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Review of Entity Information Type in Recommendation Systems

Jehan Kadhim Shareef Al-safi[1*], Wijdan Rashid Abdulhussien[2], Wasan M. Jwaid[3]

[1]University of Thi-Qar, Department of Digital Media, Media faculty, 64001, Iraq. E-mail: jihan.k.shareef@utq.edu.iq
[2]University of Thi-Qar, Department of Information Technology, Faculty of Computer Science and Mathematics, 64001, Iraq. E-mail: wijdan_rashid@utq.edu.iq
[3]University of Thi-Qar, Department of Banking and Finance, Faculty of Administration and Economics, 64001, Iraq. E-mail: wasan.maktoof@utq.edu.iq

[*]Corresponding author E-mail: jihan.k.shareef@utq.edu.iq, jihansh2020@gmail.com

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Abstract. *Users share their opinions on various products through online reviews on e-commerce sites and linked microblogs. Reviews from users are a terrific way to learn more about what kinds of things interest them. Some recent efforts have turned to reviewing texts and the abundance of information they provide to improve overall score collaborative filtering recommender systems. This paper includes review terms, review topics, and review attitudes. The works in question utilize review texts to infer user preferences. In this study, we comprehensively analyze current attempts that use review texts. We investigate how these texts are used to overcome some of the most pressing issues plaguing conventional forms of collaborative filtering.*

Keywords: *Collaborative Filtering, Content-based, Item-base CF, User-based CF, User review.*

1. INTRODUCTION

The exact modelling approach of a robot is a necessary step in achieving more excellent performance in robot control due to the robot manipulator's fast dynamic response in dynamics, which is influenced by many different variable parameters, including inertia, Coriolis, and friction forces [1].

E-commerce websites have increased, allowing millions of products to be sold [1]. A recommendation system is sound when considering many options [2] [3]. To help users discover new things, the recommender system (RS) offers an alternative. User preferences are gathered and then used to make recommendations [4]. As e-commerce platforms evolve rapidly, recommendation systems have helped users discover their preferences and suggest specific items by analyzing them.

Many e-commerce companies, including Yelp, Netflix, eBay, and Amazon, use the Collaborative Filtering (CF) approach for their recommender systems [5]. Collaborative filtering (CF) is a widely utilized algorithm in the recommender systems domain. The general acceptance of CF methods is based on their users having much in common. Similar users or items can be found by comparing the standard ratings of the users [4]. It is best to use CF methods when there is sufficient rating information. Because of the limited number of standard ratings available amongst users, their effectiveness suffers when rating sparsity occurs [6][7]. Another drawback of CF approaches is that they fail to capture the motivations behind user ratings, making it challenging to identify a target user's preferences [8] accurately. Asocial factors [9], tags [10], and item descriptions [11] [12] are only a few examples of content-based approaches that were developed to address these challenges; Figure 1.

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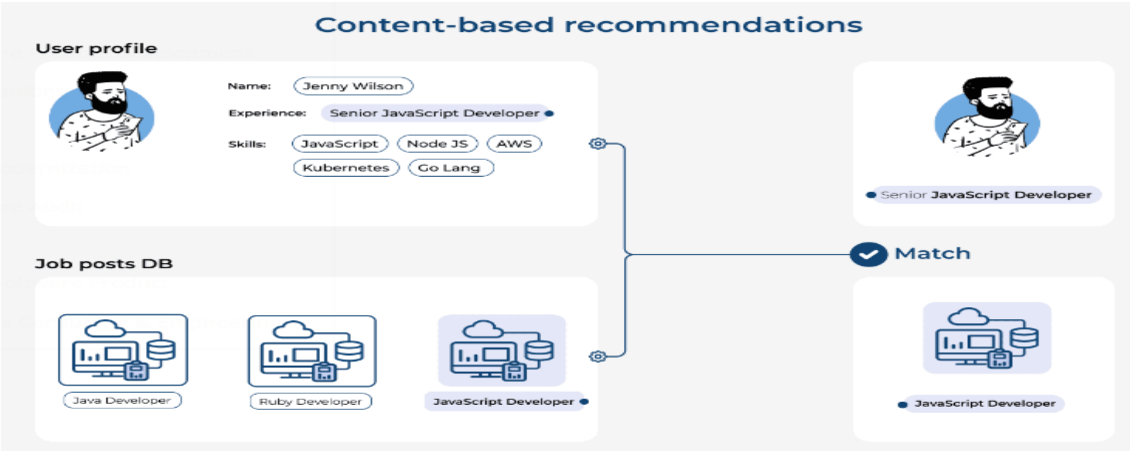

Fig. 1. Content-Based Filtering.

