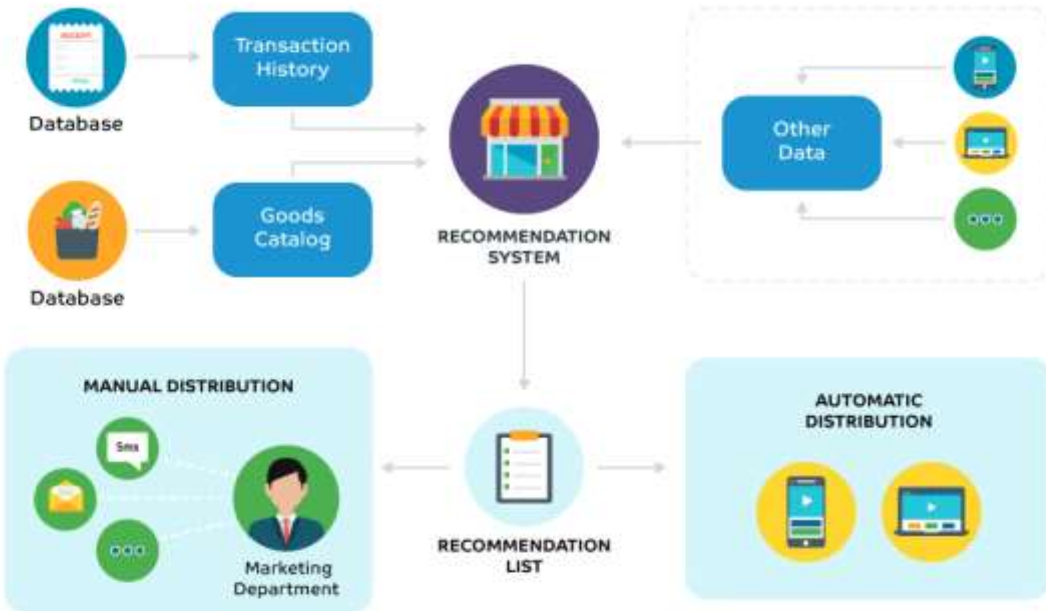


Introduction:

Recommender systems are the systems that are designed to recommend things to the user based on many different factors. These systems predict the most likely product that the users are most likely to purchase and are of interest to. Companies like Netflix, Amazon, etc. use recommender systems to help their users to identify the correct product or movies for them.The recommender system deals with a large volume of information present by filtering the most important information based on the data provided by a user and other factors that take care of the user's preference and interest. It finds out the match between user and item and imputes the similarities between users and items for recommendation. Both the users and the services provided have benefited from these kinds of systems. The quality and decision-making process has also improved through these kinds of systems.

What can be Recommended?

There are many different things that can be recommended by the system like movies, books, news, articles, jobs, advertisements, etc. Netflix uses a recommender system to recommend movies and web-series to its users. Similarly, YouTube recommends different videos. There are many examples of recommender systems that are widely used today.

Types of Recommendaton System

1. Popularity based recommendation System:

It is a type of recommendation system which works on the principle of popularity and or anything which is in trend. These systems check about the product or movie which are in trend or are most popular among the users and directly recommend those. For example, if a product is often purchased by most people then the system will get to know that that product is most popular so for every new user who just signed it, the system will recommend that product to that user also and chances becomes high that the new user will also purchase that.

2. Content-Based Recommendation System

It is another type of recommendation system which works on the principle of similar content. If a user is watching a movie, then the system will check about other movies of similar content or the same genre of the movie the user is watching. There are various fundamentals attributes that are used to compute the similarity while checking about similar content.

3. Collaborative Filtering:

It is considered to be one of the very smart recommender systems that work on the similarity between different users and also items that are widely used as an e-commerce website and also online movie websites. It checks about the taste of similar users and does recommendations. The similarity is not restricted to the taste of the user moreover there can be consideration of similarity between different items also. The system will give more efficient recommendations if we have a large volume of information about users and items.

