

# Presenting a personalized web recommender system based on hierarchical clustering and deep autoencoding

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## Abstract

The amount of information published on the web has made the use of recommender systems inevitable. Web recommender systems provide users with accurate and relevant suggestions based on their interests and tastes. These recommendations can help users quickly access the information they need and reduce search time. In this article, a hybrid recommender system based on the combination of fuzzy sequential clustering and deep self-encrypting network based on user profile information and ranking of websites by users is presented. In this recommender system, users are first clustered according to the similarity of their opinions. Then the new ranking for users is predicted according to the fuzzy membership function. Finally, the information available in the user profile and the new rating of the users to each website is used as the input of the presented deep encoder network in order to predict the rating of the websites by the users. Finally, after finding similar users, it will recommend visiting and personalizing the web page of serious users based on the favourite websites of similar users. According to the layers of in-depth training and completion of the training process in the middle layer, the proposed method has been able to outperform other classification methods in terms of statistical accuracy of about 42% and the ratio of successful recommendations to useful recommendations of about 4% and accuracy The detection of similar users has improved by about 20%.

Keywords: recommender system, user profile, self-encrypting networks, collaborative filter  
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## 1 Introduction

Recent developments in technology, along with the proliferation of online services, have provided a greater ability to access large amounts of online information at greater speeds. Users can submit reviews, comments, and ratings for a variety of online services and products. However, recent developments in ubiquitous computing have led to the problem of online data overload. This data overload complicates the process of finding relevant and useful content on the Internet. However, the recent establishment of several methods with lower computational requirements can direct users to relevant content more easily and quickly. For this reason, the development of recommender systems has attracted considerable attention in recent times. In general, recommender systems act as information filtering tools and provide users with appropriate and personalized content. Recommender systems basically aim to reduce the effort and time required by the user to search for relevant information on the Internet [11].

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Currently, recommender systems are used in a large number of applications. Therefore, it is very important to build high-quality and unique recommender systems to provide personalized recommendations to users in various applications. Despite various advances in recommender systems, the current generation of recommender systems needs further improvements to provide more efficient recommendations that can be used in a wider range of applications. Further investigation of new works in the field of recommender systems that focus on diverse applications is needed [15].

One of the most widely used methods used in recommender systems in social networks is the method based on collaborative filters [17]. In collaborative filtering, the task is to recommend items to an active user based on his and other users' preferences. In most cases, preferences are expressed as numerical evaluation scores [14].

Collaborative filter-based approaches are divided into two types: memory-based approaches and model-based approaches. Memory-based approaches recommend new items by considering neighbours' preferences. They use the preference matrix directly for prediction. In this approach, the first step is to build a model. The model is equivalent to a function that takes the preferences matrix as input.

Recommendations are then made based on a function that takes the user's model and profile as input. Here we can only recommend users whose user profiles belong to the preferences matrix. Therefore, to recommend a new user, the user's profile must be added to the preference matrix and the similarity matrix must be recomputed, which will increase the computational complexity [6].

Model-based systems use various data mining and machine learning algorithms to develop a model to predict a user's score for an unscored item. When the recommendations are computed, they do not depend on the complete data, but instead extract features from the data and compute the model. Therefore, this method is known as the model-based method. These techniques also require two steps for prediction - the first step is to build the model and the second step is to predict the scores using a function ( $f$ ) that takes the model defined in the first step and the user profile as input. Model-based techniques do not need to add new user profiles to the utility matrix before making predictions. We can even recommend users who are not in the model. Model-based systems work better for group recommendations. They can quickly recommend a group of items using a pre-trained model. The accuracy of this technique significantly depends on the efficiency of the learning algorithm used to create the model. Model-based techniques can solve some of the traditional problems of recommender systems such as sparseness and scalability by using dimensionality reduction and model learning techniques [18].

A hybrid technique is a set of two or more techniques that are used together to address the limitations of individual recommender techniques. Combining different techniques can be done in different ways. A hybrid algorithm may combine the results obtained from separate techniques, or it may use content-based filtering in a collaborative method or a collaborative filtering technique in a content-based method. This combination of different techniques generally leads to increased performance and increased accuracy in many recommender programs [9, 2].

In this article, a hybrid recommender system based on user profile is presented, in which Fuzzy Sequential Clustering (FOCA) is used based on the similarity of users' opinions, and based on this, it is used to predict the ranking of new users using the network. The neural auto-encoder has paid. Based on the combination of these two methods, the accuracy of identifying similar users and the accuracy of predicting the rating of other users' opinions can be increased. The presented method is a hierarchical approach in which, in the first step, user profile information is used to extract similar users in the educational data set and the similarity weight of educational users. This information will be used for fuzzy sequential clustering of users. Finally, the similarity weight of users along with the information in the user profile is presented as a feature for the users to the presented automatic coding neural network, so that instead of using the initial random weight for bias, the similarity weight of the users is used. Finally, the features of the users in the user profile and their similarity weight are used as the input of the provided deep automatic encoder neural network to predict the ranking given to the websites by new users. After determining the ranking given by new users to websites, the similarity between new users and educational users is calculated. Finally, the decision to recommend an item to a user is made based on the similarity between users and items of interest to similar users. Users whose features are similar and have more similarity weight can be considered as similar users, and their favourite items that they have given the highest score to each other as the top K items. be suggested The main contribution of this paper is summarized as follows.

1. Fusion of data in the form of a decision support system
2. Using fuzzy sequential clustering in order to find similar users
3. Using the deep automatic encoder neural network in order to predict the rating given by new users to websites.

4. Calculation of similarity between users based on deep self-encrypting networks based on cooperative filter
5. Find the top  $K$  items based on similar users in the social network

## 2 Research background

Due to the importance of recommender systems, recently various works have been presented in this field, some of which will be mentioned below. In [5], a personalized news recommendation framework called HYPNER is proposed. HYPNER combines both common filter-based and content-based filtering methods. The proposed framework aims to improve the accuracy of news recommendations by solving the scalability issues due to the large news collection, enriching the user profile, displaying detailed news features and characteristics, and recommending a diverse set of news. In [16], a deep learning-based algorithm for multi-criteria recommender systems is proposed, where deep auto-encoders exploit non-trivial, nonlinear, and hidden relationships between users according to multi-criteria preferences, and generate more accurate recommendations. In [8], an attempt has been made to investigate a new clustering technique called Ordered Clustering Algorithm (OCA) to reduce the effect of cold start and data sparsity problems in e-commerce recommendation systems. In [12], a recommender system based on the convolutional neural network using the outer product matrix of features and reciprocal convolutional filters is proposed. The proposed method can deal with different types of features capture higher-order meaningful interactions between users and items and give more weight to important features. In addition, it can reduce the problem of overfitting because the proposed method involves global average or maximum integration instead of fully connected layers in the structure. In [7], an auto-encoder, which is a powerful model in data dimensionality reduction, feature extraction and data reconstruction, is used to learn and predict student preferences in an e-learning recommender system based on collaborative filtering. In [3], a recommendation system for fashion retail stores is proposed based on the multi-clustering approach of items and user profiles in online and physical stores. The proposed solution relies on mining techniques, which make it possible to predict the purchase behaviour of new customers, thus solving the cold start problems typical of advanced systems. In [1], a tourism recommendation system has been introduced that extracts user preferences to provide personalized recommendations. For this purpose, users' comments on tourism social networks are used as a rich source of information to extract their preferences. Then, pre-processed comments are semantically clustered, and the sentiment is analyzed to identify a tourist's preferences. Similarly, all collected opinions of users about an attraction are used to extract the features of these points of interest. In [10], this recommendation system uses model-based collaborative filtering and recommends products based on ratings and previous purchase history of old users. Also, new users will receive recommendations of new products, popular products, and products on sale. Existing users will receive recommendations based on recently viewed products, complementary products, etc. Since we are launching a new e-commerce website, initially there are no user ratings for different products, so in this case, the recommendations are based on the textual clustering analysis of the collaborative filter product description. Model-based combined with text clustering helps us improve accuracy and target different types of users. In [4], the performance of such algorithms has been compared using different data sets and evaluation criteria. A deep learning approach called GRU4REC and simpler methods are included in the comparison. Real-world datasets from three different domains are included in our experiment. In, research has been proposed to provide personal recommendations to clients based on what similar people have with similar portfolios. This system uses customer characteristics in addition to customer portfolio data. Since the number of possible recommended products is relatively small, compared to other recommender domains, and missing data is relatively frequent, it is decided to use Bayesian networks to model the system. A deep learning-based approach is also presented to provide recommendations to prospects (potential customers) where only external marketing data is available at the time of forecasting. In [19], a convolutional neural network (CNN) is integrated with a particle swarm optimization (PSO) algorithm to generate unique recommendations. The proposed method is based on focus change points, which include unexpected and related parameters.