However, these methods still fall short when the rating sparsity is large or the intended user has a limited ratings history [6]. In the contemporary Web context, users are more at ease writing and posting textual reviews of things on e-platforms [13] [14]. User textual studies have become integral to e-commerce because of this trend. Various platforms like TripAdvisor (https://www.tripadvisor.com/) and online marketplaces like Amazon and Taobao have been developed [7]. Many studies provide valuable and insightful information to businesses and consumers [15].

Textual reviews, as opposed to ratings, contain more semantic information, allowing recommender systems to better understand their users' preferences[13]. Thus, a user-specific preference representation can be generated using information other than global rating scores [6] [16].

The extraction of user interest information from review texts for rating prediction has recently received much attention [6]. The research [6][13][17] shows that review texts significantly affect the reliability of traditional star ratings. This research addresses the dual concerns of sparsity and prediction accuracy in rating-based systems by integrating the rich data available in opinions from user evaluations and surveys from current studies.

The outline for the remaining parts of the article is as follows: Section 2 focuses on the Techniques for Standard CF-based Recommendation. In Section 3, Typical CF Algorithms. Observation and evaluation of CF-related metrics Section 4. Some of the most common CF-related issues and challenges, as well as Numerical Explicit Ratings' Limitations, are represented in sections 5 and 6. Text-Based Customer Feedback Techniques for CF are illustrated in section 7. Lastly, the conclusion is explained in section 8.

2. TECHNIQUES FOR STANDARD CF-BASED RECOMMENDATION

An RS based on CF uses user-provided ratings for items [18]. It makes recommendations that the intended user probably hasn't thought of but will enjoy [4]. An m × n matrix stores user ratings and the number of items they've given their opinions on (Table (1)). Columns represent the items, while rows represent the users. With each new user, the matrix expands by one empty row. Each new addition to the catalog is represented by a blank column.

Recommendations are generated using the connections and similarities between users and items in CF systems [19]. The RS manages user-item interactions, from which it derives these relationships. All unrated products have now received ratings from the intended audience. Final recommendations are made to the user based on an item's approximated rating.

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Table 1. Sample of Rating Matrix.

u/I	i1	i2	i3	i4
u1	4	3	2	4
u2	-	4	5	4
u3	3	2	5	-
u4	2	-	5	3

3. TYPICALCF ALGORITHMS

The research and application of the CF methodology in recommender systems have been extensively explored and implemented [4]. There are primarily two categories of collaborative filtering: memory-based and model-based techniques [19][20]. Neighborhood-based CF refers to the approach that leverages the system's rating matrix to estimate missing ratings for specific items. Conversely, model-based CF constructs a model using matrix values, which is subsequently employed to assess the relevance of new items to the target audience [19] ; figure 2.

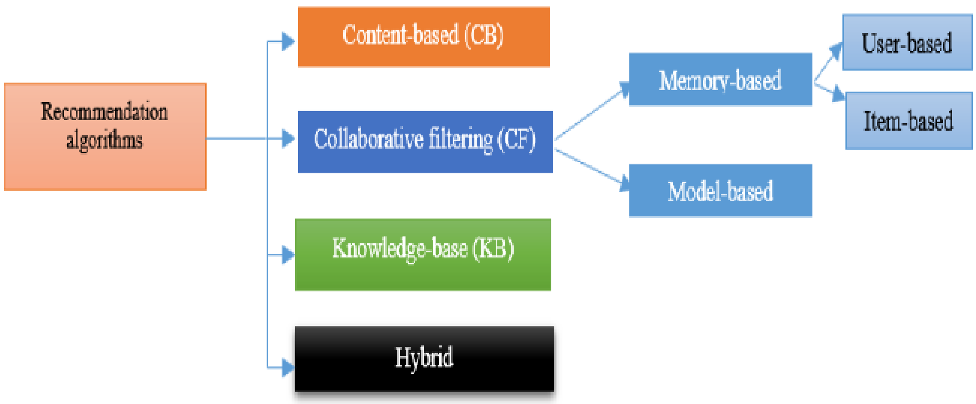

Fig. 2. Recommendation System Algotithms and Categories.

