Recommendation Systems an overview, Types, Algorithms and Artificial Intelligence

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Abstract
Recommender systems represent user preferences for the purpose of suggesting items to purchase or examine. They have become fundamental applications in electronic commerce and information access, providing suggestions that effectively prune large information spaces so that users are directed toward those items that best meet their needs and preferences. In this work, we will provide a brief review of different recommender systems' algorithms, which play an important role in the Internet world and are used in many applications. The recommendation system is a system that learns from the user's previous actions and predicts their current preferences and generally is categorized into four Main classes; these include Collaborative Filtering, Content-based, Knowledge-based, and hybrid-based Approach. We shall review and classify the main types of Recommendation Techniques and the (A.I) methods used in them . The paper also elaborates on these approaches and their techniques with their limitations and advantages as well as the challenges and Problems faced by the recommendation systems.

Keywords: recommendation systems, content-based, knowledge based, Artificial intelligence, Computational intelligence, collaborative filtering-based, Hybrid Filtering, reinforcement, Fuzzy logic, K-means, clustering.

Introduction
Information overload has become a common issue in the present era where tons and tons of data are poured into the internet each day and the user has become the center of the internet due to their importance in the e-commerce market and the preferences that the user has a large influence over the marketing strategies of that the companies follow to better target their audience. Nowadays large companies are willing to pay large sums of money in order to get an insight into what the user likes and what the user dislikes and to get to know their customers by their preference data this leads

to better marketing strategies and better product recommendation. The advancements in the Artificial Intelligence (A.I.) fields and machine learning approaches have paved the way for innovative and creative marketing strategies followed by the companies that target the users and the customer segments in a much more elaborative and precise way due to customer preference identification by the recommendation systems. Recommender systems are systems that learn from the users previous behaviors and actions, These actions can be in the form of a button click on a specific product or a family of products , a search bar description or simply by indicating how long a customer stays on a specific website in order to predict the current product preference of the customer. Information overload has been addressed by Recommender systems with the use of Artificial Intelligence (A.I.) methods and techniques to identify and analyze the customer preferences with the sole aim of enhancing the overall satisfaction of the customer and to provide a better customer experience. Artificial Intelligence (A.I) contributions and scientific research have broadened the scope of recommendation from conventional product recommendation to a precise measurement of customer preference to increase the quality of product recommendation by creating relationships between items and users.

In this paper we shall review and put forth the latest recommendation techniques used in recommendation systems and the Artificial Intelligence (A.I) techniques and learning methods that have been used in Recommendation techniques and will elaborate on each type and the advantages and disadvantages of such techniques.

Models of the recommendation systems

Recommendations systems are systems that will make a recommendation to the user by suggesting products that might suit the preferences of that specific user or customer [4].The aim of the Recommender system is to predict the importance or usefulness (utility) of an item or a product to the customer and then recommend it by making suggestions on that specific item [4]. This system will also benefit the business by increasing the amount of sales that the business sells online due to similarities with the customer likings and preferences [4]. The input of a recommendation system typically depends on the type of the filtering algorithms that is applied in the system to filter the products and recommend them [4].The input of the recommendation system is either in a numerical form such as (Ratings) also referred to as (votes) which is the users rating of the product from (1-5) , 1 being (bad) and 5 being (good) or it can be in the form of (content data) which are textual keyword used in the documents that are received by the filtering algorithm in order to make a recommendation [4]. Therefore recommender systems have 4 main categories : (1) Content-Based Recommendation System.(2) Knowledge Based Recommendation System.(3) Collaborative Filtering based Recommendation System.(4) Hybrid Filtering based Recommendation System.

1. Content-based recommender systems

Pure Collaborative Filtering only uses a rating matrix to either directly or to induce a collaborative model [3]. It treats all users as an atomic model, where predictions are made without specifying the user or item [3]. But there is a better way of doing this, like demographic or a genre of video games, for example a user may like a game such as “Total war” and “Stronghold” which indicates that the users is heavily interested in RTS type games, thus you could recommend to them “Age of Empires” a game that is very similar to both games. Content-based recommenders refer to such approaches, That provide recommendations to users by comparing these representations of contents [3]. This type of can also be referred to as content-based filtering [3]. Much research has been done in this area to try and focus on recommending items with associated textual content, such as books, games, movies, web pages and many more [3].Content-based Recommender Systems in essence recommend the items that are similar to the items that have been rated before by the user [1].Content-based recommender systems take attributes from an item such as their names , descriptions , ratings.[1] an example of the above statement can be seen in video games in which other video games are recommended to a user based on the current game that they are browsing and looking at those attributes can be (the game name , the game genre , the game platform , etc…).Content-based recommender system can analyze data from (unstructured data) such as the news articles , or from (structured data) such product specifications on an e-commerce website [1].Content-based recommender system compare the attributes it receives from sources of data with the User's profile which is the history of the products or items that the user has previously searched for in order to recommend similar items [1].One of the advantages of Content-based recommender systems is the independency of the system from the User as it solely depends on the representation of items rather than Users in which it does not suffer from data scatteredness problem [1].One of the disadvantages of the Content-based recommender systems is the fact that the system always recommends similar items to the items that the user has searched for hence leading to repetitive type of recommendation in which the user is recommended the items similar to which they have searched for and not any new sort of items [1].