## 3 Suggested method

As mentioned, in this article, an approach for recommending web pages based on user profiles in social networks using a combination of fuzzy sequential clustering and automatic encryption networks is presented. The architecture of the proposed method is shown in Figure 1.

The proposed method starts with the user review dataset. This data set includes users' characteristics as well as users' votes for the items in the data set. In the Yelp dataset, users' opinions are based on their interest in the places they have seen, and in the TripAdvisor dataset, users' opinions are based on the accommodation or hotels they have

been to. In the proposed method, users' opinions about their stay are also mentioned in the dataset, which is used as user profile information.

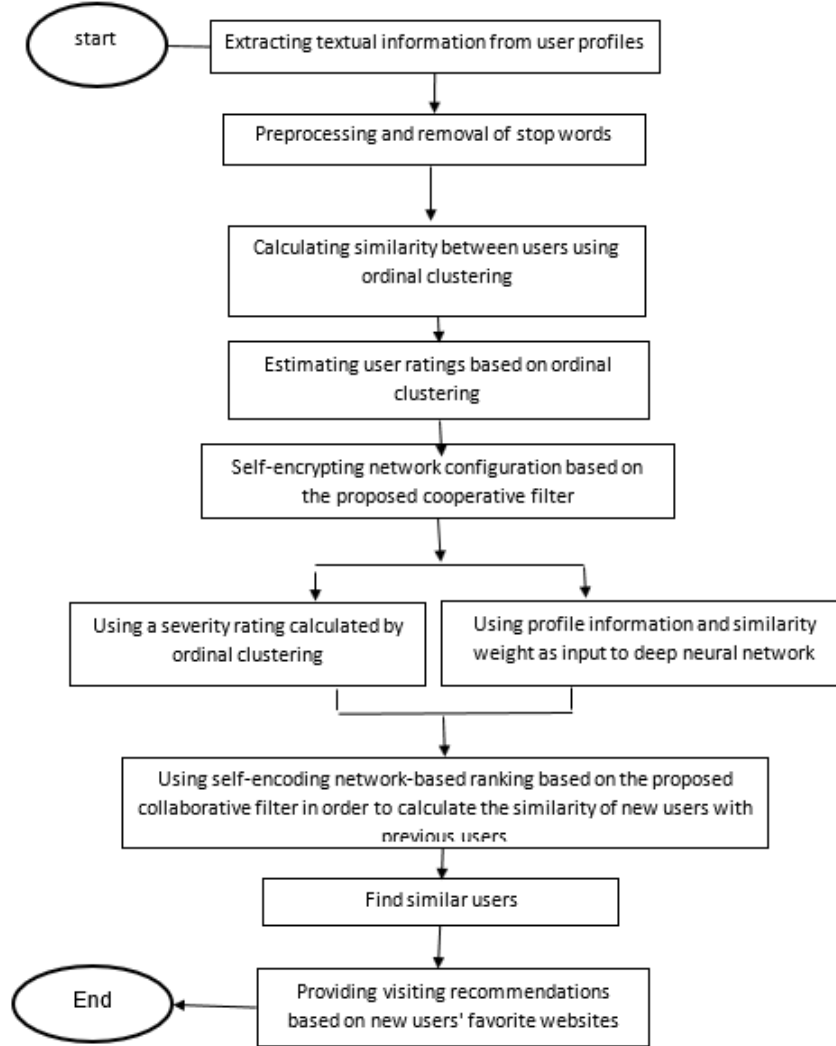


Figure 1: Architecture of the proposed method

In the proposed method, at first, according to the cosine similarity criterion, the similarity matrix of users is extracted according to their opinions. Cosine similarity is a well-known criterion in information retrieval and related studies. This benchmark models a text document as a vector of terms. Using this model, the similarity between two documents can be determined by calculating the cosine value between the term vectors of the two documents. The implementation of this criterion can be applied to both texts (sentence, paragraph, or whole document). In the case of the search engine, the similarity value between the user query and the documents is sorted from highest to lowest. A higher similarity score between the term vector of the document and the term vector of the query means that there is a greater match between the document and the query.

Cosine similarity to measure the similarity between the document and the user's query should be consistent with the meaning of the words. However, cosine similarity still cannot control the semantic meaning of the text well. Implementing the cosine similarity measure between two idiom vectors from a syntactic point of view sometimes produces invalid results. Syntactic matching may not be able to meet the problem of semantic difference optimally. For subsequent processing, such as a data recovery system, it may produce incorrect results and reduce its efficiency. The relationship of the cosine similarity criterion is expressed as follows.

$$Sim(\vec{q}, \vec{d}) = \frac{\vec{q} \cdot \vec{d}}{|\vec{q}| |\vec{d}|} = \frac{\sum_{k=1}^t w_{qk} \times w_{dk}}{\sqrt{\sum_{k=1}^t (w_{qk})^2} \cdot \sqrt{\sum_{k=1}^t (w_{dk})^2}} \quad (3.1)$$

where  $q$  and  $d$  refer to texts and  $t$  is the number of words in the text and  $w$  is the weight of each word. The similarity matrix is sent as input to the sequential clustering method. In order clustering, similarity values are first sorted in descending order. Then the first value that represents the most similarity between users is selected as the first cluster. Users who are similar based on this value are placed in the first cluster. Then the second value in the ordered similarity matrix is considered as the second cluster. Finally, a cluster is considered for each similarity value in the adjacency matrix. Then the ranking of the users of this cluster is predicted according to the fuzzy membership function. The fuzzy membership function in the proposed method is defined as follows.

$$FMEM(i, K) = \frac{\sum_{i=1}^n \sum_{j=1}^K Rate_i - F_j * Sim_{qd}}{n}, K = \{1, 2, \dots, 5\} \quad (3.2)$$

where  $n$  is the number of users in the cluster,  $K$  is the class or rank, which can be a value between the real interval of one to five,  $Rate_i$  is the real value of the rank given by the user and  $Sim_{qd}$  is the similarity between two is the user. Based on this, the membership value of users' comments is determined for each of the 5 classes, which include ranks 1 to 5. After determining the serious value of users' ratings, these values along with users' comments are used as input to the proposed self-encoding neural networks. In the following, we will examine the architecture of the presented deep self-encoder neural networks.

### 3.1 Auto encoder deep Neural Network

In this section, an autoencoder is developed to learn a compact representation of input features for a classification prediction modelling problem. First, a classification prediction modelling problem is defined. To define a binary (2-class) classification task, the profile features of users in social networks are modelled using an input matrix with feature columns  $F$  and rows of  $n$  users in the initial input matrix. Also, an  $n \times n$  matrix is entered into the autoencoder as the initial similarity weight. In the encoders themselves, the initial weight is randomly generated for the inputs, and after repeating this weight several times, it is updated and converges towards the ideal weight of the users. Provided that the initial weight is provided based on the similarity of users' opinions, which can accelerate the process of convergence towards optimal weights.

When we use our encoder network as a feature extractor, we need to remove some input data in the middle layer to extract the essential features from the inputs. Therefore, the problem is defined to include some additional input variables. This allows the coder to further learn a useful compressed representation. Encoder networks are usually restricted in such a way that they are only allowed to approximate and copy inputs that are similar to the training data. As the model has to prioritize which aspects of the input to copy, it often learns useful features of the data. The input data can then be fed from the domain to the model, and the model output at the bottleneck can be used as a feature vector in a supervised learning model, for visualization, or in general for dimensionality reduction. Also, the weight of each layer is considered as the similarity weight of users, and this weight is updated in each layer to finally extract the real similarity weight of users from the encoder network.

The encoder is defined to have two hidden layers, the first layer with twice the number of inputs ( $2n$ ) and the second layer with the same number of inputs ( $n$ ), followed by the bottleneck layer with the same number of inputs as the input data set ( $n$ ) is. To ensure better learning of the model, batch normalization and leaky ReLU activation are used.

The decoder is defined in a similar structure, however in reverse. It has two hidden layers, the first layer with the number of entries in the dataset ( $n$ ) and the second layer with twice the number of entries ( $2n$ ). The output layer has the same number of nodes as the input data columns and uses a linear activation function to output numerical values. The model is trained using the Adam optimizer with stochastic gradient descent, by minimizing the mean squared error. Figure 2 shows the proposed encoder architecture.

