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An Intuitive Sky-High View of Recommendation Systems

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Abstract - *Never in eons humanity has ever experienced an explosion of information exchange like it does today with the popularization of the Internet and the advent of social media, e-commerce and other content. People face an ever-increasing amount of options in almost all areas of human life. This, in turn, leads to a paradox of choice. To solve this dilemma the user turns to obtain recommendations from people who have faced a similar choice or whose opinions they value. But in this day and age, more and more users rely on computational recommendation systems to help with their decisions. It is suggested that the Netflix recommendation system affects about 80% of the streaming choices made by the consumer. With this in mind, it is paramount for any industry that relies on user engagement to develop effective recommendation systems [1].*

Key Words: **Recommendation Systems, Content-Based, Collaborative Filtering, Model-based Filtering, Memory-Based Filtering, User-Based Collaborative Filtering, Item-Based Collaborative Filtering**

1. INTRODUCTION

The process of making recommendations generally starts with the user providing his/her preferences to the recommendation system. The recommendation system then, based on these preferences provides recommendations when asked by the user for the same. It is also possible for the system to obtain preferences from the rest of the user's and initially recommend the baseline of those preferences to our current user.

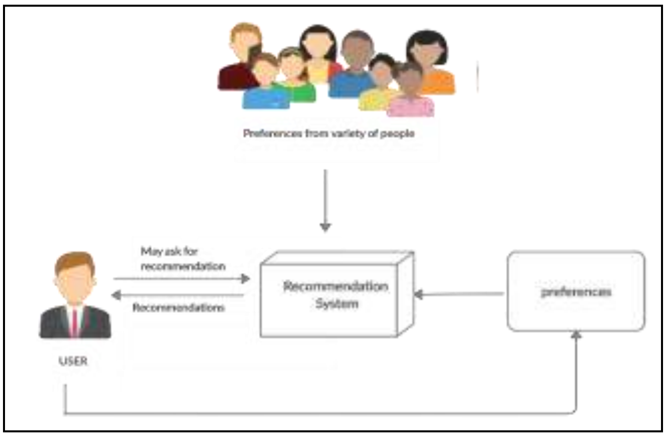

Fig -1: Recommendation Process

2. RECOMMENDATION SYSTEMS

Recommendation Systems are software tools and techniques providing suggestions for items to be of use to a user. "Item" is the general term used to denote what the system recommends to users. A recommendation system predicts the probability of a user liking a particular item and recommends the user items that the user is more inclined to prefer. To make these predictions the recommendation system uses the data obtained from the user interacting with the system. This data is represented as a Utility matrix that contains the users in the rows and the items in the columns. The preferences or lack thereof are represented by numbers [2].

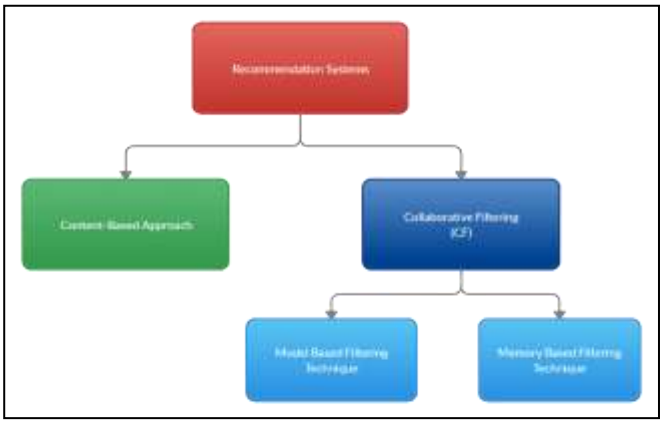

Fig -2: Recommendation System

Data about each user's rating for each item is seldom available making most utility matrices sparsely populated. This is known as the sparsity problem.

Fig -3: Utility Matrix

Recommendation systems can be broadly classified into two types:

2.1 Content-Based Recommendation System

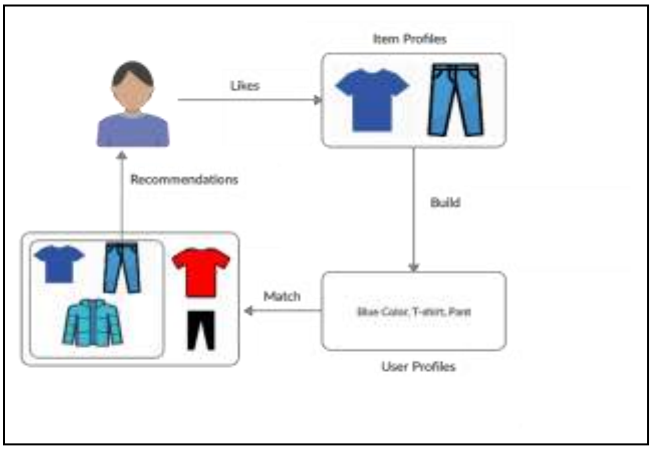

Fig -4: Content-Based Recommendation System

The content-based recommendation systems rely on the items consumed by the user. For example, in a content-based book recommendation system, someone who likes Dune by Frank Herbert can be recommended Frankenstein by Mary Shelley since both books are based on science-fiction. The content-based system works on the creation of a profile which can be described as a list of salient characteristics of the item and a user profile that summarizes the preferences of the user based on those characteristics.

