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Enhancing User Recommendations through Context-Driven Natural Language Processing (NLP) and Strategic Feature Selection

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Abstract: The surge in popularity and significance of social networks in recent years is undeniable, with social networking sites experiencing an exponential increase in user engagement. These platforms enable users to connect with others, establishing friendships and facilitating communication. A notable trend among most social network websites is leveraging the social graph's proximity for recommending potential friends to users. The study in question introduces a user recommendation system that employs various algorithms to identify similarity factors among users, thereby enhancing the precision of friend suggestions. A key technique utilized in this system is feature selection, which effectively extracts pertinent information from both text and hypertext data sources. Among the various algorithms explored, the Context-Driven Network (CDN) stands out for delivering superior performance in generating user recommendations, indicating its effectiveness in harnessing contextual information to improve the relevance and quality of connections suggested on social networking sites.

Keywords : Feature Selection, Recommendation System, Context, User Interest, Natural Language Processing (NLP).

1. Introduction

People used to have pals who lived or worked nearby when they were younger, about 20 years ago. However, as technology advanced, social networking sites such as Facebook, Twitter, Google+, Instagram, and others grew in popularity, providing us with new methods to meet friends. While this is changing some aspects of life, it is also affecting people. On social networking sites, people are more unified than they are offline. The results show that there are around 4021 million active users of the internet, 3722 million unique mobile users, 3196 million active users of social media, and 2958 million active users of social media. [1].

This past few years, social networking sites like Facebook and Twitter have become more well-known. Statistics from Facebook show that each user has an average of 130 friends, which may be more than at any other time in history [2]. Friend recommendations are a big part of social networking sites, and they may help them grow by suggesting new and more possible friends to users. How to suggest a friend to a user is the hardest thing for social networking sites to figure out. Most social media sites choose who to add as a friend based on relationships between users, like similar friends, friends of friends, etc.

Sad to say, new sociology research suggests that this method might not be the best one [3]. [4]. People are put into groups based on their habits, way of life, attitude, likes, level of income, and the number of people they know.

These sites, such as Facebook and Twitter, inform users about people they might be interested in or already know.

However, it is critical to have a powerful and well-designed suggestion system. It's critical to understand that the primary goal of a social network is to enable people interact with one another and build connections. This means that the network should be based on what users are most interested in or have in common. Most of these sites, however, use more simpler methods to make new acquaintances, such as popularity, social graphs, or friends of friends. In recent years, scientists have conducted extensive research on how friends might provide ideas. As a result, numerous recommendation algorithms have been developed, including FOF [5], graph-based [6], content-based [5], and others. On social media, there might be many items of our interest that are listed in the interest section of our profile. Here, in this paper, we use the word “interest” to find the similarity index between the users for the recommendation purpose. Adopting Facebook as a base platform for the database, the information is elicited from profiles of multiple users. The feature selection method is used to extract relevant information from text and hypertext. People on Facebook can have a lot of interests such as “Speed Cars”, “Local Business”, “Dancing”, “Football”. “AajTak”, “Cricket”, etc. These interest words are employed to make the topic which assists in mapping the interest of two users to find the similarity between them. A recommender system is a type of computer system that provides ideas or suggestions. A recommender system will then recommend a friend based on their current interests.

To address the proposed problem of recommending the friend to a user, different algorithms are used and analyzed

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to find out the most suitable one. Methodologies used in this paper are TF-IDF, Latent Dirichlet Allocation (LDA), the Successive Bigram Association (SBA), and Context-Driven Network. The results are then compared for recommendation purposes.

Here are the sections that make up the remainder of the paper. Section 2 discusses work that is related. Section 3 describes the proposed technique for the system. Section 4 describes the User Interest Based Recommendation System. Section 5 contains the results, and Section 6 concludes the paper and tells about the future scope of the proposed work.