According to Figure 2, the decoding network architecture based on defined layers is presented. The output of this step is recommended for the module. The difference between the presented neural networks and the previous ones is in the number of intermediate layers that allow deep training on user profile features and increase the accuracy of rating prediction to new users. In the following, we will explain the recommended module.

### 3.2 Recommended module provided

The recommendation module in the presented method is the last part where page visit recommendations to users happen based on the results of the presented encoder network. The output of the encoder network includes important features extracted from users' profiles and users' similarity weights, which were explained in the previous section. In

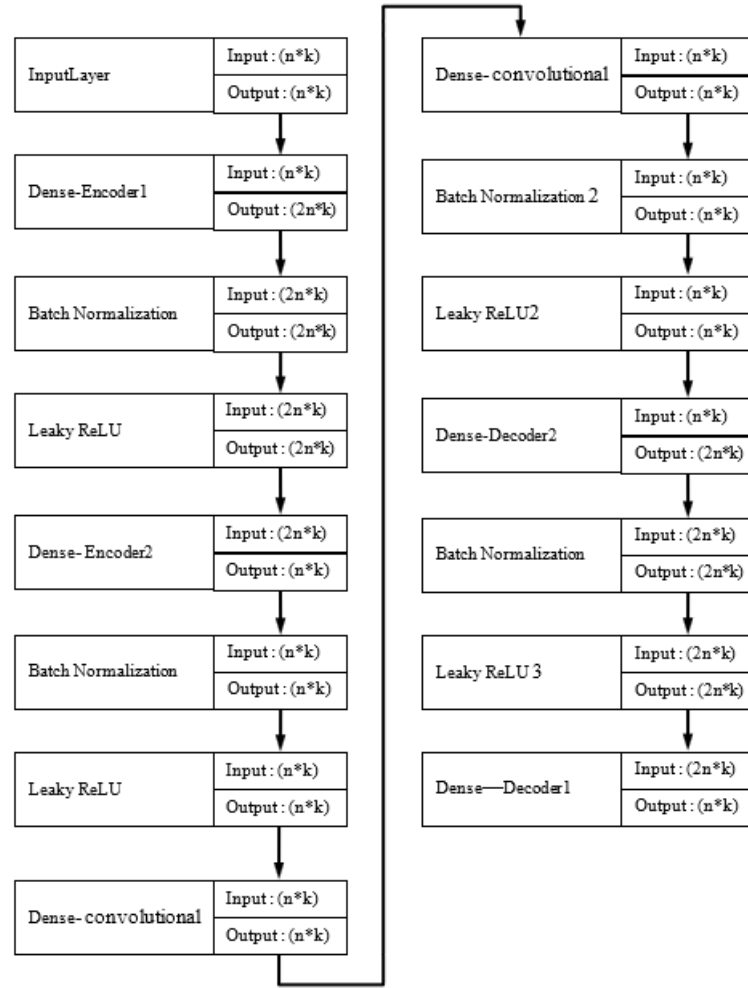


Figure 2: The proposed self-encoder network architecture

this step, based on the similarity weight of users in clusters and serious ranking based on fuzzy ordinal clustering,  $k$  top similar users are selected for each user. The value of  $k$  takes different values in several different scenarios, and finally, the system performance is measured based on the number of  $k$  similar users. These  $k$  users are considered as users who can have similar opinions and tastes in terms of the presented method. Therefore, for each user, the items to which  $k$  similar users have assigned the highest rating can be used as suitable options for recommendation. In other words, if user  $i$  and  $j$  are considered similar based on the similarity weight values, the items that are rated the highest or 5 by user  $j$  can be considered as suitable items to suggest to user  $i$ . Also, the items that are rated the most or 5 by user  $i$  can be considered as suitable items to suggest to user  $j$ .

#### 4 Implementation of the presented method

As mentioned, two large-scale real-time data sets, Yelp and TripAdvisor, have been used in the proposed method to implement a personalized recommender system based on the user's profile. This data set includes information extracted from users' profiles about products in text form and users' ratings of available products. Users are identified according to the unique identifier in the dataset. According to the data in the dataset, the presented method tries to personalize the web page based on user behaviour. The behaviour of users is deduced based on the information in the user's personal profile and the similarity between users is calculated based on it. Table 1 shows the specifications of the data set used.

In this data set, is divided into two parts: training data with a ratio of 70% of the total data and test data with a ratio of 30% of the total data. In Yelp's educational dataset, along with users' ratings for products, comments, and users and their profile information are included in text form. The textual information included in the user profile shows

Table 1: Characteristics of the data set used

Field titles	Number of fields	number of samples	The title of the data set
Review Rating	2	20492	TripAdvisor
business_id date review_id stars Text Type user_id Cool useful funny	10	10000	Yelp

the feelings and emotions of the users towards the product and along with the rating values given to the product by the user, they can be used to analyze the behavior of the users. Traditional recommender systems ignore the analysis of textual information in users' profiles and use their ratings to calculate the similarity between users. However, the textual information included in the users' profiles contains valuable hidden knowledge based on which the similarity of the users can be measured with higher accuracy. Therefore, in the presented method, we will analyze the information in the user profile.

The information in the user profile is in the form of continuous text, which needs to be pre-processed and the stop words removed before making changes. After preprocessing, the similarity between users' opinions is extracted based on the cosine similarity measure. Figure 3 shows the cosine similarity matrix for 10 users from the training dataset as an example.

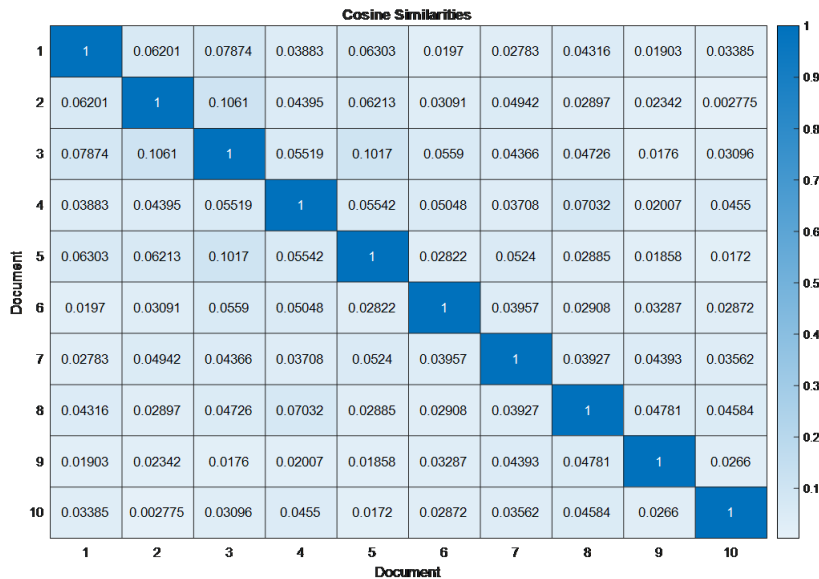


Figure 3: Similarity matrix between users

According to Figure 6, it can be seen that the similarity matrix for users in the recommender system is calculated based on the information in the user profile. As can be seen, the similarity value for each user pair is a value in the range of  $[0,1]$ , which shows the similarity between two users in terms of user profile information. The higher this value is, the more similar the two users are in terms of user profile information. Therefore, in the presented method for finding similar users, a threshold is defined, which is in the form of the following relationship:

$$\alpha = \frac{sim(i, j)}{\sum_{i=1}^n \sum_{j \neq i}^n sim(i, j)} \geq 1. \quad (4.1)$$

In relation (4.1),  $i$  and  $j$  are the index of users and  $n$  is the total number of users in the training dataset. After

calculating the similarity between users' opinions, in the proposed method clustering is done based on fuzzy ordering, where users are assigned to each cluster according to the similarity value. After assigning users to clusters, the new ranking value of users is calculated according to the fuzzy membership function. Table 2 shows an example of sequential clustering of users based on the similarity of their opinions.

