

MOVIE RECOMMENDATION SYSTEM

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Abstract:

The topic of movie recommendations is covered in this essay. The value of a movie recommendation in our social lives stems from its capacity to offer better amusement. Based on the users' interests or the popularity of the films, such a system can recommend a selection of movies to them. Utilizing a sizable collection of information, a recommendation system is used to offer goods for consumers to see or buy that will fulfil their demands. A recommender system, also known as a recommendation system or a recommender engine, is a type of information filtering system that attempts to forecast the "rating" or "preferred" a user would assign to a particular item. They are mainly applied in commercial settings.

Keywords: Recommendation System

I. INTRODUCTION:

Collaborative filtering, also known as the personality-based approach, and content-based filtering, as well as other systems like knowledge-based systems, are frequently used in recommender systems. Approaches to collaborative filtering create a model based on past actions of a user (things previously picked or purchased, and/or numerical ratings provided to those items), as well as comparable choices made by other users.

A series of discrete, pre-tagged qualities of an item are used in content-based filtering algorithms to recommend more items with related features. This model is then used to forecast items (or ratings for items) that the user may be interested in. The majority of the time, hybrid recommender systems nowadays combine one or more methodologies.

Netflix	2/3rd of the movies watched are recommended
Google News	recommendations generate 38% more click-throughs
Amazon	35% sales from recommendations
Choice stream	28% of the people would buy more music if they found what they liked

Table 1: Companies benefit through recommendation system

II. DEFINITION & MOTIVATION

A recommender system, or recommendation system (sometimes replacing 'system' with a synonym such as platform or engine), is a subclass of information filtering system that aims to predict the "rating" or "preference" a user would give to an item. There has been a significant increase in audiovisual data. They are mainly applied in commercial settings. There are many applications for recommender systems, but they are most frequently known as playlist generators for video and music services like Netflix and YouTube, as well as as product recommenders for websites like Amazon and content recommenders for social media sites like Facebook and Twitter.

III. METHODS

Machine learning experts utilise classification methods to classify data using a variety of organisational techniques. It's possible that classifiers need training data.

1. Collaborative filtering
2. Content-based filtering
3. multi-criteria recommender systems
4. Risk-aware recommender systems
5. Mobile recommender systems
6. Hybrid recommender systems

1. Collaborative Filtering

An illustration of a ratings-based collaborative filtering method. Collaborative filtering is a popular method for designing recommender systems. The premise behind collaborative filtering is that people who have previously agreed will do so again and that they will continue to enjoy the same kinds of things. Recommendations are generated by the algorithm solely based on data from rating profiles for various persons or objects. They produce recommendations utilising this neighbourhood by identifying peer users/items with rating histories similar to the current user or item. There are two types of collaborative filtering techniques: memory-based and model-based.

2. Content-based filtering

Content-based filtering is another strategy that is frequently used when constructing recommender systems. The foundation of content-based filtering techniques is the item's description and the user's preference profile. These techniques work best when information about the item (name, location, description, etc.) but not the user is known. Content-based recommenders approach recommendations as a user-specific classification issue and learn a classifier for a user's preferences based on the characteristics of an item.

3. Multi-criteria recommender system

The term "multi-criteria recommender systems" (MCRS) refers to recommender systems that take into account preference data for various criteria. These systems attempt to predict a rating for unexplored items of u by utilising preference information on multiple criteria that affect this overall preference value, as opposed to developing recommendation techniques based on a single criterion value, the overall preference of user u for the item i . Many researchers view MCRS as a multi-criteria decision making (MCDM) problem and construct MCRS systems using MCDM approaches and techniques.

4. Risk-aware recommender system

Most current approaches to recommender systems concentrate on recommending the most pertinent content to consumers using contextual data, but they do not account for the possibility of annoying the user with unwelcome notifications. Pushing recommendations during certain times, such as during a business meeting, early in the morning, or after midnight, has a risk of offending the user. As a result, how well the recommender system performs is influenced by how much risk it has factored into the suggestion process. DRARS, a system that models the context-aware recommendation as a bandit problem, is one way to handle this problem. This method combines a contextual bandit algorithm and a content-based technique.

5. Mobile Recommender system

Recommendation based on location Smart phones with internet connectivity are used by mobile recommender systems to provide individualised, context-sensitive recommendations. Given that mobile data is more complex than the data that recommender systems frequently work with, this is a particularly challenging field of research. It has issues with validation and generality, is diverse, noisy, and necessitates both spatial and temporal auto-correlation. The context, the recommendation mechanism, and privacy are three variables that could influence mobile recommender systems and the precision of prediction outcomes. A transplanting problem also affects mobile recommender systems; for instance, it would be foolish to suggest a dish in a location where all of the necessary components might not be present.

6. Hybrid Recommender System

Nowadays, the majority of recommender systems employ a hybrid strategy that combines collaborative filtering, content-based filtering, and other techniques. There is no reason why multiple methods of the same type cannot be combined. There are several ways to implement hybrid approaches, including making content-based and collaborative-based predictions separately before combining them, adding content-based capabilities to a collaborative-based approach (and vice versa), and combining the approaches into a single model (see] for a thorough review of recommender systems).

