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Non-Singular Convoluted Matrix Collaborative with Filtering and Sampling Techniques

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Abstract:

Due to the comprehensive and accessible knowledge they provide, social media platforms are developed as prominent technologies. The community strategy remains as a repository of millions of individuals for numerous application, include evaluations concerning health, services preferences investigation, and numerous others. And use this information, social media network personalized recommendation algorithms allow the user to interactively choose their alternatives via inter networks. It makes reasonable because content - based recommendation model should indeed be adequately arranged to work out the enormous quantity of information that users of social media has contributed in recent decades. In order to examine huge quantities of information (i.e., big data) efficiently, the findings suggest a beginning for something like a scientific and adaptable classification algorithm. The Fried and Function f Matrix Collaboration Recommend (F-FMCR) approach, which would be founded on a distribution personalized recommendation system that employs inter technologies for social networking sites, provides recommendations to those who use the network about some of the other individuals who have their objectives. An entity paradigm has evolved that is appropriate for assessing different concepts. Using sampling methods and Non - singular Matrix Collaborative Filtering methods, this architecture contains three elements (i.e., agencies) entitled tweeting collections agent, information retrieval agent, and networked recommendation systems agent. Here on Sentiment 140 collection, significant experiments were carried out, as well as the findings are evaluated with the present prediction models. Findings from experiments indicate demonstrated, when compared to current methodologies, the developed F-FMCR approach is superior in terms of recommended effectiveness, recommendation time, and average absolute inaccuracy.

Keywords: Social Networks, MapReduce, Friedman, Frobenius, Matrix Collaborative, Recommender.

1. Introduction

In recent years web researchers have investigated several mining models for constructing recommendation systems for social networking sites such as Whatsapp, Instagram, Twitter, and so on. However, enormous data sustaining in social networks by millions of users engenders effectiveness issues in the online application of these models for real time recommendations.

A fine-grained recommender system using Bootstrapping was proposed in [1] for social ecosystems with the purpose of recommending media content issued by the user's friends. The system design was guided by the unearthing of the user study in a qualitative manner that investigated the desirability and prerequisites of a recommendation element within a social network.

The central objective behind the Bootstrapping recommender system was to support the prosperity of previous information for generating interest profiles and to measure the similarity scores at a fine-grained manner for each friend. With this both the accuracy and the runtime involved in recommender system was found to be improved in a significant level. Despite improvement observed in both accuracy and runtime, with dimensionality change, the recommendation accuracy with recommendation time involving big data analytics remain a major concern. To address this issue, in this work, MapReduce Friedman Relevant Tweet Selection model using multi-agent system is designed.

In [2], a novel Correlative Denoising Auto Encoder (CoDAE) was proposed that considered correlation between users by taking several aspects into account to identify robust representations from sparse inputs for recommendation. In this work, three distinct autoencoders, one to rate the user features involving roles of rater, truster and trustee respectively were employed. Moreover, shared features were also utilized to measure common information that correlated to same users were also taken into account.

Finally, a related regularization term was also utilized to learn correlations between user features. With this the mean average precision was found to be improved significantly. Despite improvement observed in mean average precision, the mean absolute error incurred during the identification of robust representations for recommendation was less focused. To address this issue in this work, a recommendation system using Frobenius Matrix Collaborative Recommender model is designed.

In order to overcome these obstacles, we create new reinforcement learning models (RS models), such as the MapReduce Friedman Relevant Tweet Selection model and the Frobenius Matrix Collaborative Recommender model, which are NN-based models that use nearest-neighbor (NN) to create a reliable recommender model using a multi-agent system. We use the Bootstrapping [1] and CoDAE [2] to systematically assess and compare the performance of the suggested approaches. This work makes three contributions.

- We propose a Friedman and Frobenius Matrix Collaborative Recommendation (F-FMCR) method where multiple experts negotiate together to come up with a robust recommended list of tweets.

- First of all, in relevant tweet selection phase, we have used MapReduce Friedman function to identify the most relevant tweets in a timely manner by applying the Friedman function in the MapReducer for each tweets presented in the multi-agent system.
- Second, in recommendation generation phase, the Frobenius Matrix Collaborative (FMC) function has been also employed to find a list of robust recommendations with minimum error. Finally, we evaluate the effectiveness of F-FMCR method for several tweets against baseline methods of recommendation.
- Experimental results show that the recommendation accuracy, recommendation time and mean absolute error of our method can outperform tradition recommendation methods such as Boostrapping, CoDAE.

This is how the remainder of the paper is structured. The relevant work is presented in Section 2. We briefly describe the multi-agent system and recommendation systems for social networks individually. We create a multi-agent Friedman and Frobenius Matrix Collaborative Recommendation (F-FMCR) method for social networks in Section 3 that offers users recommendations about other users who share their interests. Section 4 presents the outcomes of the experiment. Section 5 concludes this study.

2. Related works

In this section we discuss the previous research area related to our work, recommendation systems and multi-agent for social networks.

