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Landscape view of recommender system techniques based on sentiment analysis

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Abstract

Over the last several years, sentiment analysis has emerged as one of the most popular applications of machine learning. It enables the identification of a user's attitude from a remark, document, or review. As a result of the development of Big Data, recommender systems (RS) are also finding more use in many aspects of day-to-day living. There are three basic kinds of RS: collaborative filtering, content-based, and hybrid. This article presents a quick description of the recommender systems supplemented with a sentiment analysis module. Sentiment Analysis systems may help recommender systems improve by assessing Web-based reviews.

Keywords: recommender systems, contextual meaning, sentiment analysis
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1 Introduction

The number of various types of data, such as images, videos, audio files, and text, is growing at an exponential rate in this era of big data. Because the text is the most important of them, study on textual analysis has been carried out to a significant extent from times past to the present [14]. Due to augmented reality, sentiment analysis of web material is becoming more crucial communication via websites forums, chat rooms, and e-mail on the internet, may determine people's views and opinions regarding policies, goods, brands, and other topics by gathering these articles and looking at the emotions individuals express in them this extensive information can be gathered with less expense and effort than with conventional surveys and other research methods. People can do specific information searches depending on their own demands [25]. More sentiment data is being produced as a result of the social media platforms' explosive rise in popularity, including Twitter [20].

As a direct result of the progress made in information technology and the expansion of the internet, consumers are facing a growing problem with information overload [28]. Numerous e-commerce and social networking sites, such Amazon Foursquare and Gowalla, have grown quickly, resulting in an enormous amount of data being gathered by service providers due to this massive volume of data, recommender systems more smart information retrieval systems must be designed [8]. Since the middle of the 1990s, there has been a significant surge in the usage of recommender systems that are determined by user ratings and preferences, in particular in the areas of e-commerce, media, banking,

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and utilities. Amazon uses this type of system to promote things to customers, YouTube uses it to recommend relevant movies for auto play, and Facebook uses it to advise users and websites to connect with and follow [4].

2 Types of recommender system

Recommender systems have undergone much research over the years, and depending on the methodology employed, they fall into many categories [12]. Context-based, content-based, collaborative filtering (CF), and hybrid recommender systems are the different kinds of recommender systems.

An effective recommendation system can assist customers in finding what they need as well as help retailers increase their profits [28]. The purpose of a recommender system (RS) is to offer customers with useful product or service suggestions that may be of interest to them [30].

2.1 Content-based recommender system

This technique to recommender relies exclusively on user profiles or descriptions of things based on their primary goal [5].

2.2 Collaborative recommendation

The best recommendation method is thought to be CF [5].

2.3 Hybrid Approach

By combining a large number of different recommendation component or algorithm implementations into a single recommendation system, this technique aims to increase the accuracy and performance of the RS by minimizing the drawbacks of both CF and CB while capitalizing on their respective advantages [2].

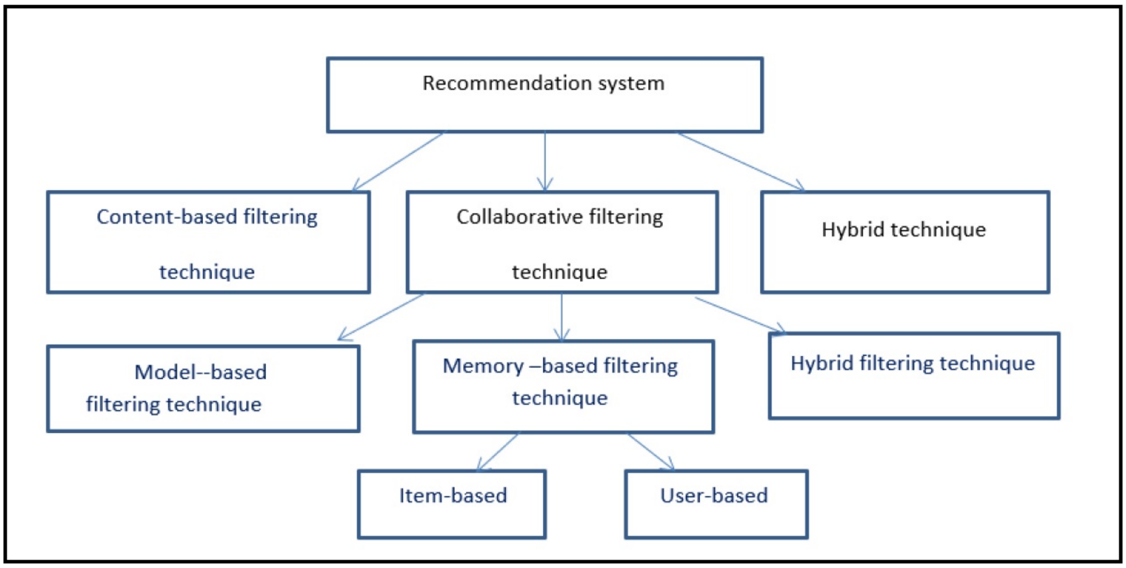

Figure 1: classification of the recommender system [26].

