Collaborative Filtering Using Explicit and Implicit Ratings for Arabic Dataset

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Abstract— As the amount of digital information recorded on the internet increases, the need for flexible recommender systems is growing. Collaborative Filtering (CF) has been widely used in the E-commerce industry. A variety of input data was used, either implicitly or explicitly, to provide personalized recommendations for specific users and helped the system to improve its performance. Traditional CF algorithms relied solely on users' numeric ratings to identify user preferences. The majority of current research in recommender systems is focusing on a single implicit or explicit rating. In this paper, we combine explicit rating and implicit rating for user reviews to build the best recommender system using a large Arabic dataset. In addition, we employ two powerful techniques in the creation of our recommender system. First, we use Item-based CF and use cosine vector similarity to calculate the similarity between items. Second, we use Singular Value Decomposition (SVD) to reduce dimensionality, boost efficiency, and solve scalability and sparsity problems in CF. The proposed approach improves the experiment results by reducing mean absolute and root mean squared errors. The experimental results show to perform better when using both explicit and implicit ratings compared with using only one type of ratings.

Keywords— Collaborative filtering (CF) Explicit and Implicit Ratings, A Large-Scale Arabic Book Reviews (LABR), LABR Lexicon.

I. INTRODUCTION

Recommender systems are intelligent systems that can analyze previous user behavior on products or services in order to make personalized recommendations [1]. Collaborative Filtering (CF) is one of the most successful approaches to building recommender systems. It offers suggestions or predictions about unknown preferences to other users based on a set of known preferences of the users in the system [2].

Collaborative filtering algorithms use two data either explicit or implicit. The first input data in the CF technique are explicit data that the user explicitly provides. This data is well understood and offers a concrete view of user preferences (e.g., star ratings). The explicit rating is more popularly used in the fields of recommender systems research [3-10]. The second data of CF is implicit data. The system infers the user's interests by observing the various behaviors of users (e.g., clicks, purchases, navigation history, search patterns, and reviews of users). Recently, sentiment analysis applied as implicit ratings which are used to identify user's preferences in recommender systems and improve the results of recommendations [11-19]. Most previous research has focused on using either explicit or implicit ratings, without exploiting all of the information available in the dataset, with only a few studies using both explicit and implicit ratings together. The combination of explicit rating with an implicit rating of user preferences overcomes the problems associated with each other. Also, it builds an effective recommender system by exploiting fully the information in the dataset. Several studies used implicit and explicit ratings together to predict the user's ratings using an English dataset [20-32].

This paper used implicit and explicit user ratings to better identify users' preferences and improve recommendation accuracy using Arabic dataset. In the explicit ratings, we used ratings that are integers in the range of 1 to 5. Also, we used the sentiment analysis of user reviews as an implicit rating, to determine the user's overall opinion (positive or negative) from each user review. In addition, we used two effective techniques in the creation of our recommended system. To start with, we used item-based CF to provide better performance in the memory-based approach. Second, we used SVD to reduce dimensionality, increase performance, and solve scalability and sparsity problems in CF. The experimental results of the proposed approach generated high results as a result of performing the explicit with implicit ratings in CF utilizing item-based and SVD-based CF. The item-based achieved 0.330 and 0.227 in terms of RMSE and MAE, and the SVD-based CF approach achieved 0.330 and 0.228 in terms of RMSE and MAE, respectively. Compared to our earlier work our recent proposed approach is better in results.

In recent years, all of the existing research that used Arabic datasets focused solely on reviews or text content as implicit ratings. In collaborative filtering, we have made a new contribution through a new approach that combines implicit and explicit ratings. Our research, As far as we know, is the first study to make a recommendation for the Arabic dataset based on both implicit and explicit ratings. Furthermore, the lack of resources and research in the field of Arabic recommender systems has motivated us to develop our proposed approach.

In the following sections, you will find the rest of this paper organized: Section 2 provides background information, and Section 3 provides an overview of the related work. Section 4 offers an overview of the proposed approach. Experimental work is presented in Sections 5 and 6, along with the results of the experiments and an evaluation of the work, in addition to the results of the experiments. Section 7

concludes with a discussion of the findings and recommendations for future research.

II. BACKGROUND

Here in this section of the paper, we will discuss our contributions in field recommender systems, which are based on Arabic data.