3.1. MEMORY-BASED CF ENCODING

The memory-based CF method, which relies on user and item similarities, can forecast a user's potential preferences for unfamiliar items by analyzing their previous interactions with similar items. The most prevalent memory-based CF techniques are user-based and item-based approaches [2].

User-based collaborative filtering estimates a prospective user's rating for target items by utilising prior ratings from like users.[19]. The following formula can be used to predict the user u's rating for item j (eq.1):

$$\hat{r}_{u.i} = \bar{r}_u + \frac{\sum_{v \in N_u} sim\ (u.v) \times (r_{v.i} - r_v)}{\sum_{v \in N_u} |sim\ (u.v)|} \qquad (1)$$

where:

$\bar{r}_u$: Represents to the average rating of user u; sim $(u.v)$: represent the similarity between the user u and v; Nu: represent group of people who are similar to u (neighbours)

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This type of CF relies on the fact that items have similar characteristics. User ratings for similar items are considered when predicting an item's rating [19]. According to these methods, if two products have received identical ratings from several users, they are classified as equivalent [4]. The following is the formula for CF's item-based rating prediction (eq. 2):

$$\hat{r}_{u.j} = \frac{\sum_{k\in N_i} \text{sim}\,(j.k)\times r_{u.k}}{\sum_{k\in N_i} |\text{sim}\,(j.k)|} \qquad (2)$$

where:
Item j has a group of counterparts denoted by Ni, and
sim $(j.k)$: express how similar j and k are to one another numerically.

Determining the degree of similarity between u and I is important in neighborhood-based CF methods since it can have a significant impact on the effectiveness of the method overall [21].

The Jaccard coefficient [22], the Pearson correlation coefficient (PCC) [23], and The cosine measure (COS) [24], are three of the most used standard criteria for identifying pairs of users or things with the highest degree of similarity. PCC uses the linear correlation between two user/item rating vectors to determine similarity. Similarity of rating vectors can be determined by squaring the cosine angle. When determining Jaccard similarity, the rating values are disregarded and only the number of shared ratings between users and things is used. The selection of a similarity measure [25] should be guided by the specific dataset being analysed. Similarity between two users can be determined based on these phrases:

Both the average rating for user u (ru) and the average rating for item i are used in these computations (ru, i). Iu and Iv are user u and user v's respective sets of rated products. There are two ways in which users' ratings are used to calculate the similarity between the two items in question:

An item's rating average can be calculated by subtracting its average rating from the sum of the ratings of all other things in its group. User sets Ui and Uj were used to rate items I and j.

On the flip side, there is a major downside to memory-based CF. These methods can raise the complexity of the system by adding processing time to find similarities between people or products [26]. These models are widely used because they can be implemented, making the calculated predictions easier to comprehend [19][27].

3.2. Model-Based CF

Although model-based CF techniques produce more accurate predictions [20], neighbourhood-based methods are simpler to build and infer unknown user ratings. Methods from the fields of data mining and machine learning are employed in the development of offline prediction models in these approaches. Estimated lost values in the user-item matrix are forecasted using these models [28]. Many different kinds of artificial intelligence systems have emerged in the last few years. For example: neural networks, Bayesian networks, fuzzy systems, support vector machines (SVMs), deep learning techniques.

Despite this, the Matrix factorization (MF) models [29] are considered the most up-to-date in RS due to their high levels of precision and scalability [20]. Latent reconstructions of MF algorithms are based on the strong connection between both rows and columns (also called as latent factors) of a selected target rating matrix [30]. Specifically, for each item I both the item's k-qualities (represented by q(i)∈R(k)) and the user's desire for those characteristics (represented by p(u) ∈ R(k)) are modeled as k-dimensional latent variables. The evaluation score for an item I is found by using the formula (eq.3) [4][6] :

$$\hat{r}_{u,i} = p_u q_i^T \qquad (3)$$

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When comparing neighbour-based CF approaches to model-based CF methods, the latter is more reliable. Compared to neighbor-based processes, the amount of space needed by these methods is typically smaller [10]. This is due to the fact that in neighbor-based CF, every rating must be kept in memory in order to make recommendations. On the other hand, model-based CF often use a model that is more compact than the primary rating matrix [10]. Even though it may necessitate additional effort and data to develop a model, it is a crucial part of the modeling process. Furthermore, when new users or products are incorporated into the system, it is essential to retrain the latest model multiple times to ensure it remains current and accurate [31], Some new methods that are used in RS are listed in Table (2).

Table 2. Some Methods that are used in RS.