2.4 Demographic Recommendation System

This kind of technology makes product recommendations based on the user's demographic profile for various demographic niches, it is assumed that different recommendations should be produced numerous websites use quick and efficient demographic-based customization techniques. Users may be directed to specific web pages depending on their language or location for instance Alternately, suggestions might be tailored to the user's age [27].

2.5 Knowledge-based

Knowledge-based algorithms provide product suggestions based on specialized domain knowledge about how various item qualities fit customers' wants and preferences and, ultimately, how useful the item is for the user. These product suggestions are derived from the data collected by knowledge-based algorithms [27].

2.6 Community-based

This kind of system makes suggestions for products based on the tastes of the users' friend [27].

2.7 Context Based Recommender System

In order to convey user preferences, authors frequently employ the concept of rating (User $*$ item $\Longrightarrow$ rating) [3]. This makes it easier to do away with the onerous procedure of requiring the user to fill out a ton of personal information [12].

3 Content-based recommender system

In the content-based filtering approach, just the behaviors and data of a single user are used to generate suggestions for other users. User profiles and product descriptions play critical roles in content-based screening [26]. As the basis for these suggestions, they are formed after reviewing the profiles [21]. These profiles include user information and preferences, The preferences are based on what the user has rated, viewed, or brought. The system will scan the user's profile for products with high ratings, and then compare those to items that haven't received any ratings from the user. The user will receive recommendations for related, highly rated products based on this comparison [21].

4 Collaborative filttering

Collaboration filtering is a technique for estimating an individual's unknown preferences by using the previously known preferences of numerous users [12]. Three primary categories, including memory-based, model-based, and hybrid techniques, are used to categorize collaborative filtering algorithms [26]. The simplest and most fundamental way to generate suggestions and forecast product sales is through collaborative filtering it does have some drawbacks, which has stimulated the creation of new strategies and tactics [12].

4.1 Memory-based filtering technique

The user can find a neighbor who has similar opinions by looking at the goods that have already been reviewed by him, Different algorithms can be used to integrate the interests and preferences of neighbors to obtain product recommendations once the neighbor or the group of users has been identified Due of this technique's efficacy, it has had significant success in practical applications [12]. Memory-based filtering techniques are primarily divided into two categories: user-based and item-based [26].

a) User-based filtering: Instead of determining the similarity of things, a user-based filtering method determines the similarity of people. It finds people who are similar to one another by comparing their ratings of the same item, makes a prediction about that item's rating, and then makes suggestions to those individuals [26].

b) Item-based filtering: In item-based filtering strategies, the similarity between items, not between people, is employed to create suggestions. It chooses the K items with the greatest resemblance to the desired item from the user-item matrix, determines how similar they are to one another, and then gives the user with recommendations based on this comparison [26].

4.2 Model-based filtering technique

The model-based filtering approach cannot use the complete dataset; rather, it generates suggestions for the user based on a model created from the information. This approach employs previous user ratings to improve the performance of the collaborative filtering procedure [26].

4.3 Hybrid collaborative filtering techniques

Hybrid recommender systems mix many collaborative methods and other recommender techniques for improved results (often content-based approaches) By using a hybrid strategy, challenges like as cold-start, data sparsity, and scalability may be circumvented [12].

There are a number of techniques to integrate CF with other recommender systems, including:

1. Recommendations Combining CF with Content-Based Features
2. Hybrid Recommendations Incorporating CF and Other Recommendation Systems
3. Hybrid Recommendations Integrating CF Algorithms [21].

Table 1 displays various sentiment analysis-based collaborative filtering techniques for recommendation systems, these techniques are based on numerous models, Over the years, several models have been integrated with recommender systems' collaborative filtering technique to improve the predictability of the outcomes.