2. Knowledge based recommender systems

Knowledge based recommender systems are recommender systems that store knowledge based on the previous records of the users which are all stored as a knowledge base[1]. This knowledge base contains information extracted from the user's past problems , constraints and possible solutions to those problems [1]. When the system encounters new recommendation problems it references the knowledge that is stored in its knowledge base to address the problem [1]. Instead of product knowledge based recommender systems refer to the product as a "case" as the representation of those products require more structured representations [1]. Similar to content-based recommender systems , knowledge-based recommender systems use comparison between the current case and the previous case in order to find similarities between the two cases and find the most suitable solution to the problem [1]. The most common technique used in Knowledge based recommender systems is the case-based reasoning that compares past knowledge "case" with the current case to find similarities and decide on the proper solution [1]. One of the main advantages of the knowledge based recommender system is the fact that the new item/user problem referred to commonly as the "cold-start" problem simply does not exist as all the information and "cases" are already stored in the knowledge base that contains the problems and possible solutions that can be compared with the current cases faced by the knowledge based recommendation system [1]. The application of the knowledge based recommendation system is emphasized in the real-estate , financial and health-support domains as these domains have highly specific domain knowledge related to their respective domains in which the situation is considered as a unique case [1]. The disadvantage of the knowledge based recommender system is its setup and maintenance cost as they are typically high and hence they are expensive to maintain [1].

3. Collaborative filtering-based recommender systems

Collaborative-filtering (CF) technique is yet another type of product recommendation Technique that is widely used in the product recommendation systems and it is considered to be the most popular technique when choosing a recommendation technique for recommender systems [1]. Collaborative-filtering uses the ratings received from the other users online to determine the importance or benefit (Utility) of an item to the current user [1]. CF recommends those items that have been rated by all the users in the past [3]. The users who are interested in a similar set of items should be recommended those sets of similar items [1]. This means that the users who are interested in one specific item will constantly be targeted by those kinds of items due to their similar preferences. CF technique works by collecting ratings for specific items based on user feedback of those items and analyzes the similarities in rating behavior of those set of users to recommend the item to the specific user [3]. The CF technique works on the User-Item Matrix which is a table with the users and their ratings for the set of items that they have rated. Traditionally CF has been used to predict user ratings for those items that have not yet been selected and used and have not been rated which are referred to as (Unconsumed Items) [1]. CF technique is classified into Two Categories [1]. Which are the Memory-based Collaborative Filtering and the Model-based Collaborative Filtering [1].

User , Item	Item 1	Item 2	Item 3	Item 4
User 1	2	3	1	4
User 2	1	2	4	2
User 3	3	2	1	5
User n	n-rate	n-rate	n-rate	n-rate

Table 1 : an example of a user-item matrix

3.1 Memory-based Collaborative Filtering

Memory-based CF is another type of Collaborative Filtering that operates on the (user-item matrix) [4]. They determine user-user similarity by operating on the rows of user-item matrix constructed as a collection of similar users which is referred to as (user neighborhoods) to generate their results [4]. As mentioned earlier one of the input types that are used in the filtering techniques is numerical values referred to as (votes) which are ratings done by the users. One of the problems that occur is the fact that some items do not have a specific rating or value hence causing issues in the filtering techniques and leading to scattered and inaccurate results, that is why we need a sparsity (scatteredness) reduction techniques, one of the sparsity reduction technique used is (Average Pre-Processing) [4] (refer to 3.1.3). The Memory-based Collaborative Filtering has two main types :