2.1 Recommendation Systems

Today, in the era of information, the evolution of web applications and social networks has resulted in the accumulation of large data from across the globe. Due to this, it is a cumbersome process in identifying the information and decides according in a significant manner. However, with the availability of different strategies and techniques for information management, identification of correct and precise knowledge from enormous data is still considered to be a demanding issue.

An inventive approach built on the principles of supply chain management (SCM) and organisational communication was put forth in [3]. Using data mining, artificial neural networks, and fuzzy approaches, the method combined traditional collaborative filtering with demographic recommendation systems into a hybrid pattern. It was said to have been achieved with this accuracy.

In [4], a matrix factorisation (MF) and nearest-neighbor (NN)-based recommender system (RSs) was created. This system used data about the user's social network and group membership to make recommendations for social voting. By employing popularity-based voting, accuracy was said to be improved in a significant manner. A group recommender system using genetic algorithm was proposed in [5] for a group of people considering weight.

In recent years, valid information extraction from big data has gained a large interest among several research persons. This is because of the abundance availability of websites acquiring user profile to provide pertinent information via recommendation.

In [6], to speed up the time involved in generating list of recommendations, a parallel recommender system on the basis of collaborative filter via correntropy was designed. This strategy evaluated user similarity to minimize the computational cost, therefore facilitating parallel computing. On the basis of local aspects considered between social network users and global aspects, a recommendation method matrix factorization framework was presented in [7], therefore improving the correctness to a greater extent.

At present, several methods utilized two-valued trust relationship to enhance the recommendation quality but however difference of trust was not taken in to consideration. To address this issue, in [8], a recommendation system called, social network adopts topical attention and probabilistic matrix factorization (STAPMF) was investigated. Here, the information pertaining to trust was combined with the topical information using matrix factorization based on probabilistic model and attention-based recurrent neural networks. With this, the recommendation performance was said to be improved. Yet another hybrid recommendation model based on review text and social communities concentrating on the recommendation accuracy was modeled in [9]. A review of social recommendation systems was investigated in [10].

2.2 Multi-agent System

A Multi-agent system consists of several collaborating agents whose sole objective differs according to the function performed by each agent and also the behaviors are said to be organized via communication links. In [11], a multi-agent system for predicting the equipment failures employing collaborative learning was presented for optimizing communication cost. However, the negative influences were not discussed. To address this issue, in [12], sentiment and stress were employed for guiding users in online social networks. However, the time delay involved was not focused. Time delays and partial information transmission was addressed in [13] via distributed even triggered scheme.

With the evolution of Internet of Things (IoT) and Big Data, group recommender system has evolved for trusted social networks. A group recommender system was proposed in [14] with the objective of improving the accuracy. An agent-based simulation using context-based recommendation was designed in [15]. Meantime, in today's era, several people and users are resisted with viral new articles via social media or social networking sites, free of cost without taking into consideration the new sites into the market. Mining these new sites has become one more key confronts. To address this issue, a fuzzy logic model for predicting users' different interest and its classifications by inspecting their inferred user profile was proposed in [16]. With this the recommendation accuracy was found to be improved.

2.3 Recommender system using multi-agent

By personalising and providing recommendations to social network users according to their interests, recommender systems (RSs) have emerged as a solution to the problems associated with information overload. The proposal in [17] involved the use of a genetic algorithm (GA) based on multi-agent negotiation (GA-MANS), in which every agent acted on behalf of a group member. It was discovered that model accuracy increased with this integration. In [18], semantic web technologies were utilised to make a timely and cost-effective contribution to the school recommender system.

Another location-based social network was used in [19] in an effort to enhance the user experience overall, which helped to produce recommendations that were more optimal.

The aforementioned techniques for making recommendations are effective in certain respects, but they fall short in addressing the issue of mean absolute error since users' preferences change over time. Therefore, utilising a recommendation model to deploy a single agent system won't aid in maximising accuracy and speed. We suggested a Friedman and Frobenius Matrix Collaborative Recommendation (F-FMCR) employing multi-agent for social networks to help users of social networks through useful recommendations in order to overcome the shortcomings of the current recommender systems. Our suggested recommendation technique offers a more effective strategy to address the multi-agent recommender system's accuracy and error problems.

3. Friedman and Frobenius Matrix Collaborative Recommendation (F-FMCR) using multi-agent for social networks

In this section, the proposed Friedman and Frobenius Matrix Collaborative Recommendation (F-FMCR) method for providing recommendations to users about other users via grading is presented. First, a system model for the design of F-FMCR is provided. Next, the framework of the relevant tweet selection using MapReduce Friedman Relevant Tweet Selection model is described. Finally, the processes of recommendation system using Frobenius Matrix Collaborative Recommender model are illustrated specifically.