A. Overview of our previous works

In this section, we discuss two of our previous works. In the first work [33], we used numeric ratings as explicit data range (1-5) which was used to predict users' unknown preferences using a large Arabic dataset consisting of over 63000 ratings. The proposed approach used the best methods in CF. Memory-based approaches were implemented using item-based, which outperform user-based algorithms in terms of both performance and quality. For the model-based technique, we applied the matrix factorization algorithm via SVD which successfully addresses the problem of scalability and sparsity in CF. The approach that was proposed produced high results. Also when compared the approach with different methods using four different datasets the proposed outperformed other methods.

In the second research [34], we used user reviews to improve the accuracy of collaborative filtering. To extract candidate features and personal opinions about each feature from the Large-Scale Arabic Book Reviews (LABR) dataset, we applied a special lexicon specifically for the dataset. After that, we extracted the score which represents the overall sentiment (positive, or negative) for a review. The overall sentiment score is input into the CF algorithm which are the item-based and singular value decomposition-based collaborative filtering methods. The proposed approach yielded significantly better results when compared with existing work.

We used in this paper implicit and explicit user ratings from the Arabic dataset to better identify users' preferences while also improving the accuracy of their recommendations. Refer to the section on the proposed approach. Ratings are expressed as integers in the range of 1 to 5, which is used in explicit ratings. The sentiment analysis of user reviews served as an implicit rating, and we used it to determine the user's overall opinion (positive or negative) based on the content of each review using a special manual lexicon. Also, we employed two highly effective techniques in the development of our recommended system: item-based CF and SVD-based CF.

B. Types of Recommender Systems

The item-based and the SVD-based are the two different collaborative filtering algorithms that are used in the recommendation phase.

1. Item-based CF

The Item-based CF approach, which is one of the memory-based CF approaches, works on the nearest neighbors search algorithm. The item-based CF approach determines the similarity between items by selecting the items that are the most similar to each other. This formula is used to determine the degree of similarity between items I and j, denoted by sim (i,j) [35]:

$$sim(i, j) = cos(\vec{\imath}, \vec{\jmath}) = \frac{\vec{\imath}.\vec{\jmath}}{\|\vec{\imath}\|^2 * \|\vec{\jmath}\|^2} \qquad (1)$$

During the following step, the predicted value for the item i for a given user u is calculated by adding up all of the ratings that the user has given on items that are similar to i. In each rating, the corresponding similarity sim (i,j) between items I and j is taken into consideration. This similarity sim (i,j) is calculated by the following equation [35]:

$$Pu, i = \frac{\sum all\ similar\ items, N(si, N * Ru, N)}{\sum all\ similar\ items, N(|si, N|)} \qquad (2)$$

Lastly, the Top N items are selected using similarly computed values not rated by the current user and recommended to the user.

2. SVD -based CF

SVD is one of the most popular and successful techniques of matrix factorization used in collaborative filtering. SVD is an extremely effective technique for dimension reduction. The most problem in SVD decomposition is locating a feature in a lower-dimensional space than the original one [36]. The SVD of the m × n matrix A has the following representation:

$$SVD\ (A) = U\ \Sigma V^T \qquad (3)$$

An orthogonal m × m matrix U is named if it is equal to a matrix with m × m identity. The diagonal elements in Σ (σ1, σ2, σ3, σn) are called the singular values of matrix A. The singular values are generally put in descending order. The column vectors of U and V are called the left singular vectors and the right singular vectors respectively. SVD has many desirable properties and is used in many important applications. One of them is the low-rank approximation of matrix A. The truncated SVD of rank k is defined [36-37]:

$$SVD\ (A_K) = U_K\ \Sigma_K V_K^T \qquad (4)$$

Where, U_K, V_K are m × k and n × k matrices composed by the first k columns of matrix U and the first k columns of matrix V respectively. K × k is the principle diagonal sub-matrix of Σ… A_K represents the closest linear approximation of the original matrix A with reduced rank k

III. RELATED WORK

The majority of the research studies in recommender systems have relied on single-rating recommendation methods, which have been widely used for many years with great success and are still in widespread use today. Several recent research studies have combined explicit and implicit ratings of user preferences to produce more accurate recommendations, which is a promising development. We will look at methods that include single-rating recommendations (implicit or explicit) as well as other methods that combine explicit and implicit ratings in a single recommendation.

A. Explicit Rating in CF

The use of explicit rating is more common in CF research because numeric data are more widely used in other areas of the field CF. A number of significant CF studies that used explicit ratings to produce personalized recommendations are presented in this section of the paper.