Several methods of hybridization include:

- **Weighted:** Adding together the numerical scores of the various recommendation component scores.
- **Changing:** Deciding which suggestion component to use and applying it.
- **Mixed:** The recommendation is offered using recommendations from a variety of recommenders.
- **Feature Combination:** A single recommendation algorithm is given a set of features that were derived from many sources of knowledge.

Computing a feature or group of features that will be used as part of the input for the following approach is known as "feature augmentation."

- **Cascade:** Recommenders are given strict priority, and the lower priority ones are used to break ties between the higher priority ones in the scoring.
- **Meta-level:** After applying a recommendation approach, a model is created that is used as an input by a subsequent technique.

IV. CLASSIFICATION AND TECHNIQUES

Over the years, several different recommendation systems have been created. These systems employ a variety of methodologies, including collaborative, content-based, utility-based, hybrid, etc. Considering the purchase. A recommender system that suggests the new product in the market was presented by Lawrence et al. in 2001 based on the behaviour and history of the shoppers. A collaborative and content-based filtering strategy was employed to improve the recommendation. The majority of today's recommendation systems rely on user evaluations to locate potential clients. These ratings are also used to forecast and suggest the desired item. According to a 2007 evaluation study by Weng, Lin, and Chen, integrating multidimensional analysis and additional customer profiles improves the quality of recommendations.

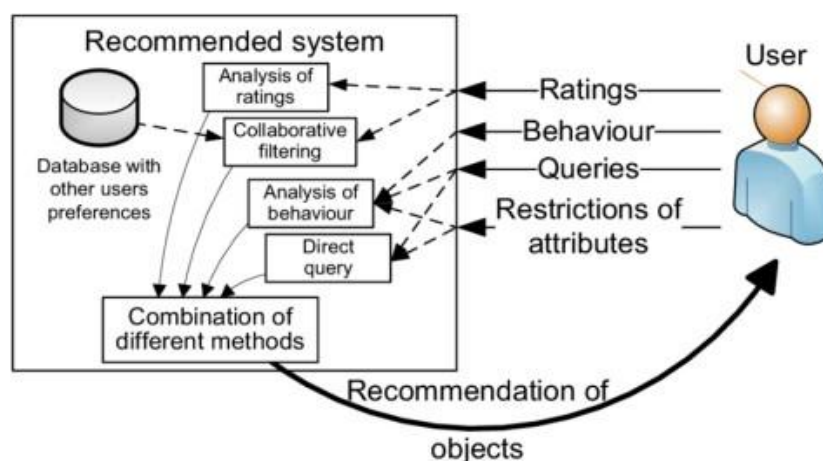


Fig 1: System

V. RELATED WORK

We will use the Movie Lens tiny dataset for this exercise and concentrate on two files.i.e., the movies.csv and ratings.csv

The three fields in the movie.csv file are:

1. Movie Id – It has a different id for each movie.
2. Title – The title of the film is it.
3. Genre – The movie's subgenre

There are four fields in the ratings.csv file, namely:

1. User id - Each user's own identification number after they have rated one or more films
2. Movie Id - Each movie's distinct identifier
3. Rating - The score a user assigns to a film.
4. Timestamp - When was a specific movie's rating given?

```
#import all necessary libraries
Import os
Import numpy as np
Import pandas as pd
Import matplotlib.pyplot as plt
plt.style.use ('seaborn-bright')
%matplotlib inline
#change directory to the folder where data
files are present
#this step is not necessary if the data files
and jupyter notebook are in same folder
os.chdir(r"C:\Users\mirza\Downloads\Compre
d\ml-latest-small\ml-latest-small")
#import ratings file in a pandas dataframe
ratings_data=pd.read_csv ("ratings.csv")
ratings_data.head ()
```

Figure 2: Code Segment

	userid	movieid	rating	timestamp
0	1	1	4.0	964982703
1	1	3	4.0	964981247
2	1	6	4.0	964982224
3	1	47	5.0	964983815
4	1	50	5.0	964982931

Figure 3: Output

VI. CONCLUSION:

We've introduced Movie REC, a recommender system for movies, in this paper. It enables a user to choose from a predetermined set of criteria and then suggests a list of movies for him based on the cumulative weight of the various attributes and the K-means algorithm. Due to the nature of our system, evaluating performance is a difficult process because there is no right or incorrect recommendation; it is simply a matter of opinions.

They responded favourably to our informal evaluations of a small group of users, which we conducted. We would like to have additional data available so that our system can produce more insightful findings.

VII. REFERENCES:

[1] <https://labeledyourdata.com/articles/movie-recommendation-with-machine-learning#:~:text=A%20movie%20recommendation%20system%2C%20or,their%20past%20choices%20and%20behavior.>

[2] <https://towardsdatascience.com/how-to-build-a-movie-recommendation-system-67e321339109>