3.1 System model

Let us consider a social communication system that shows the relationship between users in a recommender system. Here, social communication denotes the links between users in complicated networks. It represents the direct relationship between users. The nodes in social communication system of social network denotes the social network users, the edges denotes the communications made between the social network users (i.e. users) and finally, the weights denotes the ratings obtained for a particular interaction. This is mathematically expressed as given below.

$$SN = \{Nodes, Edges, Significance\} \qquad (1)$$

The social communication system above or the social network is represented as triplets. From the above equation (1), nodes 'N' represents the number of users '$U = \{u_1, u_2, \dots, u_n\}$' in social network, edges 'E' represents the multitude of communication relationships '$C = c_{u_1u_2}, c_{u_3u_4}, \dots, c_{u_lu_{l+1}}$' and significance is the rating represented by '$R = r_{u_1u_2}, r_{u_3u_4}, \dots, r_{u_lu_{l+1}}$' respectively. In addition let us consider a multi-agent system that consists of 'n' agents '$A = a_1, a_2, \dots . a_n$' respectively with each agent responsible with specific function to be performed.

These multi-agent based systems will be used as data mining and tweet collection agents to input tweets for analysing the effectiveness of the recommender system and suggesting users to other users who are similar to them. Figure 1 given below shows the sample multi-agent framework employed in the proposed method.

As shown in the above figure, the Tweet Collection Agent collects the tweets '$T = t_1, t_2, \dots . t_n$' obtained from the Sentiment140 dataset. Here, the tweets obtained from 'n' users '$U =$

$u_1, u_2, \ldots, u_n$' are collected and stored in cache for further processing by splitting the tweets into tokens '$Tns = tns_1, tns_2, \ldots, tns_n$'.

$$T \rightarrow \{tns_1, tns_2, \ldots, tns_n\} \quad (2)$$

In a similar manner for 'n' users, the data matrix representing user and tweet is mathematically represented as given below.

$$DM(UT) \rightarrow \begin{bmatrix} u_i tns_1 & u_i tns_1 & \ldots & u_i tns_n \\ u_{i+1} tns_1 & u_i tns_1 & \ldots & u_{i+1} tns_n \\ \ldots & \ldots & \ldots & \ldots \\ u_n tns_1 & u_i tns_1 & u_i tns_1 & u_n tns_n \end{bmatrix} \quad (3)$$

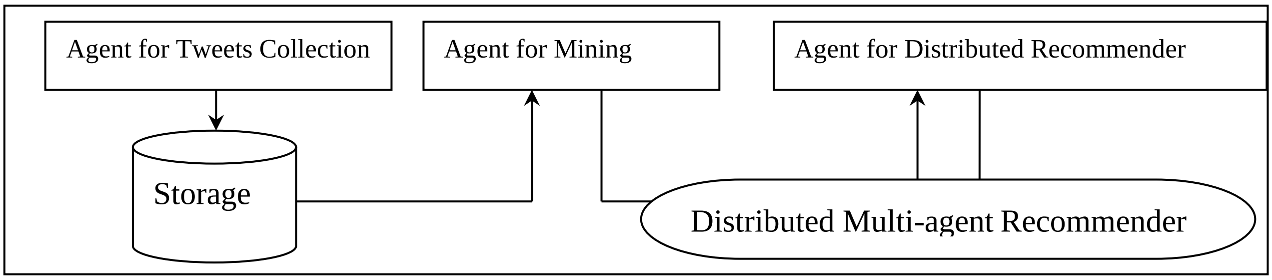

Figure 1 Sample Distributed Multi-agent Recommender model

Next, the Data Mining Agent with the aid of MapReduce Friedman Relevant Tweet Selection model finds the relevant tweets of significance in an effective manner. Data mining agent operates valuable and significant tweets to identify the relationship between different pieces of tokens for a concerned user tweets. Finally, the Distributed Recommendation Agent with the aid of Frobenius Matrix Collaborative Recommender model performs the task of recommending to users about other users with similar interests based on the tweets provided in online social network.

3.2 MapReduce Friedman Relevant Tweet Selection model

Feature selection sorts out relevant subsets of relevant features without provoking much information loss. As far as big data dataset are concerned, feature selection plays the major role. However feature selection is also not free from drawbacks, to name a few like, curse of dimensionality. Parallel processing has said to be widely employed to dispense enormous complexity burden across several nodes.

To address this issue, in this work, a MapReduce Friedman Relevant Tweet Selection model is applied to recommend user interests in a robust manner via parallel processing. Here relevant tweet selection is done with the input Big Data tweets in the domain of social network using multi-agent model to analyze the sentiments in an efficient manner.

The maximum length of Twitter message being 140 characters includes, URL, Hashtags, Mentions, Emojis, Smileys, Specific Words etc. The total number of tweets generated in each moment is found to be enormous. Enormous tweets necessitate a scalable solution to relevant tweet selection. Parallel framework is utilized to implement the relevant tweet selection. In the relevant tweet selection step, the input is a list of tweets describing the details of tweets. Figure 2 given below shows the parallel framework using MapReduce Friedman Tweet for relevant tweet selection.