Jianfang in [3] introduced a CF algorithm that was combined with the Singular Value Decomposition (SVD) and Trust Factors to produce a more reliable result (CFSVD-TF). They used the cosine distance metric to compute the similarity between two items. There were 1682 movies in total in the MovieLens 100k data contains 100,000 ratings (1-5). It contains 943 users for a total of 1682 films, with every

user having rated at least 20 films. For the purpose of determining the effectiveness of this technique, the root mean square error (RMSE) was calculated. The accuracy of the proposed method was significantly higher. When comparing it to ten neighbors, it obtained an RMSE of 0.9762.

According to the approach proposed in [6], a book recommendation system based on item-based collaborative filtering was implemented. For the purpose of calculating the similarity between books, cosine distance metrics have been employed. It was determined that the goodbooks10k dataset was appropriate because it contains ratings of 10,000 popular books from 53424 users. The proposed method carried out evaluations with the metric MAE. With regard to the MAE, the experimental results achieved a 0.72 score.

The use of CF-based items was also used in another method [9] to produce a recommendation in movies. The dataset was the Group Lens M1, which contained approximately one million ratings from 6,040 users for 4,000 films. In order to determine the similarities between films, they used an adjusted cosine similarity measure. The proposed approach was evaluated using MAE and achieved 0.938 with 20 neighbors, according to the results of the evaluation.

Mala et al. [10] used a variety of recommendation algorithms to recommend movies to users based on their profiles. It includes K-Nearest Neighbor (KNN), singular value decomposition (SVD), Alternating Least Squares (ALS), and Restricted Boltzmann Machines (RBM). When SVD was tested against KNN, ALS, and RBM, the experimental results revealed that it produced better recommendations than all of the other models tested against it. The SVD, KNN, and ALS all achieved values of 0.9002, 0.9375, and 1.069, respectively, in terms of RMSE. In addition, they achieved MAE values of 0.6925, 0.7263, and 0.9935, respectively.

In [33], there have been no studies that used explicit ratings in recommender systems based on Arabic datasets. The proposed method used numeric ratings (1-5) to predict users' unknown preferences from a large Arabic dataset of over 63000 ratings. Also, used the best CF methods that used Item-based CF for memory-based approaches, which outperform user-based algorithms. In addition, it used the SVD matrix factorization algorithm was to solve the scalability and sparsity issues in CF. The proposed strategy worked well. The proposed method also outperformed other methods on four different datasets.

B. Implicit Rating in CF

In recommender systems based on Arabic datasets, all of the existing research has focused solely on reviews or text content as implicit ratings. We will go over each of these methods in brief.

When it comes to Arabic content, Hawashin et al. [38] proposed a method for semantic recommender systems that is based on a supervised learning approach. It was determined that CHI-based semantic similarity, SVD-based semantic similarity, and Arabic WordNet-based semantic similarity were all appropriate for use in the proposed method. For the purpose of creating the dataset, three different stemmers were employed in conjunction with a synthesized Arabic dataset. The CHI-based semantic approach, on the other hand, was found to be the most

effective in terms of MAE, despite the fact that it required a longer execution time.

The model introduced by Bader [39] suggests news to users based on their personal interests and preferences. Positive Arabic news was suggested to him using collaborative filtering (CF) and content-based filtering (CB). The stemming operation was used to extract the roots of Arabic news titles from their titles. The dataset used by the system consists of news articles gathered from a variety of news sources. He used two methods to assess emotion accuracy: the EEG method and the SAM method. The EEG of the model produced a result of 90 percent accuracy, according to the model.

Amel Ziani et al. [40] introduced approaches that combine sentiment analysis with a recommendation system in order to generate recommendations for users. To determine the polarity of an opinion, the researchers used the Semi-supervised support vector machine (S3VM). In the recommendation process, User-based CF is used. Different datasets were used to evaluate the proposal: Among the datasets, the English dataset contains 2000 reviews from 50 guests in 40 restaurants, the French dataset contains 10 users, 5 smartphones, and 50 evaluations, and the Arabic and dialect dataset collected from jumia.com contains 10 users, 5 oriental clothing for women, and 50 evaluations. The Arabic and dialect dataset was collected from jumia.com and consists of ten users, five oriental clothing for women, and fifty evaluations. The experimental results achieved 0.60 in terms of MAE on the Arabic and dialect datasets.

[41] Introduced a hybrid approach that combined sentiment analysis with recommender systems to make recommendations. They used the Opinion Corpus for Arabic (OCA) dataset, which contains 500 Arabic reviews of various movies from a variety of online resources. The support vector machine (SVM) was used to analyze the data collected during the sentiment analysis phase. In this phase, they used the TFIDF matrix as an input to the SVM algorithm and obtained the review polarity values (+1 and -1) as a result of the SVM algorithm's operation. In collaborative filtering, the Singular Value Decomposition (SVD) method was used to break down data into smaller pieces. The experimental results were successful in predicting rating from reviews in 85%.