3.1.1 Item-based Collaborative Filtering

Item-based Collaborative Filtering is a type of CF that uses item-item Collaborative Filtering which basically matches the user's already rated items to similar items [3] , This means that any item that is similar to the items that have been rated by the user previously will be recommended to the user. The implementation of this technique has been proven in operation that it leads to an improved overall performance

$$sim_{jk} = corr_{jk} = \frac{\sum_{i=1}^{l} (r_{ij} - \bar{r_j})(r_{ik} - \bar{r_k})}{\sqrt{\sum_{i=1}^{l} (r_{ij} - \bar{r_j})^2 \sum_{i=1}^{l} (r_{ik} - \bar{r_k})^2}}$$

Figure 1 : Pearson Correlation Formula from [4]

when recommending products[3]. This technique uses (Pearson Correlation Coefficient) formula which is a mathematical and statistical formula that determines the relationship between two or more variables (objects) in order to find the similarities between the item the user has rated and the item that is similar to the user's rated item [3]. In other words (Pearson Correlation Coefficient) Formula it finds how strong the relationship between these two variables are and how similar they are. This version of (Pearson Correlation Coefficient) is used to calculate the similarity in ratings between the current item and the item rated by the user previously. r_{ij} and r_{ik} are the ratings of item (j) and item (k) which has been provided by the user u_i [4]. The rating for item (i) is then subtracted from the average of the ratings for item (i) for all the users who rated item (i) , and the same is done for item (k) and then they are divided by the square root of all the users who rated both of the items to find the similarity between those two items [4].

3.1.2 User-based Collaborative Filtering

User-based Collaborative Filtering states that if the ratings of some items are similar between some users then the ratings for the other items by the same set of users will be similar as well [5]. In the user-item matrix the closest set of users who are similar to the current user are chosen and their ratings of items [5]. (Pearson Correlation Coefficient) is used to determine the similarity of the users to the current user and then predict the items that the current user might be interested in [4].

3.1.3 Average Pre-Processing

Average Pre-Processing is a technique to reduce sparsity (scatteredness) of the result by filling the missing ratings of an item for a specific user [4]. It has two main approaches for the (Average Pre-Processing) are (User Average Scheme) and (Item Average Scheme) [4]. The idea of the (User Average Scheme) in essence is taking the average of a row in the user-item matrix for a specific user and then filling the missing fields of the row by the value of the average received from the calculation [4]. The aim of the (User Average Scheme) is to predict the missing rating based on the user's past ratings [4]. The (Item Average Scheme) on the other hand takes the average of an item's column and fills the item's missing ratings with the average value received from the calculation [4].

3.2 Model-Based Collaborative Filtering

Model-based Collaborative Filtering utilizes machine learning and data mining techniques to build a model that predicts the user's ratings on specific items [1]. The Model-based Collaborative Filtering has been designed to fix and replace the drawbacks of Memory-based Collaborative Filtering such as the "cold-start" problem [1]. The Cold-start problem refers to the situation when new users and new items are entered into the system , there are no available ratings for them in order for the system to make predictions hence it causes problems to the system [1]. The Model-Based Collaborative Filtering uses a model that is proposed for how the users are anticipated to behave in the system rather than depending solely on raw data and uses the available ratings to make better recommendations to the users[10]. Model-Based CF relies heavily on two algorithms or methods which are namely (K-means) and (Clustering) algorithms to make their recommendations [10] (refer to Algorithms and Learning Types) .

4. Hybrid Filtering-based recommender systems

For better results, some recommender systems combine different techniques of collaborative approaches and content-based approaches. Therefore, the advantages and disadvantages of both techniques suggest that they can be combined to eliminate both weaknesses. Table 4.1 summarize the advantages and disadvantages.

Table 4.1 collaborative filtering(CF) and content-based filtering(CBF) advantages and disadvantages

	advantages	disadvantages
CF	Content-independent Used of quality and taste Serendipity	First-rater Sparsity problem
CBF	No First-rater problem No sparsity problem	Content-dependent Non-use of quality and taste Over-specializatio n

One common thread in recommender systems research is the need to combine performance. Using hybrid approaches we can avoid some limitations and problems of pure recommender systems. All of the known recommendation techniques have strengths and weaknesses, and many researchers have chosen to combine techniques in different ways. Hybrid recommender systems combine two or more recommendation techniques to gain better performance with fewer of the drawbacks of any individual one. Most commonly, collaborative filtering is combined with content-based filtering in an attempt to avoid the ramp-up problem[6]. It recommends the items to the user of their interest as well as the items which are liked by most of the users i.e. the highest rating items[7]. Different ways to combine collaborative-based and content-based methods into a hybrid recommender system can be classified to four main categories [8]:

(1) Implementing collaborative and content-based methods separately and combining their predictions (Combining Separate Recommenders).
(2) Incorporating some content-based characteristics into a collaborative approach (Adding Content-Based Characteristics to Collaborative Models).
(3) Incorporating some collaborative characteristics into a content-based approach (Adding Collaborative Characteristics to ContentBased Models).
(4) Constructing a general unifying model that incorporates both content-based and collaborative characteristics (Developing a Single Unifying Recommendation Model).