Table 2: Sequential clustering of users based on the similarity of comments

Cluster number	Similarity value	Similar users	Predicted rank
1	0.4640	[216;680]	5
2	0.4480	[554;998]	2
3	0.4370	[18;457]	4
4	0.4240	[245;935]	5
5	0.3850	[133; 542]	5

According to table 2, it can be seen that users are placed in clusters based on the similarity of opinions. Considering that each user can fit in only one cluster, there may be only one user in some clusters. Based on the presented method, users assigned to a cluster have the highest probability of similar behaviors, based on which recommendations for visiting the web can be suggested. In fact, users with more similarity in terms of user profile information can be a suitable option for the input of the collaborative filter method based on deep learning. Deep learning has been used in the presented method to accurately identify similar users. The provided deep self-encrypting networks are suitable for finding similar users in terms of user profile information due to various applications. In this type of network, user profile information and similarity matrix between users are considered as input features of the network. Also, users' ratings of products are considered target variables. Neural networks provided with deep learning try to learn the characteristics of each user and find similar users in terms of the ratings given to websites by users. Finally, to validate their training, they use the similarity network between users as a benchmark and evaluation criterion. If the accuracy of the presented neural networks is optimal, the training results are extracted as the weight of the features and words in the user profile and are used as a model to find new similar users. Therefore, the more accurate the training of deep neural networks, the more accurately similar users are found. Finding similar users can provide more accurate recommendations to users, especially new users. Figures 4 and 5 show the neural network training process presented on TripAdvisor and Yelp training datasets. Also, in Tables 2 and 3, the accuracy of neural networks in finding similar users during iteration steps in the training dataset of TripAdvisor and Yelp is shown.

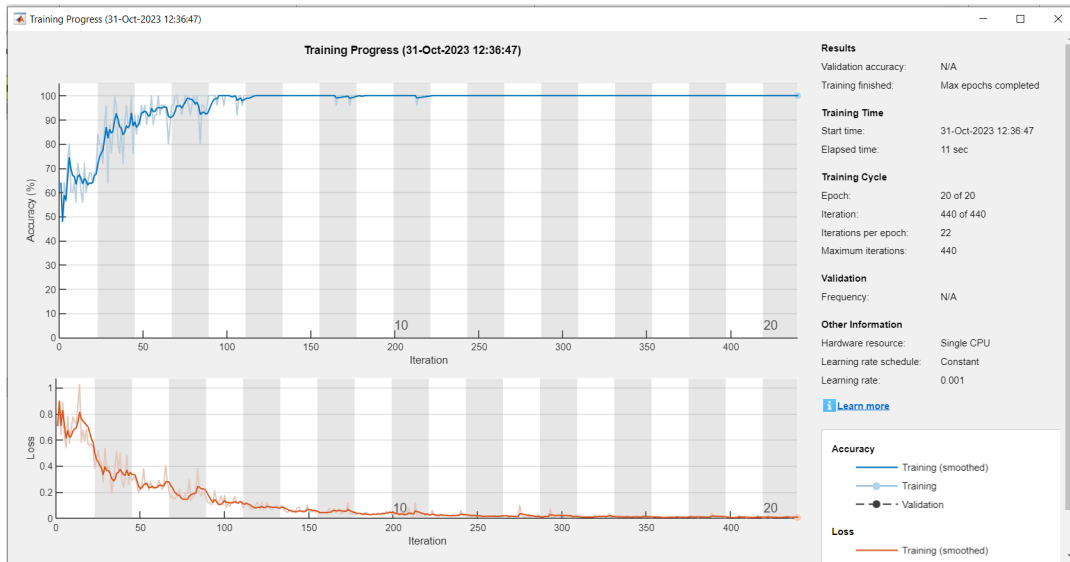


Figure 4: Neural network training process presented on TripAdvisor training dataset

According to Figure 4 and 5 and Table 3 and 4, it can be seen that the neural networks presented at the beginning in setting the weights and training the features of the users have a high error value, which increases with the increase in the number of repetitions. The value is close to zero.

At this stage, the results obtained from the deep neural network for the users in the test data set are measured based on the ratings given to the products by the test users. For this purpose, the test users who have given the

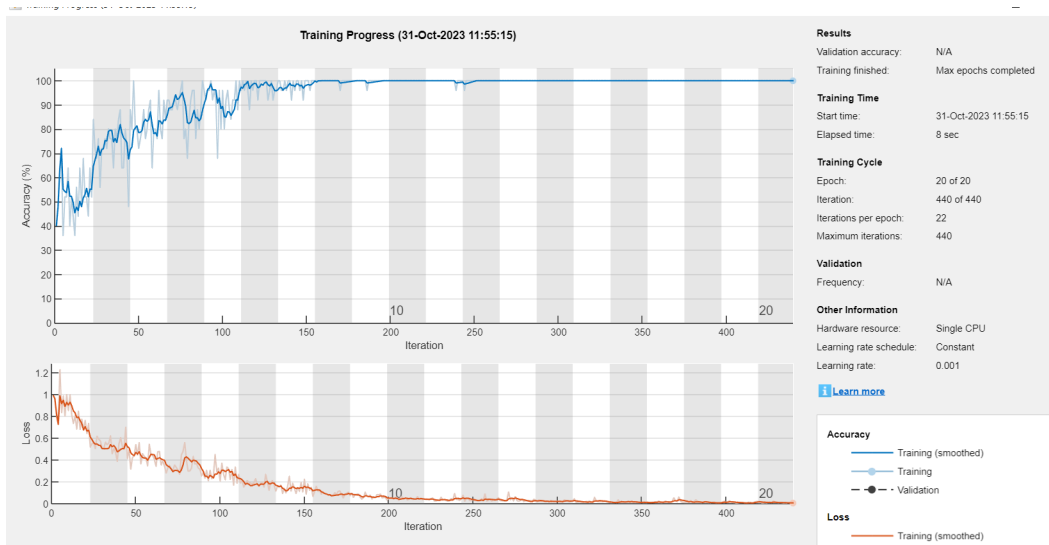


Figure 5: Neural network training process presented on Yelp training dataset

Table 3: The accuracy rate of the presented neural network in finding similar users during the iteration steps in the training dataset of TripAdvisor

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Mini-batch Loss	Base Learning Rate
1	1	00:00:04	64.00%	0.7047	0.0010
3	50	00:00:05	92.00%	0.2257	0.0010
5	100	00:00:06	100.00%	0.1763	0.0010
7	150	00:00:06	100.00%	0.0495	0.0010
10	200	00:00:07	100.00%	0.0338	0.0010
12	250	00:00:08	100.00%	0.0147	0.0010
14	300	00:00:09	100.00%	0.0273	0.0010
16	350	00:00:10	100.00%	0.0087	0.0010
19	400	00:00:10	100.00%	0.0073	0.0010
20	440	00:00:11	100.00%	0.0059	0.0010

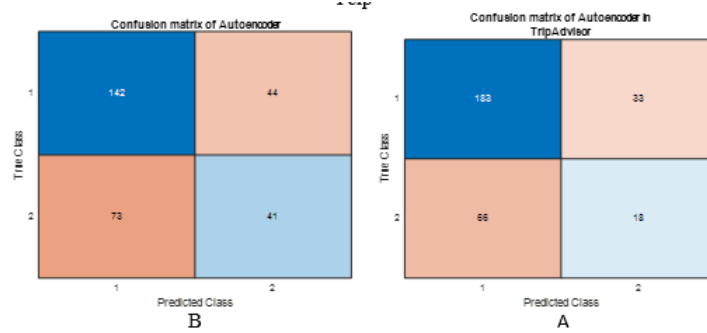
Table 4: The accuracy rate of the presented neural network in finding similar users during the iteration steps on the Yelp training dataset

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Mini-batch Loss	Base Learning Rate
1	1	00:00:03	40.00%	0.9918	0.0010
3	50	00:00:03	72.00%	0.5394	0.0010
5	100	00:00:04	96.00%	0.2060	0.0010
7	150	00:00:04	100.00%	0.2214	0.0010
10	200	00:00:05	100.00%	0.0524	0.0010
12	250	00:00:06	100.00%	0.0376	0.0010
14	300	00:00:06	100.00%	0.0220	0.0010
16	350	00:00:07	100.00%	0.0115	0.0010
19	400	00:00:07	100.00%	0.0081	0.0010
20	440	00:00:08	100.00%	0.0062	0.0010

website the maximum rating and based on the prediction of the deep neural network, the rating given by these users to the website is the maximum, are considered as true positive samples (TP). The test users who did not give the maximum rating to the website and based on the prediction of the deep neural network, the rating given by these users to the website is not the maximum, are considered as true negative samples (TN). Test users who gave the website the maximum rating, but based on the prediction of the deep neural network, the rating given by these users to the website is not the maximum, are considered as false positive samples (FP). Finally, the test users who did not give the website the maximum rating, but based on the prediction of the deep neural network, the rating given to

the website by these users is the maximum, are considered as false negative samples (FN). These four parameters together are determined as parameters of the disturbance matrix. Table 5 shows the confusion matrix related to the deep self-encrypting networks presented to the test users in the TripAdvisor dataset.