Mehdi et al. [42] produced recommender systems for Arabic-language content. First, they prepared a variety of English datasets and then generated equivalent Arabic versions of those datasets. Pre-processed the datasets that were created. In both contexts, various recommendation paradigms were then used to make recommendations (English and Arabic). Finally, they tested and compared their accuracy and efficiency. The preprocessing stage had no effect on the overall performance of RS.

C. Explicit and Implicit Ratings in CF

Several studies combined implicit and explicit ratings to predict the preferences of users, allowing them to improve the overall quality of the recommender system. In the recommender system approach for the English dataset, we will review the methods that incorporate two types of ratings (implicit and explicit).

Huan et. [26] Propose a method to combine explicit trust and implicit trust in collaborative filtering. They employed a

trust metrics approach based on the correlation of Pearson to find implicit trusting neighbors, then adopt the trust to combine more trusted active user's neighbors and merge their ratings into a single value. The dataset used were the 1986 users and 2071 items of the FilmTrust database. Three metrics were employed for evaluation: MAE, Rating Coverage (RC), and F-Measure. The methodology outperformed other approaches in terms of both accuracy, coverage, and overall performance.

Donghua et al.[27] proposed a hybrid neural network approach for combining textual information with rating information for item recommendation. Modeling and prediction of ratings are accomplished through the use of a hybrid neural network framework that includes latent representation modeling and nonlinear feature interactions. The neural network was successfully used to extract contextual characteristics from textual information. To evaluate the model presented, they used five public real-world datasets, two of them from MovieLens and three from Amazon. These data sets provide explicit user ratings of 1-5 items. No item description documents are included in the MovieLens data sets. The Amazon databases contain item description papers with customer reviews. Experimental results of the proposed approach in five datasets showed greatly outperforms comparing with several recommendation methods.

Francisco et al.[28] introduced a model that incorporates review data into the rating. The proposed model focus on a latent factor with the topic model. Learning the model was through data review and extract a themed space that embedded documents and words. Then they optimized these initial embedding by minimizing the loss function across interactive data by initializing the user and item factors of the Matrix factorization (MF) problem within these topic spaces. They used four datasets that are included Amazon Toys, Amazon Health, TripAdvisor Hotels and Amazon Pet. The proposed system was evaluated using four metrics: Hit Ratio (HT), Recall, NDCG, and Precision. The proposed model was more accurate and outperformed several recommendation methods.

Proposed in [29] introduced a hybrid neural recommendation. They used ratings and reviews to predict deep representations. The main method was that the inherent complement between ratings and reviews was used in full. Review-level mechanisms, incorporating rating-based representation as a query vector to identify useful reviews, were introduced in the proposed mechanism. To evaluate the proposed model they used four standard datasets. The proposed methodology was tested using RMSE. The experimental results showed that in recommendations the proposed model exceeds existing competitive baseline techniques.

The proposed [30] applied the Generalized Probabilistic Matrix Factorization (GPMF) model for the recommender system, which used both explicit and implicit feedback to make recommendations. There were three experiments carried out: Probabilistic Matrix Factorization with explicit feedback in the first model. Another method is Probabilistic Matrix Factorization with Implicit Feedback. Probabilistic Matrix Factorization with explicit and implicit feedback is the third experiment. The proposed method was tested using an Amazon.com online review dataset on Electronics,

Books, Movies, Music, TV, Amazon Instant Video, and Home and Kitchen. The dataset was used to test the method. The experimental results revealed that the probabilistic Matrix Factorization model performed better when both explicit and implicit feedback ware used in conjunction with it.

There has been an introduction of a novel weak supervision approach in collaborative filtering recommendation systems, which makes use of both explicit and implicit feedback [31]. Instead of relying on the recommendation model as a shaky signal of supervision, the requested data was pre-processed. When it came to explicit and implicit feedback, they used six public datasets: GoodReads (Children), GoodReads (Fantasy & Paranormal), GoodReads (Comics & Graphics), Douban dataset, Steam dataset, and Dianping dataset. The experiments that were demonstrated produced better results.