4.1 Combining Separate Recommenders

One way to build hybrid recommender systems is to implement separate collaborative and content-based systems. Then, we can have two different scenarios. First, we can combine the outputs (ratings) obtained from individual recommender systems into one final recommendation using either a linear combination of ratings or a voting scheme. Alternatively, we can use one of the individual recommenders, at any given moment choosing to use the one that is "better" than others based on some recommendation "quality" metric that can provide the recommendation with a higher level of confidence, while choosing the one whose recommendation is more consistent with past ratings of the user[8].

4.2 Adding Content-Based Characteristics to Collaborative Models

It allows for overcoming some sparsity-related problems of a purely collaborative approach since, typically, not many pairs of users will have a significant number of commonly rated items. Another benefit of this approach is that users can be recommended an item not only when this item is rated highly by users with similar profiles, but also directly. It uses a collaborative approach where the traditional user's ratings vector is augmented with additional ratings, which are calculated using a pure content-based predictor[8].

4.3 Adding Collaborative Characteristics to ContentBased Models

The most popular approach in this category is to use some dimensionality reduction technique on a group of content-based profiles. For example, uses latent semantic indexing (LSI) to create a collaborative view of a collection of user profiles, where user profiles are represented by term vectors, resulting in a performance improvement compared to the pure content-based approach[8].

Hybrid recommendation systems can also be augmented by knowledge-based techniques, such as case-based reasoning, in order to improve recommendation accuracy and address some of the limitations of traditional recommender systems. For example, the knowledge-based recommender system for restaurants, cuisines, and foods (e.g., that "seafood" is not "vegetarian") to recommend restaurants to its users. The main drawback of knowledge-based systems is a need for knowledge acquisitio a well-known bottleneck for many artificial intelligence applications. However, knowledge-based recommendation systems have been developed for application domains where domain knowledge is readily available in some structured machine-readable form, e.g., as an ontology. For example, the Quickstep and Foxtrot systems use research paper topic ontology to recommend online research articles to users.

Moreover, several papers, empirically compare the performance of the hybrid with the pure collaborative and content-based methods and demonstrate that the hybrid methods can provide more accurate recommendations than pure approaches

Artificial Intelligence , Algorithms and learning types

K-means

k-means clustering is applied to identify the segments. k- means is a clustering method that has found wide application in data mining, statistics and machine learning. The input to k-means is the pairwise distance between the items to be clustered, where the distance means the dissimilarity of the items. The number of clusters, k is also an input parameter. It is an iterative algorithm and starts with a random partitioning of the items into k clusters. Each iteration, the centroids of the clusters are computed and each item is reassigned to the cluster whose centroid is closest. The Algorithm is Described Below in which [11]:
The distance between the descriptors of two data is calculated to decide whether they are part of the same cluster or not, In a set of data.In order to implement the k-means algorithm,Structures that are referred to as centroids are used.Centroids are the key elements of the algorithm in which The kmeans algorithm relies heavily on those centroids to detect the data closest to each centroid in order to form clusters of data, and this loop continues until there is no further improvement in the distances between similar data and the data have been clustered with each centroid.

Fuzzy Techniques

Most of the time our world is dynamic and the facts cannot be easily represented to be shown in the digital realm and are in need of a way that represents these facts in a form that the A.I. the agent can understand. Fuzzy techniques are used when the facts in real-world situations cannot be modeled accurately to convey the facts hence the Fuzzy techniques are used [1]. Fuzzy techniques are used to eliminate the uncertainty of the data and results in the improvement of accuracy for both regression and the classification problems [1]. Fuzzy techniques are applied in knowledge sharing between businesses to construct models for data analysis which results in less computational costs for the business's intelligence system [1]. In recommendation systems fuzzy techniques are used to deal with uncertain information which are typically ambiguous such as the user behaviors of the system and the features of the items which are subjective and can be incomplete [1]. There are three main implementations of fuzzy techniques in recommendation systems : (1) fuzzy techniques in content-based recommender , (2) fuzzy technique in memory-based CF recommender systems , (3) fuzzy techniques in model-based CF recommender systems [1].