Table 5: Confusion matrix related to deep self-encrypting networks in the datasets: a) TripAdvisor, b) Yelp



As shown in Table 5, the confusion matrix related to the proposed deep self-encrypting networks method is presented. Next, we will evaluate the proposed method

#### 4.1 Evaluation of the presented method

The performance quality of the recommender system can be measured by many criteria. The type of criteria used depends on the filter and presentation method used. The accuracy of recommender system performance is determined based on the accuracy of recommendations provided to users. In this research, considering the combination of the collaborative filter method and deep learning, two criteria have been used to measure the performance accuracy of the proposed combined method. The first criterion is the statistical accuracy criterion to measure the accuracy of the predicted rating for users in the collaborative filter method and the accuracy in providing recommendations to similar users among new users. The second criterion is to evaluate the performance of deep neural networks to predict the rating given to the product based on the information in the user profile and compare it with other classification methods. In the following, we will first evaluate the presented method based on statistical accuracy and then we will compare the accuracy of the classification methods.

##### 4.1.1 Performance evaluation of the presented method based on statistical accuracy

As mentioned, the statistical accuracy measures examine the accuracy of the collaborative filter method by directly comparing the predicted ratings for users with their actual scores. Mean absolute error (MAE), and root mean square error (RMSE) are commonly used as measures of statistical accuracy. MAE is one of the most popular and common methods used among most methods. Naturally, the lower the value of this criterion per user, the higher the performance accuracy of the collaborative filter method. In other words, the lower the value of this criterion, the closer the predicted ranking for users is to their actual score. The relationship between these criteria is calculated as follows:

$$MAE = \frac{1}{N} \sum_{u,i} |p_{u,i} - r_{u,i}| \quad (4.2)$$

$$RMSE = \sqrt{\frac{\sum_{u,i} (p_{u,i} - r_{u,i})^2}{N}} \quad (4.3)$$

where  $P_{u,i}$  is defined as the predicted rank for user  $u$  on product  $i$  and  $r_{u,i}$  is the actual rank of user  $u$  on product  $i$  and  $N$  is the total number of ratings in the set of options. Figure 6 shows the absolute error value per test users in TripAdvisor and Yelp datasets. Figure 7 also shows the mean squared error value for test users in the TripAdvisor and Yelp datasets.

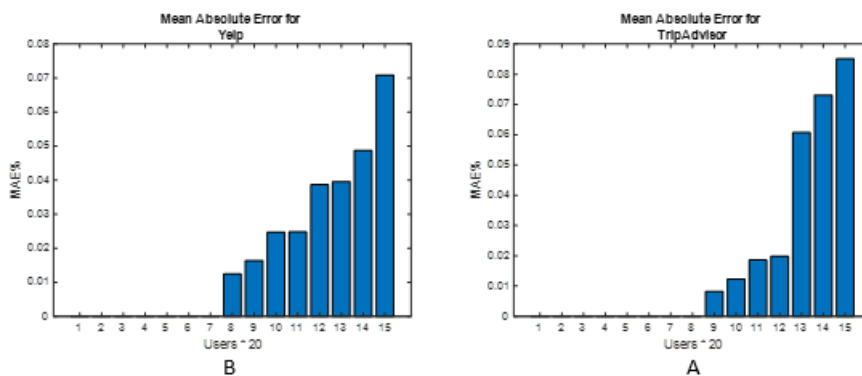


Figure 6. Absolute error value per test users

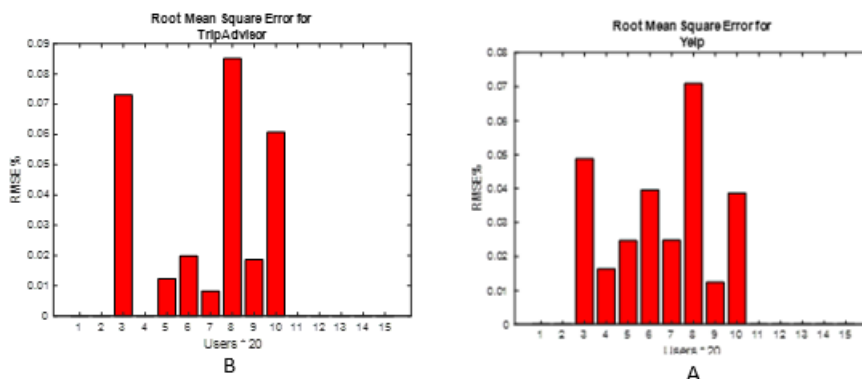


Figure 6: Mean squared error value for test users

As shown in Figures 7 and 6, the values of absolute error and mean squared error are calculated for each user in the TripAdvisor and Yelp test datasets. Now we will calculate the cumulative values of absolute and mean squared errors for all test users in the TripAdvisor and Yelp datasets. Figure 8 shows a cumulative plot of the absolute error value for all test users in the TripAdvisor dataset. Figure 9 also shows the cumulative graph of the mean squared error for all test users in the TripAdvisor dataset.

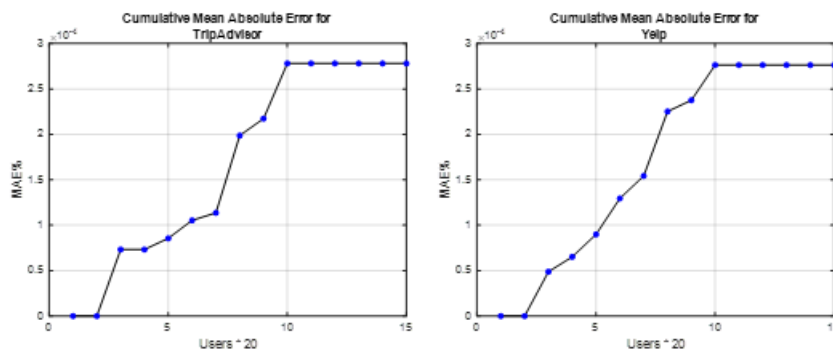


Figure 7: Cumulative diagram of mean square error

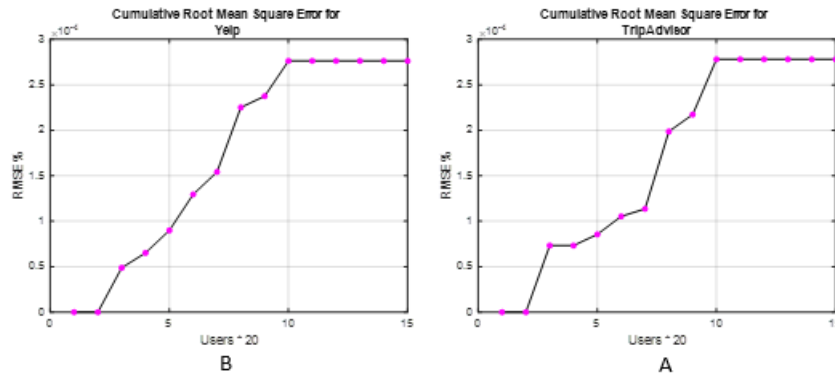


Figure 8: Cumulative diagram of mean square error value

As shown in Figures 7 and 8, the cumulative graph of absolute error and mean square error for test users in both data sets increases with a gentle slope, which indicates the high accuracy of predicting the rank given to the new user based on Deep self-encrypting networks are presented. Finally, the cumulative absolute error value in the TripAdvisor and Yelp datasets reaches the maximum value of 0.00242 and 0.00228, respectively, and the cumulative mean square error value reaches the maximum value of 0.00272 and 0.00267, respectively.

#### 4.1.2 Evaluation of the performance of the proposed method based on the accuracy of the recommendations

After calculating the statistical accuracy based on the absolute error and mean square for the test users in the TripAdvisor and Yelp data sets, now it is time to calculate the accuracy of the recommendations given to the test users in this data set. To calculate the accuracy of the provided recommendations, we identify the useful recommendations from among all the recommendations provided in the dataset. Useful recommendations include those websites that were recommended to user I and user I has given the maximum rating value to those websites in the main dataset. Because the rating value of the test users is known in the main data set, it is easy to determine the useful recommendations. After identifying the useful recommendations, we measure the proportion of useful recommendations among the total recommendations. In fact, the accuracy of the provided recommendations is equal to the ratio of the useful recommendations provided to the total recommendations provided to test users. Figure 14 shows the accuracy of the recommendations provided in the TripAdvisor and Yelp datasets.