The proposed method in [32] introduced collaborative filtering based on the implicit and explicit datasets using a k-means clustering algorithm. The dataset used was explicit rating from Douban movie short comments dataset from Kaggle contain 25 movies and 300 users. To evaluate the proposed approach, recall, precision, and F-measure were used. The experimental results have been better and they deal with the cold start problem by eliminating Wikipedia's movie information.

D. Summary of the Related Work

Explicit ratings are used to generate user preferences in the majority of works in the CF. They use several methods such as memory-based approaches like user-based and item-based CF or Model-based approaches like latent semantic methods, matrix factorization, and regression and clustering. The explicit rating in CF produces problems such as sparsity because of insufficient or missing information. Recently, user reviews (implicit ratings) were used in recommender instead of numeric ratings. Because it shows the consumer's emotional inclinations and provides a fine-grained view of the behavior of the users. Additionally, it handles scalability and sparsity problems. Recently, some researchers have combined explicit and implicit ratings in order to improve the accuracy and quality of the recommender system even further. This had resulted in a number of publications.

Our work in the recommender system uses explicit ratings only. Also, we used implicit ratings in another work. The third experiment combines explicit with implicit ratings. It is the first work that mixing explicit with implicit ratings using the Arabic dataset. All of this is a contribution to the field of Arabic recommendation researches.

IV. PROPOSED APPROACH

We expand our work for the Arabic recommender system by using both explicit and implicit ratings that used numeric ratings and user reviews. First, we find the general opinion of the user (positive, negative) for each review. Second, to obtain the overall ratings, we will combine the numerical ratings (explicit ratings) with the scores of the sentiment analysis. Third, in our recommendation system, we used collaborative filtering to predict any book for a particular user. This paper focused on two successful approaches in CF, which are Item-based and SVD based CF. See the section background. The proposed approach enhances performance quality and disposes of most of the problems in the

recommender system. In addition, achieves better results than using explicit or implicit rating method alone. Figure 1 depicts an overview of the proposed approach.
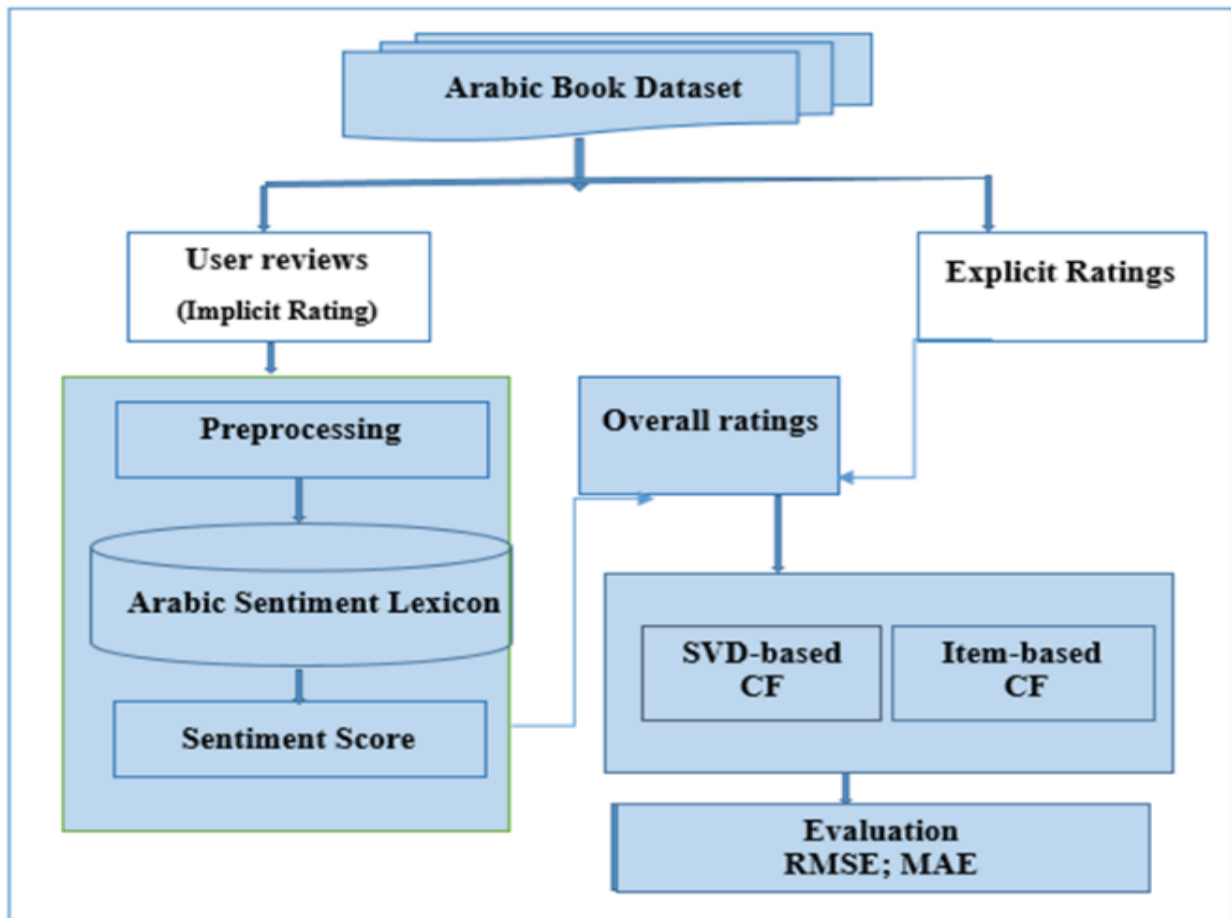