No.	Technology	Dataset	Results
1	Transformer Model using utility matrix and textual sources 2023 [32]	Movielens, Amazon-Toys ,Games, Video, and Electronic	MAE = 0.445 RMSE = 0.743 Precision =92.07%
2	Improved collaborative filtering method 2022 [33]	Amazon Electronic	MAE = 0.80 RMSE = 1.10
3	Naïve Bayes Classifier (NBC) 2022 [34]	Amazon Musical Instruments, Video, and Amazon Automotive	Precision = 0.89 Recall =0.91 F1 metric = 0.90
4	CNN - LSTM sentiment models with SVD, NMF, and SVD++ algorithms 2021 [35]	Amazon Fine Food Reviews and Movie Reviews	MAE= 0.5770 RMSE =0.8577 NMAE =0.1443
5	Combination of deep Learning technique with the latent factor model 2020 [36]	15 Amazon dataset	MSE =0.915 MAE =0.712
6	Similarity 2010 [37]	Delicious, Last.fm	Precision@N=0.364 MAP=0.145 DCG=0.39
7	Attention-Based LSTM 2020 [38]	Adressa	AUC=78% F1-measure=81%
8	Max similarity 2020 [39]	Q&A document	Precision=0.79 Recall=0.9 F1-measure=0.8
9	CNN, Softmax 2019 [40]	MSN News	AUC=0.6 MRR=0.3 Ndcg@K=0.4
10	Softmax 2019 [41]	Query logs	NDCG@K=0.5
11	DDQN 2018 [42]	New	CTR=0.0113 Precision@K=0.0149 Ndcg=0.049
12	RNN, MAX Plot 2018 [43]	Imdb (Movie lens), Yelp	Precidion@K=0.14 MRR=0.31
13	Stochastic gradient descent , logistic function 2017 [44]	Yelp	Precision@K=0.9 AUC=0.7
14	Lamdamart 2016 [45]	News	MAP=0.4 MRR=0.5
15	Rundom walk 2012 [46]	Aminer	Precision@N=37 MAP=40 Recall@K=35 ARHR=14
16	Similarity 2011 [47]	Hermes news portal	Accuracy=+4 Recall=+24 , F1-measure=+19

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4. OBSERVATION AND EVALUATION OF CF-RELATED METRICS

Evaluation is an essential step in the development process to demonstrate the system's efficacy in performing the desired tasks [48]. To gauge the effectiveness of CF-based RS, researchers have employed a wide range of evaluation measures [49].

Most fall into two broad categories: online or offline [49]. To begin, users are given recommendations and surveyed to see how they feel about them. The offline strategy does not rely on real-world interactions with users. Instead, it uses historical data from those users to train the system and then tests the predictions it has computed.

The online method is regarded as the finest evaluation strategy [50] because to its capacity to provide exact feedback on the plan's applicability to actual users. Conversely, a considerable amount of time is needed for actual communication with other people. A large body of research relies on an unconnected evaluation procedure [51]. A few of the most used measures for evaluation in CF-based RS are defined in Table (3).

Table 3. Metrics Used for Assessment in CF.

Metrics	Definition	Reference
Click Trough Rate	It computes the percentage of recommendations that are finally clicked.	[52] [53]
Mean Absolute Error	The average absolute deviation of projected ratings from actual values is what this metric measures.	[23] [54]
Novelty	It calculates the originality of the suggestions made.	[55][51]
Precision	It determines the cost of the service being offered.	[55] [56] [57]
Ranking Score	It uses a recommendation's ranking as a proxy for quality.	[51]
Recall	It calculates the success rate of each suggestion made.	[55]
ROC curve	The number of suggestions that the user does not like increases.	[55]
Root Mean Squared Error	It places more weight on the absolute differences between predicted and observed values.	[55] [58] [59] [60]
Others	-	[55][51][23][48]

5. SOME OF THE MOST COMMON CF-RELATED ISSUES AND CHALLENGES

It is deemed appropriate in CF-based RS research to look into the most widely accepted challenges encountered when deploying the technology.

5.1. SPARSITY OF DATA

User-item interaction data typically contains a lot of missing ratings, and the sparsity frequently exceeds 99% [61]. Users cannot express their interests numerically because of their difficulty in doing so [62] or due to a lack of coverage in the recommendation space [11]. As a result, the effectiveness of CF

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may be reduced because of the sparsity problem. Even when the similarities can be calculated, the information obtained may be insufficient so they may be unreliable [63].