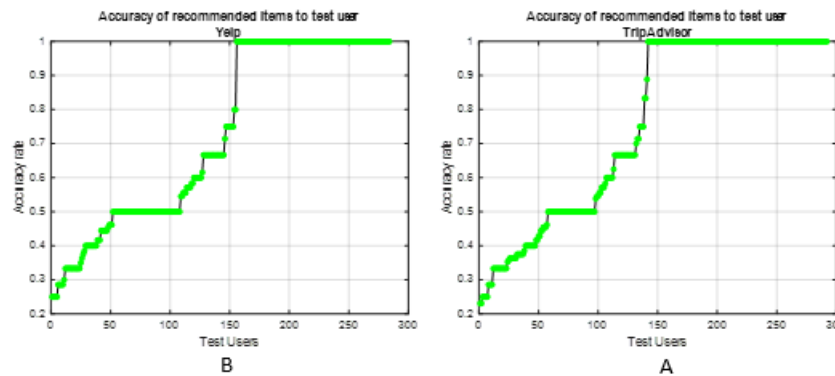


Figure 9: The accuracy of the provided recommendations

According to figures 9, it can be seen that the accuracy of the recommendations provided in the TripAdvisor and Yelp datasets increases in an upward manner, which indicates the accurate prediction of the rating given to new users and finding similar users on It is based on user profile information that leads to accurate web visit recommendations. The average accuracy of providing web visit recommendations in TripAdvisor and Yelp datasets is 74.53% and 72.22%, respectively.

### 4.1.3 Assessing the accuracy of classification methods

Evaluation of the proposed method for analyzing and checking performance D. The method presented on the new samples that The study is based on those that did not happen, for prediction. The ranking of these samples is done. To check the performance and evaluate the methods of the floor The clause that the data are distributed in different classes, the criteria There are different measures, most of these measures are based on the comparison of ratings. These samples are compared to their actual ranking, which is specified in the confusion matrix. D, are obtained. To calculate the evaluation criteria in the confusion matrix, the four main parameters positive and True (TP), true negative (FP), false positive (TN), and false negative (FN) should be obtained from the classification method. These parameters have already been introduced. Based on these parameters, the following evaluation criteria can be defined.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4.4)$$

$$Recall = \frac{TP}{TP + FN} \quad (4.5)$$

$$Precision = \frac{TP}{TP + FP} \quad (4.6)$$

$$F\text{-measure} = \frac{2 * Precision * Recall}{Precision + Recall}. \quad (4.7)$$

The above evaluation criteria are the most well-known criteria Based on them, it is a case classification method. Assessing the decision of D.A.D. These criteria are standard and based on them, a method can be presented. It has been compared with other methods in this field. R.D.A.D. In the presented method, in addition to deep self-encrypting networks, three well-known K-nearest-neighbor classifiers, support vector machine, and Bayesian classifiers are used to predict the ratings of users, using test and self-encrypting networks The presented depth are compared. In the proposed method, the value of k in the K nearest neighbour algorithm is set to 5 by default. Also, for the Bayesian algorithm, we have used the relation of Bayes theorem shown in relation (4.8). Bayes theorem can be shown as follows:

$$P(Q | R) = \frac{P(R | Q) P(Q)}{P(R)} \quad (4.8)$$

In equation (4.8), the probability of  $Q$  is calculated with respect to  $R$ ,  $P(Q)$  is the probability of  $Q$  independently,  $P(R)$  is the probability of  $R$  independently, and  $P(R - Q)$  is the probability of  $R$  subject to the realization of  $Q$ . Table 6 shows the confusion matrix related to other classification methods.

Table 6: Confusion matrix of other classification methods

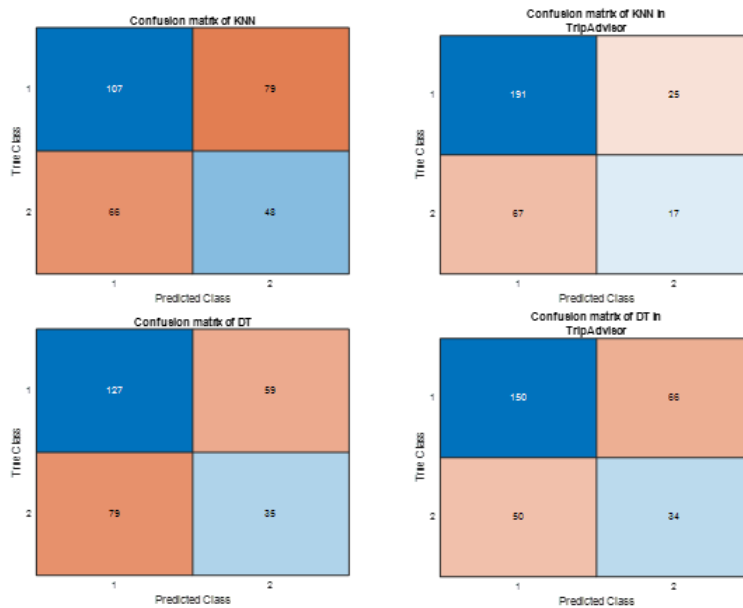


Figure 10 shows the accuracy criteria of the classification methods. It has been shown in different datasets of TripAdvisor and Yelp.

Table 7: shows the accuracy criteria of the classification methods. It has been shown in different datasets of TripAdvisor and Yelp

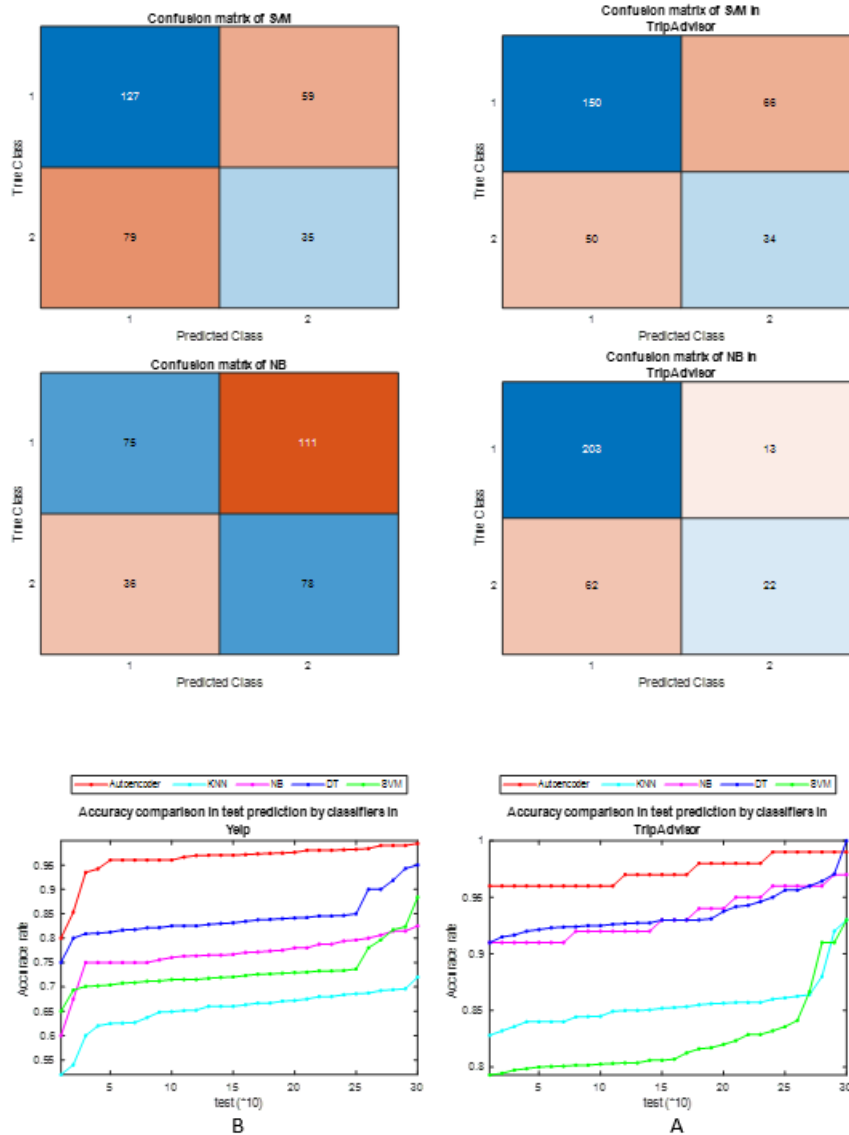


Figure 10: Accuracy criteria in classification methods

As can be seen in Figure 10, the presented method Based on the information in the user profile and users' rating of web pages and its combination with deep neural network and other classifications, Deep neural network has a better value than other classification methods for the criterion. It has achieved accuracy. According to Figure 10, it is possible to find the number of test users of 300 users, and the prediction accuracy values of each 10 tests have appeared once in the figure. This work is to prevent the crowding of points in the shape of accuracy and other The diagrams have been created to show the images related to accuracy and Other evaluation criteria should be increased.

