing any particular movie [11]. It is also known as adaptive Filtering as it provides suggestions according to user's field of interest and adapts user's likes and dislikes. It represents the comparison between the content contained in the item with the content of items of user's interest.

By using Bayesian hierarchical model, better user profiles for upcoming users is made by collecting feedbacks from the old users. Content based collaborative filtering is more widely used to compare pure CF and pure Content-base. In CF, the problem of sparsity is overcome (converting sparse user filled matrix into full user rating matrix) by using content-based prediction. Fig 3. displays the flow of information in a content based recommendation system. Relevant entities of an item and relations are kept together as input. Main features of items are extracted from item ontology. Features of items, user's ratings and user modeling data are applied to content based recommender system. After applying, various recommended items are given as output.

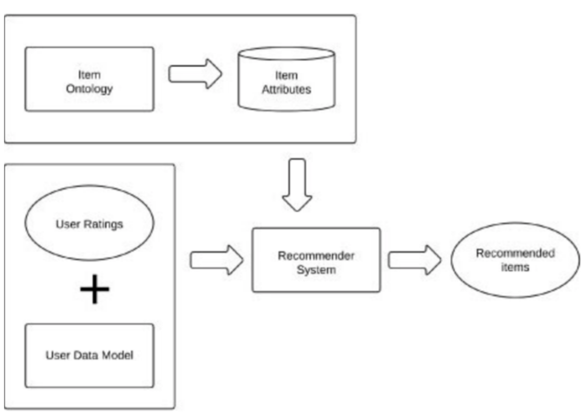

Fig 3. Content-based Recommender System

Table 2 shows different content based methods using sentimental analysis for recommendation system. These methods are based on a variety of different models. Different researchers have studied the relevance of various techniques that can be implemented in content based recommendation systems. Accuracy and relevance of the recommendation systems have become better by extensive research. Content-Boosted Collaborative filtering technique was implemented by Prem Melville et. Al. Recommendation system using content based technique and Bayesian Hierarchical Model (BHM) was built by Marko Balabanovic.

METHOD	DESCRIPTION	RESEARCHERS
Content-Boosted Collaborative Filtering	It gives an approach to combine content and collaboration to enhance existing user data and to give better performance than a pure content based predictor.	Prem Melville, Raymond J. Mooney, RamadassNagarajan
FAB Technique	An adaptive recommendation service for collection and selection of web pages. It makes the system more personalized and combines the benefits of content analysis with the shared user interests.	Marko Balabanovic
Bayesian hierarchical model(BHM)	Proposes a faster technique to gather a huge number of individual user profiles even if feedbacks available are less. It uses various parameters of BHM for optimization of joint data likelihood.	Yi Zhang, Jonathan Koren

Table 2. Content-based Recommendation Methods

V. CONTEXT-BASED RECOMMENDER SYSTEM

Recommender systems which use collaborative filtering technique or which are based on the contents and features of items have achieved great success but can be further improved. The higher level of personalization is required in recommender systems to give more appropriate suggestions.

In order to achieve this, the contextual information of users is also taken into consideration while designing a recommender system. Context refers to the time, location, area and environment of the user which define a user's status. Incorporating contextual information in a recommender system helps to get a clear picture of the situation of any individual, place or object which is of relevance to the system for prediction [12].

It aids in extracting information about a particular community of individuals and this information proves to be of high importance to improve the suggestions provided to a user and makes the system more efficient. Recommender systems require situational information of the user and context based recommender system accesses this information directly using various techniques (such as GPS) and does not bother the user with this.

Fig 4. displays the flow of contextual information in a context based recommender system. The user's location data, social data, current time, weather data is taken into consideration as the contextual data and is given as input to the system. An approximate address of the user is determined and the location is saved. Social data of a user can be accessed by requesting permission to a social account of the user.