Reinforcement learning

Reinforcement learning is a semi-supervised learning technique in which the user learns from the feedback it receives from interacting with the outside environment [9]. Reinforcement learning uses the feedback it receives from interacting with its environment to decide on the action that needs to be performed [1]. Reinforcement learning has been seen as a solution to the problems that arise with the use of the typical types of recommendation systems which can be in the form of "cold-start" problems , Scalability and high expenses.[9].Most agents in reinforcement learning follow Markov's Decision Process in which it specifies how an agent should interact with its surrounding environment [1]. The agent's representations of its environment are called "states" in which the agent makes the decision based on the current state the system or the agent is in and receives a numerical value as a reward and the agent then moves onto the next state [9]. The interaction of the recommender system comprises the interaction and communication of the users with the states and actions of the recommender system which follows the same basic operations of agents with reinforcement learning [1]. The recommender system is treated as a learning agent when following reinforcement learning in which the actions of the agent are the recommendations and the states are the user's behaviors on the system and the rewards are the feedbacks received from the user whether in a form of a click on a certain product or the amount of time that is spent on a specific website [1]. The main point to consider while following the reinforcement learning process is the policy or value function that is aimed at granting the long-term reward for the agent to learn [1]. The product recommendation can be seen as a sequential problem in which the users are required to rate the items in order for the agent to be able to make appropriate recommendations to like-minded users hence the product recommendation can be expressed and labeled using Markov's Decision Process (MDP) and solved using the Reinforcement learning methods[9].

Transfer learning

One of the problems that face the application of a system in multiple domains is the fact that the test data and the training data are different from each other in reality when applied to a domain hence one application cannot be applied to all the domains which results in the application being redesigned and built based on the domain's data requirements [1]. Transfer learning is a method that was created with the intention of addressing the mentioned problem by transferring knowledge from a rich-data domain (source domain) to a relatively much lesser and scattered data domain (target domain) [1]. Transfer learning provides information from one or multiple source data from the (source domain) to the (target domain) with the aim of helping the (target domain) with its learning tasks [1]. Transfer learning in Recommendation Systems has proven to be a successful integration by extending the recommendation system from one domain to multiple domains [1]. Transfer Learning depends on the correlation and similarities of multiple domains when it comes to the user's preferences [1]. Exploiting the user's preferences in multiple domains results in the elimination of cold-start and data sparsity (scatteredness) problems that might be faced in a single domain by transferring the knowledge from a rich-data domain to a poor-data domain [1]. An example for this would be if a user has much more ratings in a movie rating website than the ratings they left on a book rating website then the data from the movie rating website can be used to assist the learning tasks in the book rating website with the use of Transfer Learning [1]. The accommodation of data sparsity problems gave birth to the development of the cross-domain recommender system (CDRS) [1]. The CDRS is a combination of multiple practical transfer learning techniques applied in practice [1].but for the sake of simplicity we shall not dive into the different types of the CDRS.

Multi-Layer Perceptron in Recommender Systems

Multi-Layer Perceptrons are mostly in Artificial Intelligence and Machine Learning to Solve Nonlinear Problems. Multi-Layer Perceptrons in Recommender System are used to Model both the Linear and Non-Linear problems [1]. Multi-Layer Perceptron can be combined with Collaborative Filtering (CF) to form Neural Collaborative Filtering (NCF) that can be used to model the non-linear relationships in the matrix factorization between the Items and Users which can be really helpful to further analyze the non-linear complex concepts and make a relationship between them to improve the recommendation [1].

Problems Facing Recommender Systems

Recommender Systems despite their advantages in terms of their performance and the domains they are used in but there are still many challenges and problems that the recommender systems face and they are : (1)Data Sparsity.(2)Cold-Start Problem.

(1) In Data Sparsity the data are scattered throughout the system due to the non-existent rating of the items by the users especially the new items that are being submitted to the system that may

not be rated by the Users to be recommended [3].Collaborative-Filtering Recommender Systems are one of those recommender systems that do suffer from data sparsity in which the process of finding users with similar ratings for an item is difficult this is caused by either very high number of items compared to the number of system users or the system is in the starting stages of its use and not many items and users have been submitted to the system [3].

(2) Cold-Start problems or commonly referred to as the "first-rater" problem occurs when new items have been submitted to the system but none to very limited number of users have rated the system making the process of recommending that item to users difficult due to poor ratings that is common in Collaborative Filtering (CF) recommender Systems [3].However Content-based Recommender Systems have an advantage over the Collaborative-Filtering (CF) recommender system in which the recommendation of items relies solely on the attributes that are present in the item itself and not based on the ratings of the users who have rated the item , making the content-based recommender systems independent of Users [3].

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