Another criterion that we have used in the presented method, is a measure of sensitivity. The sensitivity criterion is defined as the ratio of the maximum predicted ranks, which is correctly It is predicted among all the maximum ranks in the set of test data. Figure 11 shows the sensitivity criteria of different classification methods in TripAdvisor and Yelp datasets are displayed.

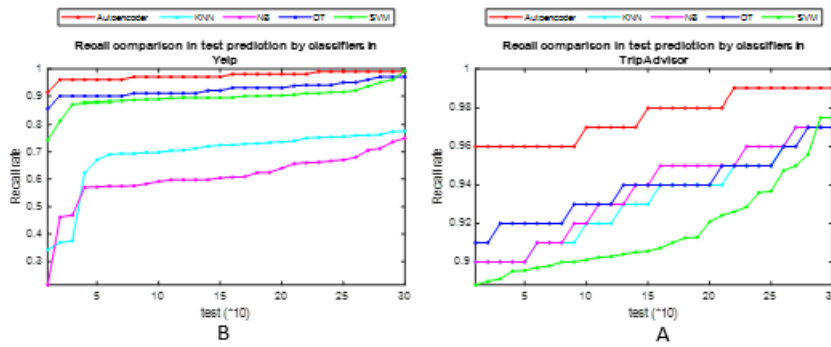


Figure 11: Chart of sensitivity criteria in classification methods

As can be seen in Figure 11, the presented method Based on the information in the user profile and users' rating of web pages and its combination with deep neural network and other classifications, Deep neural network has a better value than other classification methods for the criterion. It has achieved sensitivity.

The third criterion in the presented method is the accuracy criterion. The accuracy criterion shows the correctness of the predicted maximum ranks among the maximum ranks of the test users discovered in It is among deep learning methods. Figure 12 shows the accuracy criteria of different classification methods in TripAdvisor and Yelp datasets are displayed.

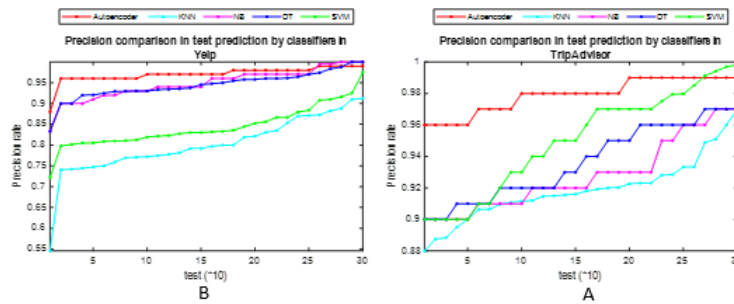


Figure 12: Chart of accuracy criteria of different classification methods in Yelp dataset

As can be seen in Figure 12, the presented method Based on the information in the user profile and users' rating of web pages and its combination with deep neural network and other classifications, Deep neural network has a better value than other classification methods for the criterion. He has achieved health.

The last criterion that we have used in the presented method is criterion F is the result of the combination of accuracy and sensitivity. This criterion shows the overall performance of the presented model to recognize the overall rating of users. It is the standard data. Figure 13 shows the  $F$  criterion of different classification methods in TripAdvisor and Yelp datasets are displayed.

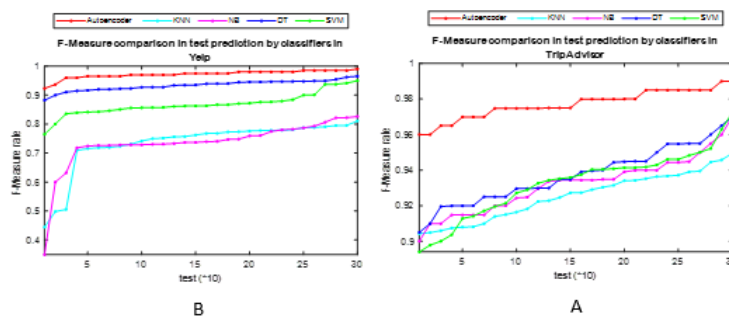


Figure 13: F-criterion diagram of classification methods

As can be seen in Figure 13, the presented method Based on the information in the user profile and users' rating of

web pages and its combination with deep neural network and other classifications, Deep neural network has a better value than other classification methods for the criterion.  $F$  has been achieved.

According to the obtained results, it can be said that the method presented using the information available in the user profile and user rating compared to websites is very suitable for the classification method. Provide a deep neural network. The deep neural network method according to the suitability of the input data, the strength of his learning, and high prediction on this group and The features have been achieved. Among the classification methods, the deep neural network method gives the most suitable results. for classifying training samples and predicting user rating samples in the test data set It has been achieved. Figure 14 shows a bar graph of the separate comparison of the evaluation criteria for different classification methods in the TripAdvisor and Yelp datasets. Figure 15 shows a bar graph of the cumulative comparison of evaluation criteria for different classification methods in the TripAdvisor and Yelp datasets.