As illustrated in the above figure, by utilizing parallel framework workload is said to be significantly distributed over a cluster of users and obviously over different machines. To start with a tweet server from data matrix is created with processes and let us further assumes that the number of processes is equal to the number of user considered as samples in data matrix. In addition, each tweet is allocated to each process in a dynamic manner.

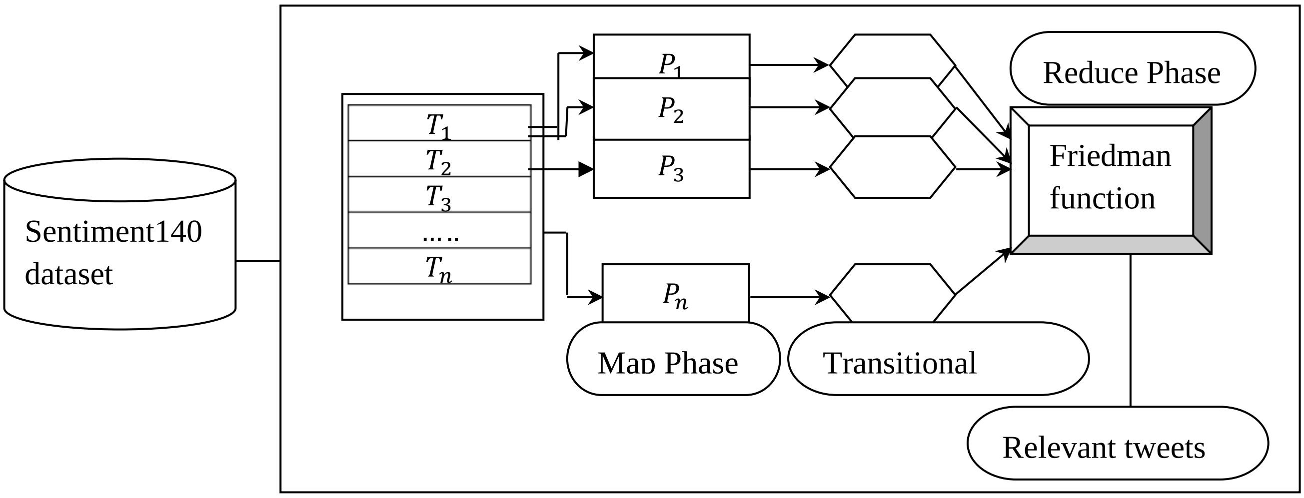

Figure 2 Block diagram of MapReduce Friedman Relevant Tweet Selection model

Given data matrix '$\{DM_{ij}\}_{n*k}$', a tweet data matrix with 'n' rows or blocks, 'k' columns, the grades within each block are measured as given below.

$$tg_j = tg(DM_{ij}) \quad (4)$$

Upon occurrence of tied values, the mean of the tweet grades is assigned therefore eliminating the possibility of ties. Now, the data matrix is replaced with the new matrix '$\{tg_{ij}\}_{n*k}$' where the 'tg_{ij}' refers to the tweet grade of 'DM_{ij}' within block 'i'. This is mathematically formulated as given below.

$$tg_j = \frac{1}{n}\sum_{i=1}^{n} tg_{ij} \quad (5)$$

Finally, the hypothesis or the Friedman test results are mathematically formulated as given below.

$$RT = H = \begin{cases} 0, & presence\ of\ identical\ tweets \\ 1, & atleast\ one\ tweet\ is\ different\ from\ atleast\ one\ other\ tweet \end{cases} \quad (6)$$

With the above hypothesis results, the computationally efficient and relevant tweets are obtained by means of tweet grade. The pseudo code representation of Friedman Relevant Tweet Selection for retrieving computationally efficient and relevant tweets is given below.

Input: users '$U = \{u_1, u_2, \ldots, u_n\}$'
Output: computationally efficient relevant tweets '$RT = rt_1, rt_2, \ldots, rt_n$'

Step 1: **Initialize** Tweets '$T = t_1, t_2, \ldots . t_n$'
Step 2: **Begin**
Step 3: **For** each users 'U' with Tweets 'T'
Step 4: Split tweets into tokens as given in (2)
Step 5: Obtain data matrix as given in (3)
Step 6: **For** each tweet data matrix with 'n' blocks
Step 7: Measure grades using equation (4)
Step 8: Measure grade using equation (5) in case of ties
Step 9: Return hypothesis
Step 10: **End for**
Step 11: **End for**
Step 12: **Return** (relevant tweets 'RT')
Step 13: **End**

Algorithm 1 Friedman Relevant Tweet Selection

As given in the above Friedman Relevant Tweet Selection algorithm, two important tasks are performed. First, the tweets of each corresponding users are broken into tokens and second, the relevance of the tokens are identified by applying Friedman function. The advantage of utilizing the Friedman function is it analyze of tokens pertaining to specific tweets with respect to several sample tweets and replacing the original grades based on the grade-ordered values. In this manner, less significant tweets are eliminated and only the relevant tweets are selected in a time efficient manner.