4. Hybrid Model:

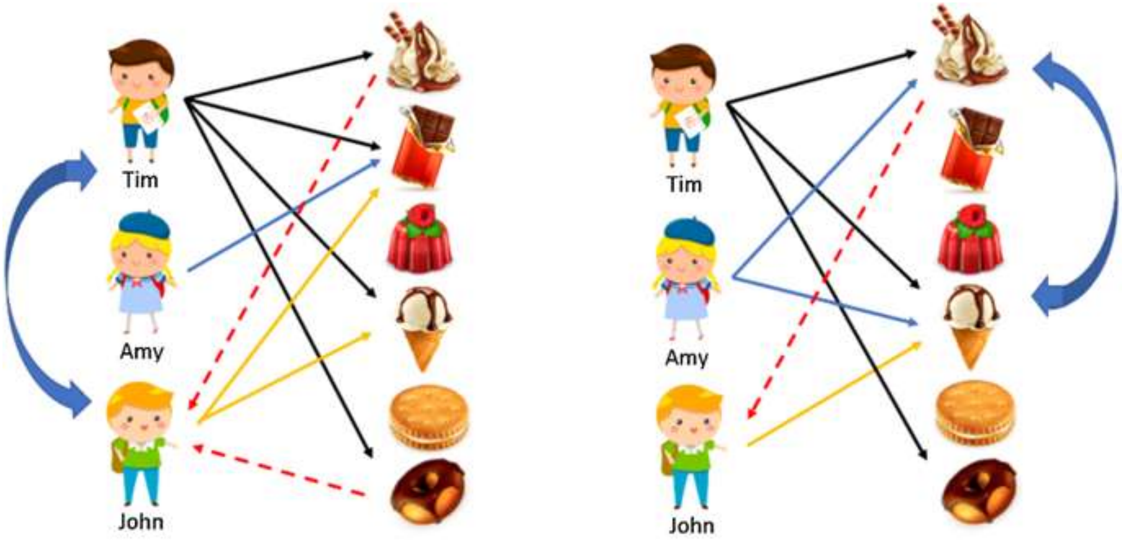
Hybrid filters combine several passive or active filters, their structure may be of series or parallel topology or a combination of the two. this type of filtering is used for advanced level recommendation systems

Advantages of Collaborative filtering:

- We don't need domain knowledge because the embeddings are automatically learned.
- The model can help users discover new interests. In isolation, the ML system may not know the user is interested in a given item, but the model might still recommend it because similar users are interested in that item.
- To some extent, the system needs only the feedback matrix to train a matrix factorization model. In particular, the system doesn't need contextual features. In practice, this can be used as one of multiple candidate generators.

Knearest Neighbors:

we will understand the basics of Recommendation Systems and learn how to build a Movie Recommendation System using collaborative filtering by implementing the K-Nearest Neighbors algorithm. We will also predict the rating of the given movie based on its neighbors and compare it with the actual rating.



(a) User-based filtering (b) Item-based filtering

Item-based nearest-neighbor collaborative filtering:

Figure b shows user X, Y, and Z respectively. The system checks the items that are similar to the items the user bought. The similarity between different items is computed based on the items and not the users for the prediction. Users X and Y both purchased items A and B so they are found to have similar tastes.

Limitations

- Enough users required to find a match. To overcome such cold start problems, often hybrid approaches are made use of between CF and Content-based matching.
- Even if there are many users and many items that are to be recommended often, problems can arise of user and rating matrix to be sparse and will become challenging to find out about the users who have rated the same item.
- The problem in recommending items to the user due to sparsity problems.

Results of Movie recommendation system:

I have created a function that will take 5 parameters title of the movie, model, number of recommendations, and dataset. I have chosen the title of the toy story. Now you can see the recommendation engine is giving 20 suggestions which closer to the toy story.

```
recommendation('toy story',mat_movies_users,model_knn,20)
```

```
Movie Selected :  Toy Story (1995) Index:  0
Searching for recommendations........
0                                                      NaN
2353                                    'night Mother (1986)
418                                     Jurassic Park (1993)
615                      Independence Day (a.k.a. ID4) (1996)
224                      Star Wars: Episode IV - A New Hope (1977)
314                                      Forrest Gump (1994)
322                                     Lion King, The (1994)
910      Once Upon a Time in the West (C'era una volta ...
546                               Mission: Impossible (1996)
963                                              Diva (1981)
968                               Arsenic and Old Lace (1944)
3189                    Rififi (Du rififi chez les hommes) (1955)
506                                           Aladdin (1992)
123                                         Apollo 13 (1995)
257                                      Pulp Fiction (1994)
897                       Cheech and Chong's Up in Smoke (1978)
815                     Willy Wonka & the Chocolate Factory (1971)
1182                                              Fall (1997)
31                       Twelve Monkeys (a.k.a. 12 Monkeys) (1995)
277                              Shawshank Redemption, The (1994)
Name: title, dtype: object
```