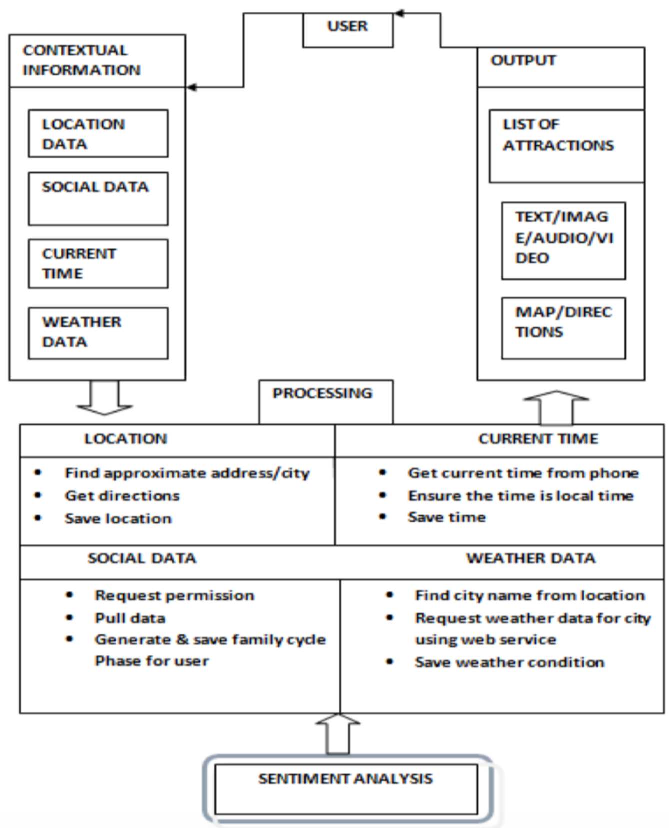

Fig 4. Context-based Recommender System

The device the person is using can be used to get the time of the day which play a role in finding suitable recommendations for the user. Accessing the location can also help in finding the weather of the place. All the information gathered is processed in a system and sentiment analysis is done.

After processing the system gives an output of a list of attractions for the user. Depending on the application of the system, desired results are produced. If the application is for a tourist, destinations or shortest routes or hotels might be given as recommendations.

Contextual factors are of two types: Dynamic and static, depending on whether they change with time or not.

A. Dynamic

When the contextual factors change over time and hence unstable. They may change by explicit user feedback. User feedback is generally used for refining the profile of user to get better results of recommendations. The biggest challenge is that if a system is considered to be dynamic then the system should be able to find out when to switch to a different underlying context model.

B. Static

The contextual factors don't change over time and hence stable. For e.g. to buy a cell phone the contextual factors can be Time, purpose of purchasing and only them while entire purchasing purpose recommendation application runs.

Furthermore, contextual factors can also be categorized into three types: Fully observable, partially observable and unobservable, depending on what is being observed.

- **Fully observable**: Complete structure and values of contextual factors are known explicitly, at the time when recommendations are made.
- **Partially observable**: Some of the information is known explicitly about the contextual factors.
- **Unobservable**: There is no information of contextual factors explicitly available in it.

How Contextual Factors Change	Knowledge of the RS about the Contextual Factors		
	Fully Observable	Partially Observable	Unobservable
Static	Everything Known about Context	Partial and Static Context Knowledge	Latent Knowledge of Context
Dynamic	Context Relevance Is Dynamic	Partial and Dynamic Context Knowledge	Nothing Is Known about Context

Fig 5. Contextual Information Dimensions

Table 3 shows different context based methods with sentiment analysis for recommendation system. The tables give recommender system by Norma Saiph Savage in which context based technique using Hidden Markov Model is used.

It helps improve location recommendations. Maciej Baranski et al. used a multidimensional database to help increase credibility of a system. Gediminaset. Al. used Fuzzy Bayesian Networks. Human memory model was used as the base for a context based system by Sarabjot Singh Anand et al. Víctor Codina et al. created a recommendation system based on Matrix-factorization Predictive Context Model and observed more accurate results.

METHOD	DESCRIPTION	RESEARCHERS
Hidden Markov Model	Improved version of a location recommender system by implementing Decision Tree along with discrete Hidden Markov Model. Together they differentiate b/w transport modes and reduce noise.	Norma Saiph Savage, Maciej Baranski, Norma Elva Chavez, Tobias Höllerer
Multidimensional approach	It provides additional CI on user and item, also supports multiple dimensions, profiling info and hierarchical aggregation of RS	Gediminas Adomavicius, Ramesh Sankaranarayanan, Shahana Sen, Alexander Tuzhilin
Fuzzy Bayesian Networks	It gives a recommender system which exploits the fuzzy system, bayesian networks to get appropriate recommendation with respect to the context.	Han-SaemPark, Ji-Oh YooSung-Bae Cho
Human memory model	A recommender system is proposed which retrieves relevant preference info from long term memory and uses in conjunction with the info stored in short term memory.	Sarabjot Singh Anand and Bamshad Mobasher
Matrix-factorization Predictive Context based Model	Distributional-Semantics Pre-filter approach is used to build more precise context aware rating prediction models. shows how DSPF can be improved by using clustering techniques.	Víctor Codina, Francesco Ricci, Luigi Ceccaroni