3.3 Frobenius Matrix Collaborative Recommender model

Recommender model or Distributed Recommender Agent is in charge for carrying out two types of tasks. First from the name itself, it bestows recommendations to the requesting users in social network platform and the second task is to measure the grades for words of tweets for all users in social network association with the Distributed Recommender Agent. This is performed by applying Frobenius Matrix Collaborative (FMC) function.

The FMC function projects user's favors and tweet's features into the same latent factor space (i.e. indicated by x axis and y axis) and distributed recommender system predicting grading based on the magnitude of matching between user's favors and tweet's features and correspondingly detect sentiment. The FMC function is written as given below.

$$G \sim A_{n*d} B_{m*d} = G' \quad (7)$$

From the above equation (7), 'G' indicates the grading matrix of '$n * d$' that is split into dual matrices 'A_{n*d}' and 'B_{m*d}' respectively. Here 'A_{n*d}' denotes the feature matrix of tweet users and 'B_{m*d}' represents the feature matrix of actual tweets respectively. The innermost matrix multiplication of 'A_{n*d}' and 'B_{m*d}' characterizes the coarse-grained matrix represented by 'G''. However, the objective in our work remains in minimizing the difference between 'G' and 'G'' and hence the mathematical formulated is as given below.

$$obj = MIN(G - G') = MIN\left(\sum_{i=1}^{n} \sum_{j=1}^{m} \left(g_{ij} - A_i B_j^T\right) + \alpha(|A|^2 + |B|^2)\right) \quad (8)$$

From the above equation (8), 'A_i' and 'B_j' represents the feature vector of two sample matrices 'A' and 'B' respectively and '$\alpha(|A|^2 + |B|^2)$' represents the normalization tweet that is used to avoid overfitting that specifically is said to occur while employing FMC function. Next, the values of 'A_i' and 'B_j' are proximate using stochastic approximation involving Big Data dataset, therefore minimizing the computational burden and is formulated as given below.

$$A_i = A_i - \beta \frac{\partial obj}{\partial A_i} \quad (9)$$

$$B_j = B_j - \beta \frac{\partial obj}{\partial B_j} \quad (10)$$

From above equations (9) and (10), 'β' refers to the learning rate subject to the objective function 'obj'. The difference between the actual and approximated grade for an observed tweet sample is reduced by differentiating '$(g_{mj} - g'_{mj})^2$' as follows.

$$\frac{\partial}{\partial a_{id}}(g_{mj} - g'_{mj})^2 = -2a_{md}(g_{mj} - \sum a_{md}b_{dj}) \quad (11)$$

$$\frac{\partial}{\partial b_{dj}}(g_{mj} - g'_{mj})^2 = -2b_{dj}(g_{dj} - \sum a_{md}b_{dj}) \quad (12)$$

With the aid of the above two equations (11 and (12), finally, the grading is mathematically formulated as given below.

$$G_{ij} = \frac{\partial}{\partial a_{id}}(g_{mj} - g'_{mj})^2 * \frac{\partial}{\partial b_{dj}}(g_{mj} - g'_{mj})^2 \quad (13)$$

With the above obtained grade 'G_{ij}' from equation (13), the distributed recommendation agent provides recommendation to tweet users on social networks about other users with similar interests in a significant manner. The pseudo code representation of Frobenius Matrix Collaborative Recommender is given below.

Input: relevant tweets '$RT = rt_1, rt_2, \ldots, rt_n$'
Output: Robust recommendation with minimum error
Step 1: **Begin** Step 2: **For** each relevant tweets 'RT' Step 3: Evaluate the grading matrix using equation (6) subject to objective function using equation (8) Step 4: Obtain proximate values by means of stochastic model using equation (9) and (10) Step 5: Obtain difference between the actual and approximated grade for an observed tweet using equation (11) and (12) Step 6: Evaluate grade using equation (13) Step 7: **If** '$G_{ij} = 0\ to$ 1.9' Step 8: Tweet polarity is negative Step 9: **End if** Step 10: **If** '$G_{ij} = 2\ to$ 3.9' Step 11: Tweet polarity is neutral

Step 12: **End if**
Step 13: **If** '$G_{ij} \geq 4$'
Step 14: Tweet polarity is positive
Step 15: **End if**
Step 16: **End for**
Step 17: **End**

Algorithm 2 Frobenius Matrix Collaborative Recommender

As given in the above Frobenius Matrix Collaborative Recommender algorithm, for each relevant tweet's obtained from the feature selection algorithm as input, the objective here remains in a robust recommender system that possess trust based on the grading that provides more reliability. With this objective, a grading pattern using Frobenius Matrix Collaborative (FMC) function is designed subject to the minimization of loss incurred while involving Big Data employing relevant tweets. Next, minimizing the computational burden via differentiation function is performed for each user and corresponding tweets therefore minimizing the mean absolute error or prediction error. Finally, the grade is obtained with which according to the results of the polarity sentiments are detected in an efficient manner.