Fig. 1: Collaborative Filtering Using Explicit and Implicit Ratings for Arabic Dataset

User	Item				
1	5	3	4	?	4
2	?	4	?	?	2
3	?	?	?	5	?
4	4	?	?	?	?
5	?	2	5	3	?

Item	Reviews
1	هو ممتع في المجمل احداثه مشوقه هيبا شخصيته غريبه فعلا تراه في اوقات مثال للعابد المستمتع بقربه من الله ثم ينقلب فجاه مع اقل اغراء مبادءه لكنه حتى مع استسلامه للحب فهو منهزم في التمسك به يريد ان ياخذ ولا يعطي ...اسوأ شيء فيه
2	يتحدث الكاتب عن فتره تاريخيه تقريبا لا احد يتكلم عنها فتحمل بيعض المعلومات عن اللاهوت ولكن لم يعجبني في الرواية التفاصيل الكثيرة.....
3	محبتهوش خالص مع ان اصحابي كتيير حبينة
4	رواية عبقرية بكل المعاني
5	إني أقدّر هذه الرواية كثيرا، لسبب مختلف عن أسباب الآخرين، ألا وهو أنها علمتني درسا قيما، حتى وإن كانت العبرة قد أتت بعد فوات الأوان، وذلك عهدنا بدروس الحياة. علمتني الرواية أن الصديق الذي يشجعك على قراءة مثيلاتها دون أي إشارة إلى المقاطع الإباحية التي هي فيها،الثانية

Fig. 2: Example of the dataset that contains both explicit rating and implicit rating