5.2. *THE COLD-START*

New users and/or items can cause this problem when added to the rating matrix. If the system hasn't collected enough ratings about the items, CF methods cannot recommend them to these users [64]. Scalar ratings can be used in conjunction with the substance of user reviews to help with this problem.

5.3. *SCALABILITY*

Calculating the similarity between users in a CF algorithm is time-consuming because the algorithm searches the raw data to find the target user's possible neighbors [65]. Consequently, as data sets grow, algorithms need more memory or processing power, limiting their ability to scale [66].

To address this issue, It is possible to employ CF strategies that restrict their searches to localized groups of users rather than the full database [67] [68], or dimensionality can be reduced using singular value decomposition (SVD) [68][69]. To overcome Scalability, a promising approach to address scalability challenges is the implementation of distributed computing mechanisms. Various studies have integrated fundamental collaborative filtering algorithms into their computing frameworks to enhance computational efficiency in recommendation systems [70][71]. These frameworks are designed for rapid and effective parallel processing of large-scale data.

6. NUMERICAL EXPLICIT RATINGS' LIMITATIONS

The fundamental issue with conventional CF approaches [13] is that they rely solely on users' numerical evaluations to learn about user preferences. On the other hand, scalar rating data is sometimes devoid of adequate semantic explanations to effectively reflect the user's choices [10]. The diverse recommendation method combines ratings and customer reviews to address this issue [72][73].

With the rise of online shopping, consumers have become more comfortable providing their product feedback through reviews. Free-form text is the most common format for user reviews, which allows reviewers to express multiple perspectives on their experience with a product. Therefore, they are a priceless source of information about user preferences, which can be mined for more nuanced user-profiles and better-tailored recommendations. To better understand how RS uses the data it pulls from reviews, Chen et al. [74] broke down its various data points. Words, categories, and user sentiment have all been found to be useful in constructing accurate user models from reviews. We introduce these components and briefly discuss their potential application in CF-based RS below.

Review Words: The review text is presented in an open format, as submitted by the user. Capturing the most representative words is the simplest method of mining them. One method to show how important each word is in the review is to use a TF-IDF weight measure [75]. In CF [76], the extracted review words can be used to compute user similarity instead of numerical ratings [77][78][79].

Review Topics: These are the specific facets of the item being reviewed that serve as the review's focus. Many different approaches exist for identifying review topics; these include frequency-based methods, syntax-based methods, Conditional Random Fields [80], and topic modeling techniques like Latent Dirichlet Allocation [81], Latent Semantic Analysis [82],and Probabilistic Latent Semantic Analysis [83]. Then, the review topics in regular CF can boost the actual ratings [30]. The similarity measure and latent factors [84] are useful in combination with model-based CF [85][86][87][88].

General Opinions: The overall sentiment of users regarding the reviewed items is represented by a positive or negative score. It is common practice to determine the consensus by either reclassifying the opinions of all sentiment-laden words in the reviews [89], semi-supervised [90], [91]. The collected opinions can be converted into numerical ratings, thereby enhancing the efficiency of collaborative filtering methods [92][93]. Aspect opinions provide detailed evaluations of various attributes of an item.

A review that includes the phrase "The waiters' attitude is great." would reveal that the reviewer had a favourable impression of the service they received. Studies can focus on a variety of different things, from the product itself to a particular quality (like the "attitude of waiters" rather than "service"). Language science and statistics both contribute to feature extraction [94][95][96][97][98][99], as do structured models such as Conditional Random Fields (CRF) [100] [101] and their variants.

Then, they use word distance or pattern mining to figure out which features have associated opinions [94]. The aspect opinions (aspect, sentiment pairs) can also be identified using a support vector machine (SVM) [74]. The users in CF were grouped based on their similarities, which were determined using the aspect sentiments described in Reference [102]. They were used to find commonalities between users and incorporated into the usual user-based CF in [7].

7. TEXT-BASED CUSTOMER FEEDBACK TECHNIQUES FOR CF

The valuable information in user reviews has been the subject of numerous attempts to be incorporated into the recommendation task [74].Words, themes, and points of view can categorize these works into three main methods.

7.1.USING REVIEW WORDS-BASED METHODS

These methods utilize the review words by factoring them into CF. In [76], they proposed tweaking the user-based process to calculate user similarities based on similarities in text reviews rather than ratings. To determine how similar the two users are, we compare the words used in their studies of jointly-reviewed products. After calculating scores based on similarities, these are used as a factor in the rating prediction stage.