4. Experimental setup

In the context of social networking, designing assistant distributed applications is supposed to just be extremely hard. The objective is to develop recommendation systems which analyze enormous amounts of social data instantly using centralized and filtering techniques. A multi-agent driven platform is developed for this kind of deployment to simulate customers in the Twitter ecosystem. The vast majority of research on the examination of optimization techniques has typically focused on duration and performance [1].

In the interest of evaluating prediction models, investigators have much more recently started looking at the challenges related to determining client interaction based on generalized linear terms [2]. Even so, software applications are limited to use with a simple prospect. These observations, together with the most new state strategies described in the literature, are employed to evaluate the preferred algorithm in the areas of recommender system correctness, recommender systems time, and necessarily imply error percentage with regard to the amount of twitter posts, and also to start comparing that to multiple numerous different recommendation approaches, Framework employs [1] and CoDAE [2].

4.1 Dataset

In order to create a recommendation system, the Sentiment140 dataset, which consists of 1.6 million tweets, was taken from https://www.kaggle.com/kazanova/sentiment140 [20]. Using a keyword search, the dataset includes tweets expressing both happy and negative emotions. 1,600,000 tweets were collected for the sentiment140 dataset via the Twitter API. Table 1 below lists the six columns that make up the dataset.

Table 1 Dataset description

Column Name	Description
Sentiment	The sentiment of the tweet: 0 = Negative, 2 = Neutral, 4 = Positive
Tweet_ID	The unique identifier for the tweet
Tweet_Date	The date the tweet was posted
Query_Flag	Indicates the presence of a query: 1 = Query present, 0 = No query present
Username	The user who posted the tweet
Tweet_Text	The content of the tweet

The Friedman and Frobenius Matrix Collaborative Recommendation (F-FMCR) plan, which was developed using the dataset extracted from kaggle.com, calls for conducting an experimental and analytical evaluation of developing a multi-agent system to simulate users in the Twitter environment. The evaluation of the experiment is done based on metrics such mean absolute error based on the number of tweets and users, recommendation time, and accuracy. To recommend users based on relevant tweets, a total of 250 tweet users in the 8MB to 80MB range were picked from the dataset as input.

4.2 Performance metrics

In this section, the performance metrics considered for recommending users are provided. They are recommendation accuracy, recommendation time and mean absolute error with respect to tweets considered for simulation.

4.2.1 Recommendation accuracy

Recommending news articles is one of the most demanding recommendation chores. This is due to the reason that the news zone varies from other zones in several aspects. The expedition of new up to data content is specifically very high due to frequent changes in the acceptance and pertinence of the articles changing in a drift manner. Hence, recommendation accuracy plays a major role due to the involving of several surrounding factors to be concerned by a recommendation agent. The recommendation accuracy is mathematically evaluated as given below.

$$R_{acc} = \sum_{i=1}^{n} \frac{T_{CR}}{T_i} * 100 \quad (14)$$

From the above equation (14), the recommendation accuracy 'R_{acc}' is obtained based on the percentage ratio of tweets correctly recommended 'T_{CR}' and the tweets considered for simulation 'T_i'. It is measured in terms of percentage (%).

4.2.2 Recommendation time

In the current scenario, the frequency of data makes it very cumbersome to identify what we need. However, search engines today also provide data found to be more relevant based on keywords, but found to be confined by the user's potentiality to search the correct content. On the other hand, even recommendations are mushrooming by tracking interests and provided right content to requested users by consuming a specific time. Recommendation time refers to the time consumed in recommending tweets for users based on the other similar user of interests in online social network. This is mathematically expressed as given below

$$R_{time} = T_i * Time\ [RecT_i] \qquad (15)$$

From the above equation (15), the recommendation time 'R_{time}' refers to the time consumed in recommending tweets '$Time\ [RecT_i]$' and the number of tweets considered for experimentation 'T_i'. It is measured in terms of milliseconds (ms).

4.2.3 Mean absolute error

Finally, to evaluate the effectiveness of the recommendation method made, mean absolute error is measured. In other words, mean absolute error 'MAE' is measured based on the predicted values and the true values respectively. The mean absolute error is measured as given below.

$$MAE = \frac{\sum_{i=1}^{n}[P_i - T_i]}{n} \qquad (16)$$

From the above equation (16), the mean absolute error 'MAE' is measured based on the prediction recommendation 'P_i' and the true recommendation made 'T_i' using our proposed method to the total numbers of tweets 'n' used for simulation. It is measured in terms of percentage (%).

4.3 Discussion

In this section, a series of experiments was conducted to verify the significance of the proposed method F-FMCR with Sentiment140 dataset. Then, we adopted three commonly used evaluation metrics, recommendation accuracy, recommendation time and mean absolute error to compare the performance of the recommendation in our method with that of two existing methods, Bootstrapping [1] and CoDAE [2].