Table 1: Displays various sentiment analysis-based collaborative filtering

Method	**Description**
Porter Stemmer algorithm is used for stemming proposed by [17]	Built a domain taxonomy and applied sentiment analysis on review data to create a user-specific, customized recommendation system.
a hybrid recommendation model and sentiment analysis proposed by [29]	in order to increase the precision of recommender systems, this study proposes a framework for movie recommendations based on sentiment analysis and hybrid recommendations
1. A hybrid RS is proposed by combining CBF and CF 2. Sentiment analysis is used to boost up this RS proposed by [16]	Put forward the idea of a hybrid rating system (RS) for films that takes the most fruitful ideas from both CF and CBF and adds in a study of the sentiments expressed in tweets. Utilizing movie tweets allows one to have a better understanding of current trends, public opinion, and user reaction to the movie being discussed.
using a text mining technique proposed by [15]	The purpose of this work is to offer a unique method that can quantify the sentiments expressed by users in reviews published by other users and transform those feelings into quantitative data that can be directly represented in recommendation systems. The purpose of this investigation is to put a numerical value on the emotions that are conveyed in the reviews and to include those results into the star ratings.

5 Context Based Recommender System

As its tailors' recommendations to the user's preferences and area of interest, adaptive filtering is another name for it [12]. It shows a comparison of the item's content with the content of items the user is interested in by gathering input from current user the Bayesian hierarchical model creates better user profiles for incoming users [12]. In order to process user preferences that have not been taken into account by prior assessments in compliance with laws in force (GDPR) and other anti-tracking difficulties, a context is defined as any information that characterizes the state of an object (time, place, product, person, etc) [3]. Contextual meaning may be included into a recommender system through Contextual pre-filtering, Contextual modelling, and Contextual post-filtering [3].

1. **Contextual pre-filtering approach** removes measurements that are not as appropriate for the adopted context by labeling them according to the contextual information, the method draws out of the basic set all appreciations connected to the provided C context, and then generates a "item ∗ user" matrix using only the information related to the C context.
2. **Contextual modeling approach**: The algorithm used in the multi-dimensional recommender system framework during the recommendation phase (Users ∗ Items ∗ Context) incorporates contextual information.
3. **Contextual post-filtering approach**: The primary two-dimensional recommendation strategy (User ∗ Item) is launched first, and then contextual post-filtering is used, following the evaluation of the unknown ratings and the generation of recommendations, the system examines the data for a specific user in a precise context to identify models of item usage and employs them to contextualize the recommendations (Item ∗ User ∗ Context) resulting from the traditional recommendation approach (Item ∗ user), such as collaborative filtering [3].

Table 2 displays various content-based recommendation systems using sentiment analysis.

These techniques are based on a wide range of models Researchers from diverse fields have investigated the applicability of various strategies that can be used in content-based recommendation systems [12].

Table 2: Context Filtering Methods

Method	Description
Contextual sentiment analysis in collaborative recommender systems proposed by [24].	presents a framework for contextual sentiment-based recommendations to enhance recommender system services by lowering data sparsity and system performance error rates
Merging Textual Reviews with Rating Data and Integration of Sentiment Rating with Actual Rating, suggested by [23]	By including textual evaluations in the user-item ratings matrix, the suggested contextual sentiment-based recommendation model primarily seeks to increase the efficiency of collaborative recommender systems. The major issue with recommender systems, data sparsity, might be lessened by combining textual reviews with rating data, which would then increase the quality of recommendations
recommendation process using both filtering technique and context modeling techniques suggested by [10]	Use user emotion and behavior as contextual parameters to introduce context-aware recommendations for tourism destinations
used Labeled-LDA to build the context classifier Rating can be predicted based on any conventional recommendation algorithms such as kNN, suggested by [7]	Offer a context-aware recommender system that uses user reviews and rating histories to mine user information to determine the context of a group of items and calculate a utility function over them
Collaborative filtering proposed by [9]	advocates the use of context-aware information to produce a personalized hotel recommendation system, or context-aware hotel recommendation (CAPH). This study takes into account suggesting hotels based on the accommodations' attributes and the kind of travelers
Novel weighted algorithm for text mining proposed by [18]	The text of the reviews serves as the system's primary source of data in the author's cold-start hotel recommendation system based on reviews taken from Venere.com and TripAdvisor.com, we define context groupings

6 Sentiment analysis techniques

Sentiment Analysis: Opinion mining (sentiment analysis) is a difficult undertaking that combines data mining and Natural Language Processing (NLP) approaches to computationally deal with subjectivity in textual resources [1, 30]. Sentiment analysis (SA) is frequently used in a variety of fields, such as marketing, social media, and customer relationship management, typically analyzes the organization of a textual review and deduces if it expresses favorable or negative opinion [24].