2.2 Collaborative-Filtering

Collaborative-Filtering is based on characterizing users and items based on their previous interactions [3]. There are mainly two types of collaborative filtering:

2.2.1 Memory-Based

This approach uses the entire user-item database to generate a prediction. It uses statistical techniques to find users that share similar interests as that of the user and have rated different items similarly [4]. The similarity is often calculated by using Pearson Correlation:

$$P_{a,u} = \frac{\sum_{i=1}^{m}(r_{a,i} - \bar{r}_a) \times (r_{u,i} - \bar{r}_u)}{\sqrt{\sum_{i=1}^{m}(r_{a,i} - \bar{r}_a)^2 \times \sum_{i=1}^{m}(r_{u,i} - \bar{r}_u)^2}}$$

Where $r_{a,i}$ is the rating given to item i by the user a; r_a is the mean rating given by users; and m is the total number of items. The predictions are calculated based on

$$p_{a,i} = \bar{r}_a + \frac{\sum_{u=1}^{n}(r_{u,i} - \bar{r}_u) \times P_{a,u}}{\sum_{u=1}^{n} P_{a,u}}$$

Where $p_{a,i}$ is the prediction for the active user a for item i; $P_{a,u}$ is the similarity between users a and u; and n is the number of users in the neighborhood. The model then recommends the top-N recommendations using a variety of algorithms to combine the preferences of the user's neighbors [3].

2.2.2 Model-Based

In this approach, instead of working with a sparsely populated dataset the algorithms first predict the value of a user's rating for a particular unrated item based on their previous ratings for similar items.
There are multiple machine learning algorithms such as Bayesian network, clustering, and rule-based approaches [4].

2.2.3 Collaborative-Filtering Methods

There are two main methods for implementing collaborative filtering.

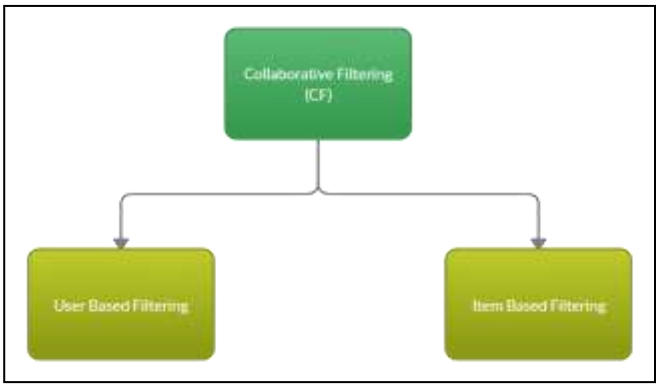

Fig -5: Collaborative Filtering Methods

2.2.3(a) User-Based

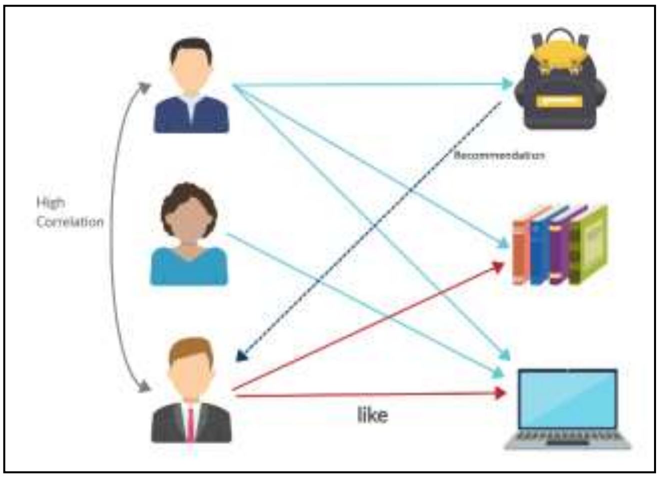

Fig -6: User-Based Collaborative Filtering

This method is based on the principle that users who share the same preferences will like similar things. We first find a set of users that have interests similar to our current user. We then use their utility matrices to fill in the blanks in our current user's utility matrix [5].

2.2.3(b) Item-Based

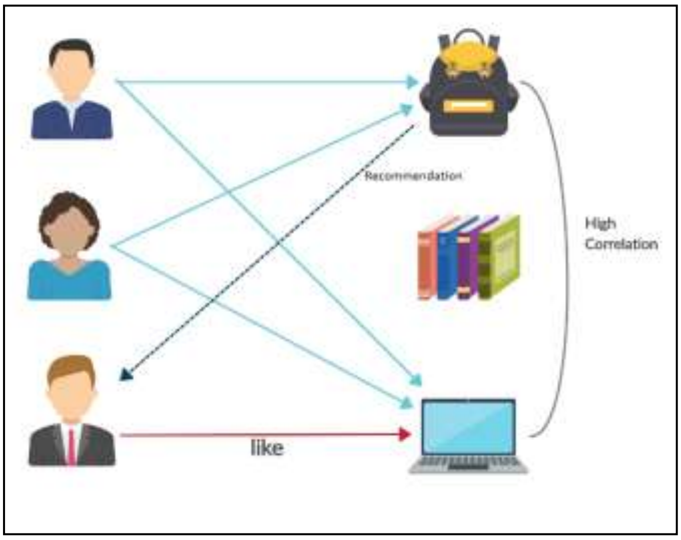

Fig -7: Item-Based Collaborative Filtering

This method focuses on the items instead of the users where the items that are similar to the current user's purchased products are recommended to the user. It works on the principle that the user is more likely to buy something similar to what they have already purchased before. This method provides more reliable results because it has been observed that it is easier to find items with similar characteristics than it is to find users that have completely similar interests [5].

3. SUMMARY

Content-based recommendation systems are advisable where the items can be clustered together and the user's picks don't vary greatly from the choices, they already have a predilection to make. Whereas Collaborative-Filtering should be preferred when the consumer's preferences are based more on their personality instead of the current item that they are accessing. The prevalence of recommendation systems is unquestioned in our day to day choices, thus for any product/customer-oriented enterprise, it is of paramount importance to have an appropriate recommendation system setup to guide the consumers in their decision-making process.

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