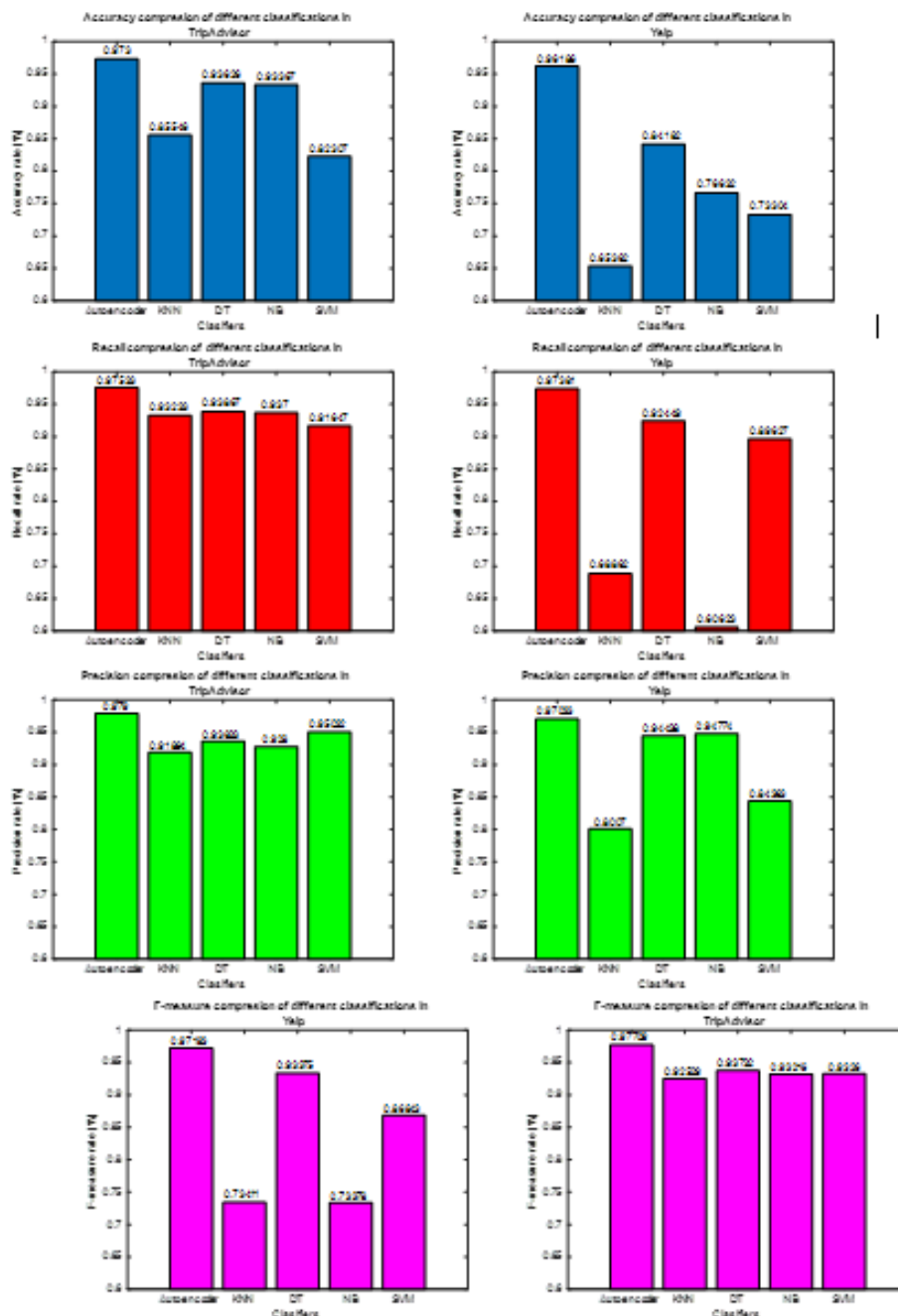


Figure 14: Bar graph of the separate comparison of evaluation criteria

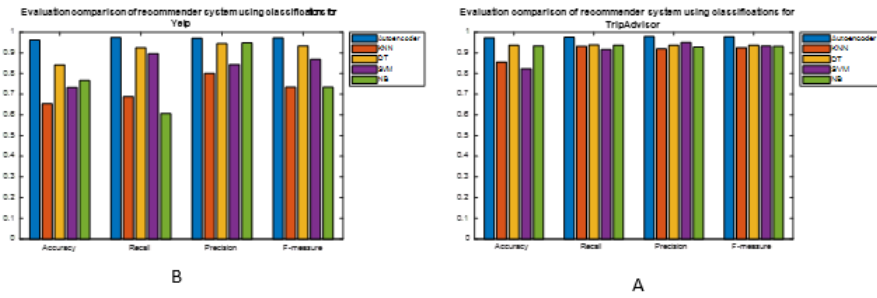


Figure 15: Bar chart of cumulative comparison of evaluation criteria

According to Figure 15, it can be seen that the presented deep self-encryptor networks, based on deep learning based on the information in the user profile in the TripAdvisor and Yelp datasets, have been able to predict the product ratings for new users with the highest accuracy. The presented method has performed better than other classification methods in terms of evaluation criteria due to the layers of deep training and the completion of the training process in the middle layer.

### 4.2 Comparison of the proposed method with previous methods

After implementing and evaluating the proposed method, to validate the proposed method in this treatise, we will compare it with previous methods including [13] in this field. What is certain is that the comparison is made on the results of the previous methods on the same data set, including the Yelp and Trip Advisor data sets, under the same conditions. Therefore, the results obtained in the proposed method in the same conditions and the same data set are compared with other methods to determine the amount of improvement obtained from the proposed idea in this thesis. Since in the proposed method, a combination of deep learning and participatory filtering has been used, hence it is possible to use criteria such as the average absolute error, encounter rate and the accuracy of finding similar users for comparison. Figure 16 shows the comparison of the proposed method with previous methods in terms of the average absolute error criterion.

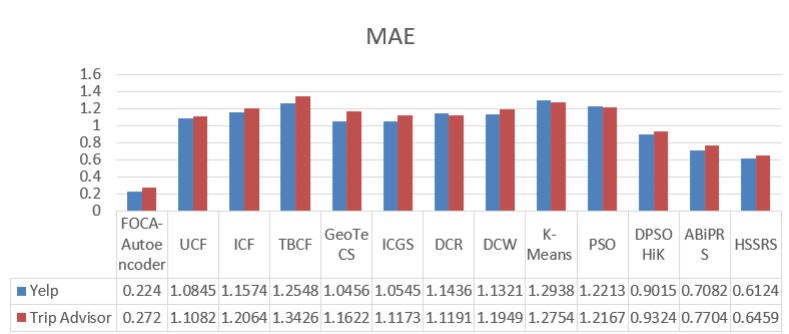


Figure 16: Comparison of the proposed method with previous methods in terms of average absolute error

As can be seen in Figure 16, the proposed method has obtained a lower average absolute error than the previous methods. The reason for this is the deep learning of user profile features and finding similar users with high accuracy by the proposed self-encoding neural network. Therefore, it is expected that due to the low value of absolute error, the accuracy of the provided recommendations, which is also referred to as the collision rate in the articles, will be better in the proposed method than other existing methods. In Figure 17, we will compare the proposed method with the previous methods in terms of hit rate or accuracy of recommendations provided to users.

According to Figure 17, it can be seen that the proposed method, relying on deep training in the networks of the proposed self-encoder, has been able to learn the characteristics of the users well, which reduces the absolute error in providing recommendations and increases the hit rate or the accuracy of the recommendations. It has been provided. What can be seen in Figure 17 is that the proposed method has obtained a higher collision rate than the previous methods on the same data set.

Considering the use of deep learning and other classification methods in the field of identifying similar users based on user profile information, the proposed method can be compared with previous methods in terms of the accuracy of

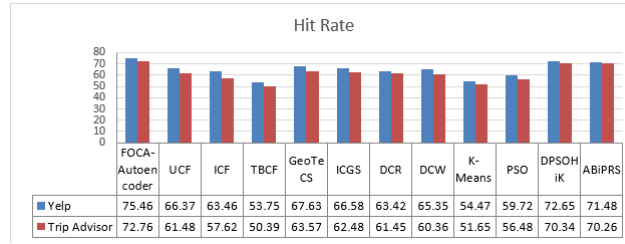


Figure 17: Comparison of the proposed method with previous methods in terms of collision rate

identifying similar users. In the proposed method, in addition to a self-encoding neural network, other classification methods such as k nearest neighbour (KNN), Simple Bayesian (NB), and Support Vector Machine (SVM) are also used to find similar users based on user profile information. The comparison of the proposed method with other classification methods and previous methods in publications in terms of the accuracy of finding similar users is shown in Figure 18.

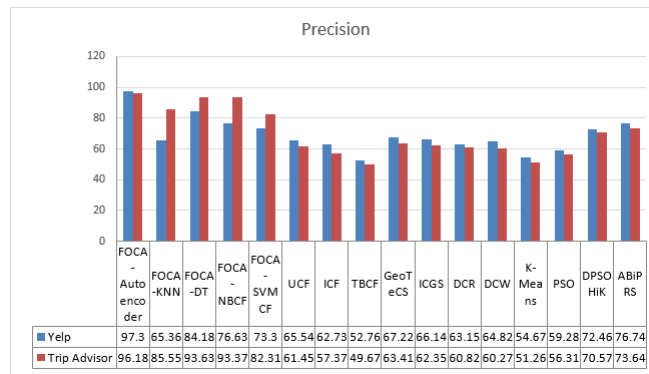


Figure 18: Comparison of the proposed method with previous methods in terms of the accuracy of identifying similar users

As shown in Figure 18, the proposed method, due to the use of deep learning on the characteristics of users that are extracted from their profiles, has been able to achieve higher accuracy in identifying similar users than these classification methods and methods. He got the previous ones.

## 5 Conclusion

The recommender system provides recommendations based on complex algorithms and machine learning models, by analyzing user behavior and using available information about them. These recommendations may suggest relevant and interesting content to users based on their viewing history and interests. Similar and related products are suggested if the user is searching for a specific product. In addition, based on the behaviour of users who have similar tastes and interests, users are suggested to get the best experience by viewing and using their experiences. Also, based on the time and activity of the users, recommendations can be provided to them at appropriate and optimal times. By using these systems, users can easily access the information they need and enjoy a better user experience. Also, by providing detailed recommendations, websites can attract more visitors and increase their satisfaction level. Therefore, in this research, a hybrid recommender system based on the combination of fuzzy sequential clustering and deep self-encrypting network based on user profile information and ranking of websites by users is presented. In this recommender system, users are first clustered according to the similarity of their opinions. Then the new ranking for users is predicted according to the fuzzy membership function. Finally, the information in the user profile and the new rating of the users to each website is used as the input of the provided deep self-encoder network to predict the rating of the websites by the users. The deep self-encrypting network predicts the ranking of new users concerning websites and uses this ranking to find similar users based on the collaborative filter method. Finally, after finding similar users, it provides recommendations to visit and personalize the web page of serious users based on the favourite websites of similar users. The presented method using deep neural networks and according to deep learning on the information in the user profile in the TripAdvisor and Yelp dataset, has been able to predict the product ratings for new users

with the highest accuracy. The presented method has performed better than other classification methods in terms of evaluation criteria due to the layers of deep training and the completion of the training process in the middle layer. The simulation results show that the presented method performs well from the point of view of statistical accuracy and the ratio of successful recommendations to useful recommendations.

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