

METHODS OF CONTENT-BASED FILTERING IN RECOMMENDER SYSTEMS

Today, the need for innovations to attract customers and stand out from competitors is growing. One effective method is creating personalized recommendations using content-based filtering (CBF). This approach analyses object attributes and generates recommendations based on the similarity between user preferences and object characteristics.

CBF allows the similarity of objects to be determined using parameters such as genre, author, tags, or keywords. The main advantages of content-based filtering include independence from other users' data, transparency of recommendations, ease of adding new objects, and the ability to operate with limited data [1].

Thus, recommendations are generated solely based on an individual user's data, avoiding issues associated with the behaviour of other system users. This ensures the accuracy of results and minimizes the risk of including irrelevant preferences. Users can easily understand why a particular item has been recommended, as the suggestions are based on clear parameters, such as characteristic similarity.

Additionally, new products or services can be integrated into the system without waiting for feedback from other users. The system performs well even in its initial stages, when user preference data is minimal, ensuring satisfactory personalization despite limited information.

Thus, content-based systems can operate effectively without a large volume of data on other users' preferences, making them suitable for startups or niche domains [2].

However, this approach has its limitations. Specifically, the system recommends only items similar to those already rated, failing to surprise users with novelty [3]. This currently poses a problem, as users value the opportunity to get a ready-made solution, selected for them, something new and interesting, more than to come up with it themselves, using only what was there before.

Another significant challenge is the "cold start" problem, where the system struggles to provide recommendations for new objects with no prior ratings [4]. As a result, new objects that could be pretty interesting are "lost" among ordinary users, turning the mass into a homogeneous one. Additionally, particular objects, such as music or artwork, have complex characteristics that are difficult to analyze effectively.

Hybrid models are increasingly utilised to address these limitations and enhance efficiency, combining content-based approaches with collaborative filtering. For instance, systems like Fab integrate content analysis by finding similarities in other users' preferences, improving recommendation quality, and ensuring adaptability across various usage scenarios [4].

Among the examples of content-based filtering applications are several popular systems that effectively implement this approach. For instance, Netflix generates movie and TV show recommendations by considering genres, actors, and user viewing history, providing personalized suggestions for each viewer. Online stores like Amazon or Rozetka use content-based filtering to suggest products similar to those the user has previously purchased or viewed. This approach helps to increase sales and retain customers.

Educational platforms like Coursera recommend courses based on previously selected topics and rated content. This allows users to receive learning materials that best match their interests and level of preparation.

In conclusion, content-based filtering methods remain crucial to modern recommender systems, especially when combined with other approaches. They are a powerful tool for creating individualized user experiences while requiring further refinement to overcome limitations.

References:

1. Korniychuk, V. O. "Research on recommender systems for searching for vacation spots on the Internet", 2019. URL: <https://openarchive.nure.ua/entities/publication/e7f78418-deef-4db7-8758-4600bf348926> (accessed: 27.11.2024).
2. Zeynep B. A. «Recommendation Systems: Content-Based Filtering», электронный ресурс. URL: <https://medium.com/@zbeyza/recommendation-systemscontent-based-filtering-e19e3b0a309e> (accessed: 27.11.2024).
3. Prem Melville, Raymond J. Mooney, and Ramadass Nagarajan. Contentboosted collaborative filtering for improved recommendations. In Proceedings of the Eighteenth National Conference on Artificial Intelligence (AAAI02), Edmonton, Alberta, 2002 P. 187-193. URL: <https://cdn.aaai.org/AAAI/2002/AAAI02-029.pdf>
4. Marko Balabanovic and Yoav Shoham. Content-based, collaborative recommendation. Communications of the Association for Computing Machinery, 40(3): 66–72, 1997. <https://dl.acm.org/doi/pdf/10.1145/245108.245124> (accessed: 27.11.2024).