A. Combining Explicit and Implicit Rating

In this work, we employed explicit ratings of 1 to 5 stars. We added user reviews as implicit ratings in our dataset. After performing the sentiment analysis process produced two opinions: positive and negative opinion by applying a special LABR dataset manual lexicon [43]. In order to determine whether a review is positive or negative, the sentiment scores are calculated by aggregating the sentiment scores of each word in the review. If the number of positive words outnumbered the number of negative words, the review was considered positive; otherwise, it was considered negative. We converted the positive opinion to a score of 5 and the negative opinion to a score of 1, where 5 represents the highest score and 1 represents the lowest score. To combine two ratings, first, we compute the average of explicit ratings and sentiment scores to obtain overall ratings. Then, we normalize the overall rating to go into the collaborative filtering algorithm. We used the two types of CF that were discussed in the background section. The algorithm shown in Figure 3 explains all of these steps, including how to combine explicit and implicit ratings, calculate the overall sentiment score for any review, and compute the overall ratings for sentiment score with ratings.

```
Input: Reviews, Ratings (1-5)
Output: overall ratings
Lexicon=dict ()
Sentiment score=0
Function Senti_Score (reviews)
#Read the Lexicon
Read lexicon (sentiment word)
# Preprocessing reviews
 For each review R in Dataset
  Remove stop words
    Score=0
    Sentiment score=0
  For each word in review
        If word found in Lexicon   then
            Score=Score + Lexicon (word)
    End For
                                    If Score > 0 then
                                        Score=5
                                 Else
                                        Score=1
                            Sentiment score = Sentiment score + Score
                              End if
                        End For
                        Return: (Sentiment score).
                        Function Merge _Exp_Imp (Rating, Sentiment score)
                            For each Rating, Sentiment score in Dataset
                            Overall ratings = the average of (Rating, Sentiment score)
                            Return: (overall ratings)
                        Normalize (overall ratings)
```
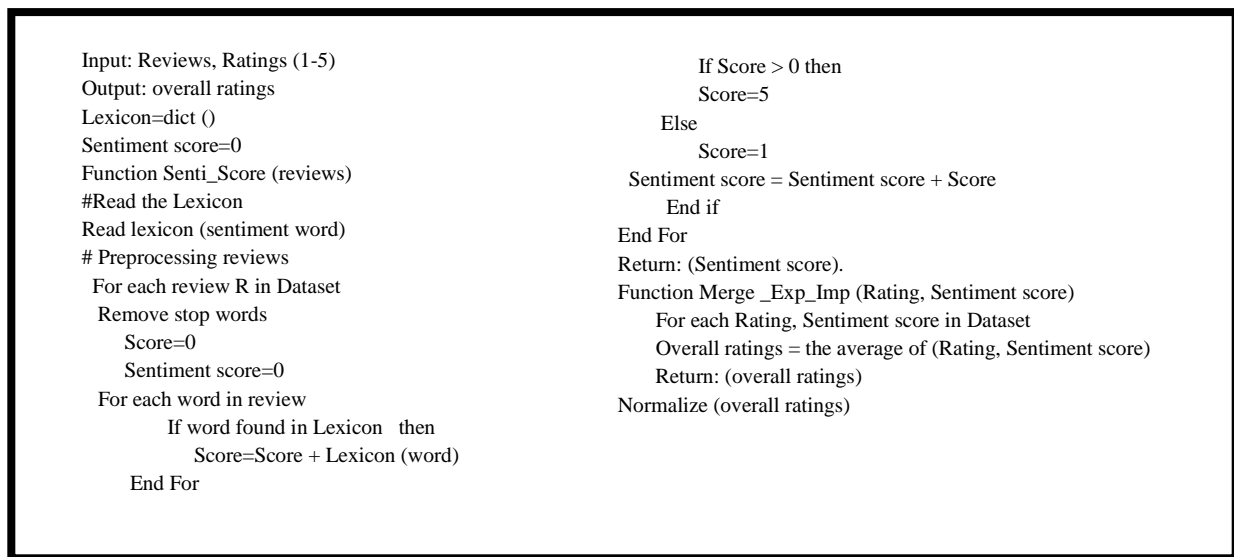
Fig. 3: Algorithm for calculating overall ratings

V. EXPERIMENTAL WORK

The dataset used in the experiment was the Large Scale Arabic Book Review (LABR). It has over 63 thousand user reviews and ratings [44]. Table 1 shows the dataset that was used to evaluate the proposed method. After conducting sentiment analysis for user reviews, four fields were considered to predict user ratings using collaborative filtering: user ID, book ID, ratings, and reviews.

Table 1: Dataset used in proposed approach evaluation

Number of ratings	63257
Number of unique book id's	2131
Number of unique users	16486
Number of unique reviews	60152
Average number of ratings every user	3.6500
Average number of ratings every book	28.230
Average number of reviews every user	3.6500
Average number of reviews every book	28.2300

For evaluation, we employed statistical accurate measurements that are the most popular prediction accuracy measure to evaluate performance in the CF method.

Mean Absolute Error (MAE) is a metric used to compute the average of all the absolute value differences between the algorithm's predicted rating and the actual rating [35, 45].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|p_i - q_i| \qquad (5)$$

Where, pi is the actual rating, qi is the predicted rating and n is the amount of ratings

Root Mean Squared Error (RMSE) is a metric computes the mean value of all the differences squared between the true and the predicted ratings. Then, it proceeds to calculate the square root out of the result. RMSE metric is the most valuable metric when significantly large errors are unwanted [46, 47]. It is computed as follows:

$$RMAE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(|p_i - q_i|)^2} \qquad (6)$$

Cross-validation is a technique used to verify statistical evidence. Cross-validation divides a dataset into partitions of equal size k. One of the partition will be used as a test partition while the remaining partitions will be used as

training partitions. The algorithms then train a model with the training partitions, and the when the training is complete, the model is tested with the test partition, producing test data. This process proceeds until each partition is the test partition [47].

We split the datasets into 80% for training, and 20% for data testing. Both item-based CF and SVD-based CF are evaluated 5-fold using the LABR dataset. The results are evaluated, interpreted, and compared using an absolute mean error and a square root mean error. In the results, this will be seen.

VI. RESULTS

This section presents a summary of the overall results of the experiments conducted in this paper, which included both explicit and implicit ratings. Also shown are the results of our previous work when used a single rating implicit or explicit

A. Results of using Explicit Rating in CF

There are two experiments that are carried out. In the first experiment, we evaluated Item-based. The second one experiment the effectiveness of SVD-based CF. See Table 2and Table 3.