4.3.1 Performance measure of recommendation accuracy

First, the analysis of the work in terms of recommendation accuracy is made in this section. Table 2 given below reports the recommendation accuracy obtained using three different methods, F-FMCR, Bootstrapping [1] and CoDAE [2].

Table 2 Performance comparisons on recommendation accuracy using F-FMCR, Bootstrapping [1] and CoDAE [2]

Number of tweets	Recommendation accuracy		
	F-FMCR	**Bootstrapping**	**CoDAE**
1000	98.5	97	95.5
2000	97.55	95.25	91.25
3000	96.25	91.55	88.35
4000	96	88.35	86.15
5000	95.25	86.25	82.35
6000	94	82.15	80.45
7000	93.15	80.35	75.35
8000	90.2	82.15	77.25
9000	91.55	83.55	76.16
1000	93.15	85.15	75

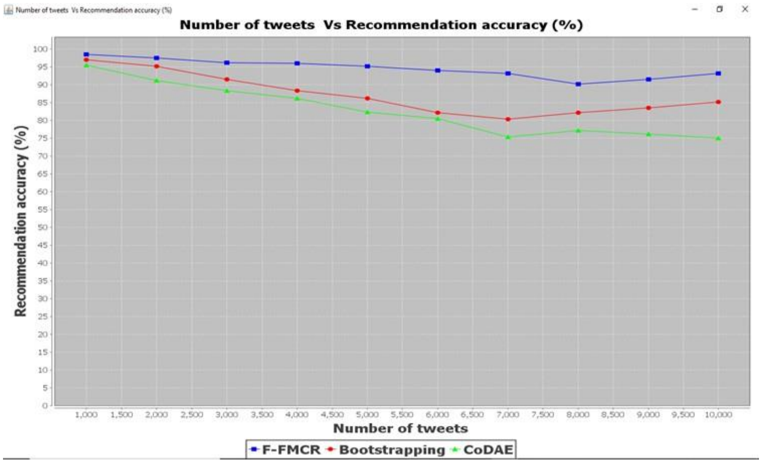

Figure 4 Graphical representation of recommendation accuracy

Figure 4 given above graphically compares the proposed F-FMCR, [1] and [2] Sentiment 140 dataset in terms of recommendation accuracy. In figure 4, X coordinates indicates number of tweets and Y coordinates indicates the measure of recommendation accuracy. The number of tweets is defined as the tweets made and used for experimental purpose so that recommendation made by multi-agents in terms of recommendation accuracy be measured. The reported result from Figure 4 shows that the proposed F-FMCR method outperforms other methods, [1] and [2] compared from 9% and 15% in term of recommendation accuracy.

This is evident from the simulation with 1000 number of tweets involved in recommender system and '985' number of tweets were correctly recommended by the agents using F-FMCR method, '970' number of tweets correctly recommended by the agents using [1] and '955' number of tweets correctly recommended by the agents using [2]. It is because F-FMCR method utilizes Friedman function that eliminates the occurrence of tied values by assigning the mean of the tweet grades, therefore terminating the probability of ties, therefore ensuring recommendation accuracy into F-FMCR method while other methods do not consider this factor, which indicates it is efficient to solve ties into the F-FMCR method.

4.3.2 Performance measure of recommendation time

Second, the recommendation time another significant factor or performance measure used in the analysis of recommendation system is provided in this section. Table 3 given below reports the recommendation time obtained using three different methods, F-FMCR, Bootstrapping [1] and CoDAE [2].

Table 3 Performance comparisons on recommendation time using F-FMCR, Bootstrapping [1] and CoDAE [2]

Number of tweets	Recommendation time (ms)		
	F-FMCR	**Bootstrapping**	**CoDAE**
1000	1015	1030	1050
2000	1030	1095	1135

3000	1090	1215	1325
4000	1120	1325	1555
5000	1185	1455	1925
6000	1215	1563	2135
7000	1295	1835	2235
8000	1325	1925	2315
9000	1415	2020	2455
10000	1525	2080	2525

