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Analysis of Collaborative, Content & Session Based and Multi-Criteria Recommendation Systems

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Abstract

The recommendation systems are performing the role of information filtering in different scenarios. To provide a better recommendation, different approximation methods and soft computing strategies such as machine learning and evolutionary computing are applied. The recommendation systems fulfil the requirements of the users on time. Concerning organizations, the company like to keep their users long on the platforms to maximize the profit. Better recommendations are expected to generate positive feedback for both users and organizations. The recommendation systems utilize approaches like collaborative filtering, knowledge-based systems, and content-based filtering. Most of the common recommender systems nowadays include video and music, online stores, web content, online dating, restaurants, and social media recommendations. These systems use inputs like music, news, books, search queries, etc. The recommendation systems have also been developed for experts, research articles, collaborators, and online commercial services. This research explores the analysis of the collaborative, content & session based, and multi criteria recommendation systems.

Keywords

Recommender systems, recommendations, collaborative filtering, content & session, multi criteria recommendation

1. Introduction

The recommendation systems utilize approaches like collaborative filtering (CF), knowledge-based systems, and content-based filtering (Francesco et al., 2011). CF models a user's prior behavior like products bought or picked, ratings provided, and comparable choices made by other users (Prem et al., 2010). This model predicts things or ratings as the user may like. Content-based filtering uses pre-tagged item attributes to propose comparable things. Some of the recent recommender systems are hybrids (Rubens et al., 2016).

Last.FM builds a "station" of suggested music by comparing the user's favorite bands and tracks to those of other users. Last.FM plays songs that aren't in a user's collection but are popular with comparable listeners. This is a CF strategy that uses user behaviour (Bhaskaran et al., 2020; Bhaskaran et al., 2021). Pandora utilizes qualities to seed the "station" to play comparable and soft music using content-based. At the time the user "dislikes" a song, the station deemphasizes some features and emphasizes others. Last.FM needs plenty of user data to generate reliable suggestions. Cold start problems are a common feature in most CF systems. Pandora requires less knowledge to start but is more restricted (Bi et al., 2017).

2. CF

CF assumes individuals who accepted earlier would agree in the future and enjoy comparable goods. The algorithm provides suggestions based on user or item ratings. By finding related users or items, the systems provide neighborhood-based suggestions. CF approaches are memory and model-based. The CF technique may propose complicated objects like movies without "knowing" them. In recommender systems, several methods measure user or item similarity (Waila et al., 2016; Xin et al., 2020; Zou et al., 2019; Cañamares et al., 2020)

The common issues in CF are as follows:

- Cold start: There isn't enough data for a new person or item. Multi-armed bandit is a frequent solution.
- Scalability: These systems suggest to millions of consumers and items in numerous situations Recommendations need a lot of computing power.
- Sparsity: Major e-commerce sites sell many things. Active users have a limited fraction. Many popular products get minimal ratings.

3. Content-based Filtering

The recommender system also applies content-based filtering that uses item descriptions and user choices. These methods operate best when object data like location, name, etc. is known. These recommenders categorize items based on user preferences. In this method, keywords define items and a user profile reveals preferences. These algorithms recommend stuff a user liked earlier or is seeing currently. This temporary profile is generated without login. The best-matching goods are recommended. Information retrieval and filtering research inspired this strategy. TF–IDF is a popular content-based algorithm with the weighted vector of item characteristics as profile information. The weights are generated using individually rated content vectors. Complex approaches utilize different machine learning techniques to predict the user's chance of enjoying the item (Bhaskaran et al., 2020; Bhaskaran et al., 2021).

- The problems in these approaches are as follows:
- This depends on whether the algorithm can acquire user preferences through one input source.
- When the algorithm can only propose the same sort of material that the user currently uses, its value is much lower.
- Newspaper surfing recommendations are fantastic, but it would be much better to advise music, films, goods, discussions, etc.

4. Session-based Recommenders

Recommender systems employ a user's session interactions to provide recommendations. Youtube and Amazon utilize session-based recommenders. These are helpful when a user's click or purchase history isn't accessible or relevant in the current session. Most session-based recommender systems focus on current interactions without user history or demographics. Session-based recommendations use RNNs, Transformers, and deep learning (Waila et al., 2016; Xin et al., 2020; Zou et al., 2019; Cañamares et al., 2020).

The problems in session-based recommender systems are as follows:

- Sessions may be ordered or unordered, thus user interactions may or may not record when they occur. When buying online, the order in which products are added may not matter.
- Song order may reflect the user's mood and interests in real-time. In such scenarios, co-occurrence-based techniques may function better than sequence models, depending on the order of the entries.
- Defining the issue should include session durations. Long (>10 interactions), medium (4-9 interactions), and short (4 interactions) are the three-session durations. Additional interactions may give more context, but they may also generate noise due to unpredictable user behavior, leading to poor performance.
- Shorter sessions provide less context and information. Medium sessions capture enough contextual information without too much unnecessary information, according to research, especially for commercial transactional data.
- Domain-dependent assumptions are made while choosing a session length.

5. Multi Criteria Recommenders

Multi-criteria recommenders have several uses. For the experiential items like music, movies, and books the customers may have diverse subjective likes and preferences for numerous product characteristics. The greater information on user preferences helps to enhance suggestions. Travel and tourism use multi-criteria recommendation systems. Customers have varying preferences on service quality, room size, friendliness, and tidiness. Instead of explicit evaluations, mobile banking businesses may implement multi-criteria algorithms by observing user behavior. Restaurants may be judged on value, service, location, and overall experience. Research articles may be suggested with authors, keywords, titles, domains, publication year, and reference URLs. These systems enhance clinical decision-making by integrating illness knowledge and patient preferences (Waila et al., 2016; Xin et al., 2020; Zou et al., 2019; Cañamares et al., 2020).

The problems in multi-criteria recommender systems are as follows:

- Increased dataset size and scalability issue: Multiple criterion rating datasets are bigger than single rating datasets. Zagat's restaurant, Yahoo! Movies, and Goibibo hotels give large datasets containing ratings on restaurants, movies, and hotels based on several factors. Space complexity must also be decreased. Data may not necessarily be numerical but contextual. Context-aware recommender systems may help in such circumstances.
- Dealing with trust-based issues: Whenever consumers give systems with personal details to preserve their preference dataset, security is their top concern. The suggestions should be relevant to the interests and preferences of the users. For this reason, the systems must be able to create trust with their customers by offering more attractive suggestions and protecting their data.

6. Recommenders Analysis

The collaborative, content & session based, and multi criteria recommendation systems are analyzed in Table 1 (Waila et al., 2016; Xin et al., 2020; Zou et al., 2019; Cañamares et al., 2020).

Table 1. Recommenders Analysis

Model	Approaches	Advantages	Limitations
CF	Memory or model based	Neighbourhood based suggestions.	Cold start, scalability and sparsity issues
Content based	TF–IDF	User-specific categorization.	Hinges on user preferences from one source to others.
Session-based	RNNs and deep learning approaches	User's session interactions.	Sessions may be ordered or unordered.
Multi criteria	CCA, CCC, CIC	Used in various tastes and preferences.	Dealing with trust and scalability issues.

7. Conclusions

The recommendation systems can be considered as an alternative to searching engines as they help consumers find new goods. These systems use search engines to index other types of hybrid data. Hence these systems are also mentioned as a "digital bookshelf". This research analyzed the collaborative, content &session based, and multi criteria recommendation systems. These recommendation systems are applied in solving several real-world problems (Marappan et al., 2018, 2020-2022; Raja Marappan et al., 2022).

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