Table 2: Results of Item-based CF using Explicit Rating

	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Average
RMSE	1.199	1.190	1.196	1.206	1.193	1.197
MAE	0.921	0.921	0.922	0.932	0.914	0.922

Table 3: Results of SVD-based CF using Explicit Rating

	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Average
RMSE	1.021	1.008	1.020	1.019	1.023	1.019
MAE	0.813	0.801	0.809	0.804	0.810	0.808

B Results of using Implicit Ratings in CF

Table 3 and Table 4 show results of using implicit ratings in both methods CF: Item-based and SVD based CF.

Table 4: Results of Item-based CF using Implicit Ratings

	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Average
RMSE	0.562	0.552	0.556	0.557	0.561	0.558
MAE	0.158	0.152	0.154	0.155	0.157	0.155

Table 5: Results of SVD -based CF using Implicit Ratings

	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Average
RMSE	0.539	0.566	0.571	0.561	0.56	0.560
MAE	0.152	0.167	0.171	0.166	0.165	0.164

C Results of using Explicit and Implicit Rating

It is shown in this section that results of explicit and implicit ratings in two types of collaborative filtering: item-based and SVD-based CF

1) Item-based CF

In this experiment, the similarity of books is measured via a cosine similarity measure. We used the LABR dataset with a 10-neighborhood-size algorithm which was cross-validated. We have experimented with training data and used a test set to calculate MAE and RMSE. The mean RMSE and MAE values of 0.330 and 0.227, respectively, are presented in Table 6 and Figure 4.

Table 7: Results of item -based CF

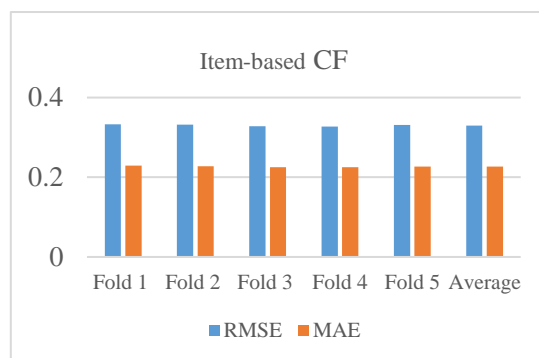|	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Average
RMSE	0.333	0.332	0.328	0.327	0.331	0.330
MAE	0.229	0.228	0.225	0.225	0.227	0.227

Fig. 4: Results of Item-based CF

2) SVD-based CF

In this experiment, SVD-based CF was presented. The dataset was cross-validated. We conducted a training experiment and utilized a test set to determine RMSE and MAE. Table 7, Figure 5 shows the RMSE and MAE results. The mean of RMSE and MAE respectively were 0.330 and 0.2278.

Table 7: Results of SVD -based CF

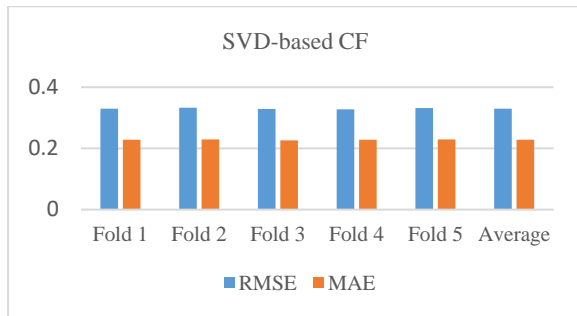|	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Average
RMSE	0.330	0.333	0.329	0.328	0.332	0.330
MAE	0.228	0.229	0.226	0.228	0.229	0.228

Fig. 5: Results of SVD-based CF

VII. CONCLUSION

In recent years, much work has been dedicated to using implicit ratings to enhance recommendation systems due to the appearance of sentiment analysis techniques. Explicit and implicit ratings give varying levels of expression about the user's preferences. This work aims to improve the overall quality of Arabic collaborative systems and achieve a minimum error rate. This paper proposed collaborative filtering based on explicit and implied ratings on LABR data. We used the user reviews as implicit ratings and numerical ratings as explicit ratings. The proposed approach improved the accuracy of the Arabic recommendation system and reduced the average error values in terms of RMSE to 0.33. Compared to our previous works on the same dataset, the proposed approach yields better results using explicit and implied ratings than using the single-rating in CF.

For future work, we will employ novel of methodologies for the Arabic dataset in order to achieve the highest accuracy and speed possible.

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