Recently, machine learning methods including Decision tree, SVM, Naive Bayes, and Random Forest were used to do sentiment analysis [13]. Sentiment categorization requires the development of an efficient set of features, like the majority of machine learning applications Here is a list of some of the current features [1].

Terms and their frequency: These characteristics include frequency counts for specific words or word n-grams word placements could occasionally also be taken into account. It is also possible to use the TF-IDF weighting algorithm from information retrieval. These characteristics been demonstrated to be quite efficient in sentiment classification [1]. After comparing them with real review data, eliminate less important emotion word clusters in order to generate more accurate findings, author [6] estimated the formula below provides the term frequency (tf: term frequency) of each sentiment word cluster (t)

$$tf(t,d)\sum_{i=0}^{j} f(wi,d)$$

j = number of words in sentimental group t

Using the inverse document frequency (idf), the frequency with which the word t appears in document d was used to reduce the weight of the general.

generated from this equation Inverse document frequency (idf) refers to the logarithmically scaled inverse fraction of documents containing the term.

$$idf(t, D) = \log \frac{N}{|\{d \in D : t \in d\}|}$$

N = total number of documents in the corpus $N = |D|$

D = document set.

TF-IDF score of sentiment word clusters on each movie was calculated using the following formula:

$$TFIDF(t, d, D) = tf(t, d) * idf(t, D)$$

The number of sentiment words was then reduced by taking into account the highest TF-IDF score that might result from each sentiment word For instance, the word "Aghast" had a maximum TF-IDF score of 0.8% in each movie, whereas "Sweet" had a minimum TF-IDF score of 42% in at least one movie [6].

Part of speech: Numerous studies have revealed the significance of adjectives as opinion indicators.

Opinion words and phrases: Words that are frequently employed to convey either good or negative feelings are known as opinion words For instance, positive opinion adjectives like lovely, great, good, and amazing are contrasted with negative opinion terms like awful, poor, and dreadful Although many words that express opinions are adjectives and adverbs, other words like "hate" and "like" can also convey opinions [1]. the authors [22] uses machine learning models to suggest an efficient framework for a sentiment analysis recommender system.

Three core supervised machine learning algorithms are applied to a dataset of airline tweets, and their performance in terms of accuracy, precision, recall, and f-measure is then assessed. Taking into account the chosen machine learning models [22].

Deep learning, one of the machine learning approaches, has been more popular for sentiment classification in recent years [14].

Table 3 displays sentiment analysis using various deep learning technique

These techniques are based on a wide range of models The usefulness of various strategies that can be used by numerous researchers, the recommendation systems' accuracy and relevancy have improved better by extensive research [12].

Table 3: Sentiment analysis using Deep learning technique

Method	**Description**
deep learning system, which we call Binary Neural Network (BNet) suggested by [11]	This article describes the development of a novel deep learning-based method to handle the multiple emotion categorization problem on Twitter.
random word-embedding and the word2Vec method and used CNN structure suggested by [25]	By examining the topics that people debate on Twitter, it is possible to determine how customers feel about health insurance. The purpose was to identify consumer opinions toward health insurance and healthcare providers using sentiment analysis.
through a Convolutional Neural Network (CNN) and a Bi-directional Long Short-Term Memory (BLSTM). Recurrent Neural Networks (RNN) proposed by [28]	The Knowledge-Based Recommendation System (KBRS) described in this study contains an emotional health monitoring system to identify users who may be experiencing probable psychological disorders, in particular, depression and stress The solution also features a system for alerting authorized individuals.
Neural Collaborative Filtering (NCF) suggested by [19]	We use a lexicon-based opinion mining approach to unearth concealed opinions in reviews, and we integrate them with real ratings. In addition, the authors use a method of deep learning that overcomes the limits of standard collaborative filtering.

7 Conclusions

Regarding the various recommendation systems, it appears that the more data is used the more effectively the systems perform. In this service, the concept and methods of recommendation systems are summarized, as well as sentiment analysis and its use with recommendation systems.

Utilizing user reviews is an effective method for gauging the public's diverse thoughts on a product, hence integrating concept sentiment analysis with a recommender system.

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