Table 3. Context-based Recommendation Methods

VI. EXTENDING CAPABILITIES OF RECOMMENDER SYSTEMS

Recommender systems, as described in Section 2 and summarized in Table 2, can be extended in several ways that include improving the understanding of users and items, incorporating the contextual information into the recommendation process, supporting multi-criteria ratings, and providing more flexible and less intrusive types of recommendations. Such more comprehensive models of recommender systems can provide better recommendation capabilities.

A. Comprehensive understanding of users and items

As was pointed out in [13], most of the recommendation methods produce ratings that are based on a limited understanding of users and items as captured by user and item profiles and do not take full advantage of the information in the user's transactional histories and other available data.
Although there has been some progress made on incorporating user and item profiles into some of the methods since the earlier days of recommender systems still these profiles tend to be quite simple and do not utilize some of the more advanced profiling techniques. In addition to using traditional profile features, such as keywords and simple user demographics, more advanced profiling techniques based on data mining rules, sequences, and signatures that describe user’s interests can be used to build user profiles.

Also, in addition to using the traditional item profile features, such as keywords, similar advanced profiling techniques can also be used to build comprehensive item profiles. With respect to recommender systems, advanced profiling techniques that are based on data mining have been used mainly in the context of Web usage analysis, i.e., to discover *navigational* Web usage patterns (i.e., page view sequences) of users in order to provide better Web site recommendations; however, such techniques have not been widely adopted in rating-based recommender systems.

B. Multidimensionality of recommendations

Current generation of recommender systems operates in the two-dimensional *User-Item* space. That is, they make their recommendations based only on the user and item information and do not take into the consideration additional *contextual* information that may be crucial in some applications. However, in many situations the utility of a certain product to a user may depend significantly on time.

In such situations, it may not be sufficient to simply recommend items to users; the recommender system must take additional contextual information, such as time, place, and the company of a user, into the consideration when recommending a product. For example, when recommending a vacation package, the system should also consider the time of the year, with whom the user plans to travel, traveling conditions and restrictions at that time, and other contextual information. As another example, a user can have significantly different preferences for the types of movies she wants to see when she is going out to a movie theater with a boyfriend on a Saturday night as opposed to watching a rental movie at home with her parents on a Wednesday evening.

It is important to extend traditional two- dimensional *User-Item* recommendation methods to multi-dimensional settings. In addition, the inclusion of the knowledge about user's task into the recommendation algorithm in certain applications can lead to better recommendations.

C. Multi-criteria ratings

Most of the current recommender systems deal with single-criterion ratings, such as ratings of movies and books. However, in some applications, such as restaurant recommenders, it is crucial to incorporate multi-criteria ratings into recommendation methods. Although multi-criteria ratings have not yet been examined in the recommender systems literature, they have been extensively studied in the Operations Research community.

D. Non-intrusiveness

Many recommender systems are intrusive in the sense that they require explicit feedback from the user and often at a significant level of user involvement. For example, before recommending any newsgroup articles, the system needs to acquire ratings of previously read articles, and often many of them. Since it is impractical to elicit many ratings of these articles from the user, some recommender systems use non-intrusive rating determination methods where certain proxies are used to estimate real ratings.

E. Flexibility

Most of the recommendation methods are inflexible in the sense that they are "hard-wired" into the systems by the vendors and therefore support only a predefined and fixed set of recommendations. Therefore, the end-user cannot customize recommendations according to his or her needs in real time. This problem has been identified and Recommendation Query Language (RQL) has been proposed to address it. RQL is an SQL-like language for expressing flexible user-specified recommendation requests.

VII. CONCLUSION

Recommender structures are proving to be a useful device for addressing a part of the records overload phenomenon from the internet. Its evolution has followed the evolution of the internet. The primary technology of recommender system used conventional web sites to gather information from the following sources: (a) content material-primarily based records (b) demographic statistics, and (c) memory-primarily based information.

Latest research shows the use of Sentimental Analysis in development of more accurate recommender system. These types of methods are commonly used in e-commerce businesses. In this paper, I have classified various approaches to recommender system. Future research will deal with advancing the prevailing techniques and algorithms to enhance the niche of recommender structures predictions and hints.

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