The Convolutional Matrix Factorization (ConvMF) model, proposed by Kim et al. [72], treats review text as supplementary data. This model extracts the items' latent characteristics from the reviews using convolutional operations and word embedding. Once the latent features have been inferred, they are incorporated into a matrix factorization model that estimates user approval ratings for the target items.

Chen et al. [73] developed a model, termed NARRE, that use CNNs to generate latent embedding's of users and things from review texts., much like DeepConn [103] Learning the latent embeddings uses a scoring system based on an attention network rather than a simple binary classification to identify the unique value of each review. NARRE combines user latent rating factors and attention scores to predict missing ratings into an extended MF.

Reviews and ratings were combined in a single model in Reference [104]. To learn the necessary latent features, the model uses convolutional neural networks (CNNs) and an attention mechanism that considers related reviews. The model derives latent rating embedding from the interaction matrix for users and items using the rating component. FM factors in the learned content features and latent rating embedding to produce an overall rating.

Liu et al. [105] recently presented a hybrid neural recommendation model (HRDR) that utilises user and item embedding's obtained from ratings and reviews. A Multilayer Perceptron (MLP) network was initially utilised to derive rating visualisations from the rating data. Convolutional neural networks (CNNs) incorporating an attention mechanism are employed to extract insights from reviews, with each review receiving a score indicative of its in formativeness. Ultimately, matrix factorisation is utilised to assess users' evaluations of goods by using implicit ratings and review attributes.

7.2. METHODS DETERMINED BY TOPIC AREA EXAMS

This method takes ratings and review data and uses them together to make suggestions. The LDA-based topic model is first employed to model reviews, while the standard MF model is used to model ratings. The latent issues are then incorporated into the latent features model's learning phase with the help of a Softmax transformation function. The final rating scores are calculated using the trained model.

Since the LDA method is inadequate for modeling the spread of compound topics, the authors of [106] proposed the TopicMF framework as an extension of HFT [107].

Latent element ratings are calculated by giving each word in the reviews a certain weight. By comparing the evaluations the user has given each item's latent features, we can deduce the relative importance of these qualities. Last, a modified Latent Factor Model calculates an aggregate rating for any user-item pair by summing the ratings of all relevant elements (LFM) [108].

8. METHODS DETERMINED BY SENTIMENT EVALUATIONS

Several studies have found that the reviewer's emotional reaction to the product or opinions about its various features improves rating prediction accuracy. Example: Poirier et al. [92] aggregate reviewer sentiment into numerical scores using a machine learning approach.

This trained model is then used to infer book reviews' star qualities. Review ratings are used to build a rating matrix that combines conventional neighbor-based CF methods to predict future ratings.

User feedback can be simplified into aspect-emotion pairs using an Explicit Factor Model described in Reference [109]. Rating prediction in an MF-based model is performed by simultaneously decomposing the rating matrix, the user-aspect attention matrix, and the item-aspect quality matrix, all based on phrase-level sentiment analysis.

In order to facilitate CF, Diao et al. [110] suggest the JMARS model, which is based on the correlation between reviews' aspects, reviewers' opinions, and reviewers' ratings. Using the MF, ratings for each facet are generated, and then those values are merged with latent components to get an overall rating. In contrast, the word pattern of the reviews is captured by the Dirichlet-Multinomial method.

9. CONCLUSION

As modern text mining techniques have emerged, there has been a concerted effort to include review texts in the suggested activity. Various review elements, such as review words, topics, and opinions, have been used to represent items and user interests better to supplement traditional rating-based CF models. In this study, we survey the current state of the art in CF recommender systems based on reviews, and we categorize these systems into three broad classes: word-based, subject, and phrase. Based on the above methods, we suggest some solutions for the recommendation system: Graph-based Recommendation Systems (Entity Relationship Graphs (ERGs), Knowledge Graphs). Secondly, Context-Aware Recommender Systems (Contextual Embeddings, Contextual Bandit Algorithms).Thirdly, Entity Embedding and Hybrid Models (Entity Embeddings for Collaborative Filtering, Hybrid Deep Learning Models), and Finally, Causal Inference for Recommendations. Despite major advancements in the field of review-based CF RS research, our survey of existing review-based methods revealed the need for additional studies. For example, future work could focus on using sophisticated text mining techniques to uncover hidden patterns of association between reviewers' scores and comments. There is some evidence to suggest that combining the results of several review-based CF RS could be more effective than relying on a single system to make predictions about users' preferences.

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