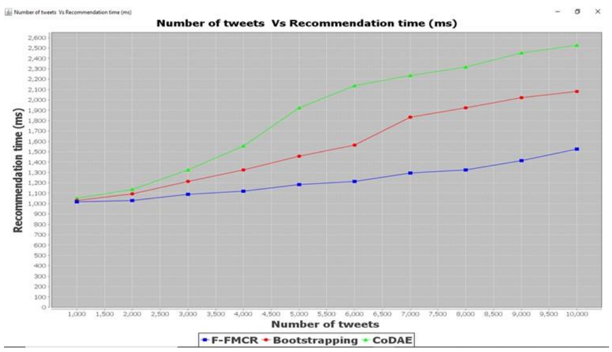

Figure 5 Graphical representation of recommendation time

Figure 5 given above shows the graphical portrayal of recommendation time using the three methods, F-FMCR, [1] and [2]. From the figure it is inferred that the recommendation time increases with the number of tweets to the multi-agent system. This is because of the reason that with larger number of tweets placed in the recommender system, the time involved in recommending the user's interest content also increases. So a direct proportionality is observed. However, with simulations conducted using 1000 numbers of tweets, build a reliable recommendation system, the time consumed in recommending right content to a particular user being '$1.015ms$', the overall recommendation time using F-FMCR was 1015ms, the time consumed in recommending right content to a particular user being '$1.030ms$', the overall recommendation time using [1] was 1030ms and finally observed to be 1050ms using [2]. From this result it is inferred that the recommendation time consumed in recommending the users by tracking their interests and activity using F-FMCR is better than when compared to [1] and [2]. The improvement is due to the application of Friedman Relevant Tweet Selection algorithm in F-FMCR. By applying this algorithm, initially, the tweets of each social network users were broken into tokens and then, the token relevance were identified by incorporating Friedman function. With this function, less significant tweets were eliminated and only the relevant tweets were obtained, therefore reducing the recommendation time using F-FMCR by 19% compared to [1] and 31% compared to [2] respectively.

4.3.3 Performance measure of mean absolute error

Finally, the mean absolute error is experimented and discussed in this section. Table 4 given below shows the mean absolute error values obtained for the three different methods.

Table 4 Performance comparisons on mean absolute error using F-FMCR, Bootstrapping [1] and CoDAE [2]

Number of tweets	**Mean absolute error (%)**		
	F-FMCR	Bootstrapping	CoDAE
1000	2	5	7
2000	3.5	5.85	7.55
3000	4.25	6	7.9
4000	4.55	6.55	8
5000	4.75	7	8.15
6000	4.9	7.35	8.35
7000	3.25	8	8.5
8000	3.55	7.25	8.25
9000	3.95	7.15	8.1
10000	4	7.45	8.25

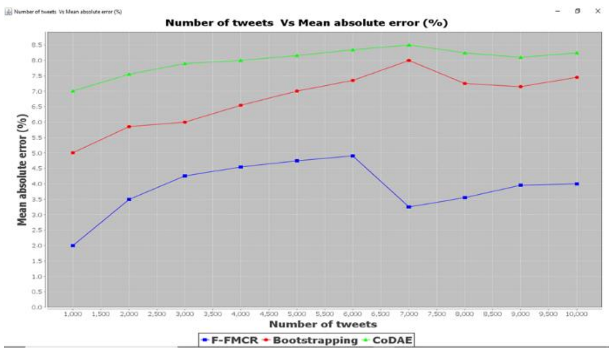

Figure 6 Graphical representation of mean absolute error

Figure 6 given above shows the impact of mean absolute error for different numbers of tweets in the range of 1000 to 10000 collected at different time intervals. From the figure it is inferred that the mean absolute error is neither inversely or directly proportional to the number of tweets considered for simulation. This is because of the reason that with different number of tweets posted and changes of views and interests changing over time for the same set of users itself, either an increasing trend or decreasing trend is said to be observed when evaluating mean absolute error. However, with the simulations conducted using 1000 numbers of tweets, and the predicted value of tweets to be '970' and the true values evolved using the proposed method being '950', the mean absolute error for F-FMCR is found to be 2%, the true values evolved using the bootstrapping being '920', the mean absolute error, the mean absolute error for Bootstrapping [1] was found to be 5% and 7% using [2]. From these results it is inferred that the mean absolute error is lesser using F-FMCR when compared to [1] and [2]. The results behind is due to the application of Frobenius Matrix Collaborative

Recommender algorithm. By applying this algorithm, a grading pattern using Frobenius Matrix Collaborative (FMC) function is employed with the objective of reducing the loss employing relevant tweets. Another reason is with the aid of differentiation function, the computational burden involved in recommendation is reduced, therefore minimizing the mean absolute error or prediction error using F-FMCR by 43% compared to [1] and 52% compared to [2].

5. Conclusion

Accuracy as compared that are computed in a fine-grained approach are commonly used during content - based recommendation methodologies. The above article seems to suggest a novel social recommendation technique called Grossman and Hermitian Composite Integrating Suggestion (F-FMCR) which employs a multiple-agent for social networking sites framework based on client communication to start reducing the average absolute error while enhancing the accurateness of the socioeconomic recommender. This technique differs from the majority of presently had been using review of the decision. Our technique's key contribution seems to be the development of a measurement for equivalent ratings by bringing forward the concept of a match anytime equivalent ratings within a frame are developed using Fermi product. This Friedman Relevance Tweets Feature selection technique is employed to identify and communicate the neural network - based relevant tweets after one original dataset would be first built and projected to identify and articulate the individuals and credentials for every tweet to present communication relationships between individuals. In hopes of offering an in-depth recommendation for something like the potential customer, the Function f Matrix Collaborative Proposal methodology is implemented in the second place. In conjunction with the experiments, a conversation quantitative assessment of our methodology was performed to contrast it to reducing techniques using the Sentiment140 datasets. In accordance with the findings, the F-FMCR method achieves higher than that of the previous methodologies.

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