2. Related Work

There has been a lot of research on recommendation, whether it is recommending a friend on social networking sites, goods or items on shopping sites, books, journals, and other learning materials on educational sites, or anything else. People that research friend recommendations put in a lot of effort and employ a range of techniques. Kacchi et al. [7] proposed a solution approach based on a filtering and recommendation system. The suggested solution, which includes a friend matching graph and ranking processes, is based on a method for collecting and analyzing data. Wang et al. [8] state that machine learning and data mining techniques can be used to provide recommendations. They assert that these methods, which use semantic analysis to produce the recommendation, can function in a manner akin to a buddy recommending someone on social networking sites. According to user personalities, Bian et al.'s method [9] used collaborative filtering to make recommendations.

Kwon et al. [10] Presented a method for recommending buddies using a matching graph. The authors discussed how a person's lifestyle could be an innovative technique to identify similarities across social networking users. This study proposed a hybrid approach to person recommendation that included filtering and grouping strategies. Du et al. [11] demonstrated a responsible and effective friend recommendation algorithm based on friends of friends. This algorithm was based on a social network system used on a college campus to improve its complexity and scalability performance.

Yang et al. [12] advised that friend suggestions be based on content, social relationships, and filtering ideas in order to obtain a more accurate and comprehensive formula for the recommendation system. Zhao et al. [13] developed a hybrid friend recommendation architecture for Friend Recommendation based on both user location information and friend ties, employing a collaborative filtering mechanism.

Raghuwanshi et al. [14] Method for creating a friend recommendation system that connects people based on comparable interests. The similarity factor is calculated using the k-mean clustering algorithm and the closeness factor formula. Deng et al. [15] proposed a new approach to making suggestions by integrating the present FOF algorithm with the content-based method. This would provide more useful and accurate recommendations, speed up calculations for vast volumes of data, and resolve the accuracy issue. Farikha and team. [16] developed a produced a trusted friend’s calculation method for the task of recommending a friend. They performed this by probing the user’s profile and also drew the user’s model as an ontology that reflects all trusted friends’ preferences and the degree of trust between friends.

Yu et al. [17] This study investigates the use of preference coverage to maximize friend recommendations in Location-Based Social Networks (LBSNs). Recognizing that current recommendation algorithms usually disregard users' diverse preferences, our solution incorporates location and personal interests to improve user satisfaction. We utilize an innovative algorithm to combine user preferences and geographic proximity to identify nearby friends who share similar interests.

Zhou Zhang et al. [19] Our approach is unique in that it prioritizes preference coverage, resulting in more contextually relevant and personalized friend recommendations. Abbas et al. [20] Our findings demonstrate that FE-ELM outperforms other models when evaluated on real-world datasets, underscoring its potential to enhance the quality of friend recommendations in online social interactions.

Kumar et al. [21] ELM is used in FE-ELM to assess user preferences and take advantage of non-linear correlations, yielding more nuanced and accurate recommendations. Our solution beats traditional recommendation systems by collecting a wide range of user interests through the use of content-based and collaborative filtering techniques. [22]. It offers friends to users based on their lifestyles, regardless of their social networks.

Facebook Statistics, Stats, and Facts for 2011 [23] supplied with information about millions of users, and this infographic, made possible by the website Online Schools, displays it all. Facebook, a social networking site with over 500 million users, is used by approximately one in every thirteen individuals worldwide. More than 250 million of these users (more than half) log in every day. The average user still has approximately 130 friends, the same number as in 2011. This number has increased year after year.

Jiang et al. [24] Our method evaluates trust levels based on user proximity and interaction history, increasing the accuracy of friend recommendations. The system uses a complicated algorithm to evaluate interpersonal encounters, prioritizing connections with higher trust scores. This dynamic technique adapts to shifting social dynamics, resulting in precise and context-aware friend recommendations.

Dharmale et al. [25] the efficacy of our trust-based technique in establishing meaningful connections through extensive simulations on real-world PMSN data, making a substantial contribution to personalized and reliable friend recommendations in the context of mobile social networks.

Guy et al. [26] In a business social media app suite, personalized product recommendations were examined. This suite had communities, wikis, blogs, bookmarks, and sharing files. People and tags, which are two of the most important parts of social media, are used to make recommendations. Zheng et al. [27] suggested using a temporal-topic model to determine the identity of a potential microblogging friend by monitoring the user's projected behavior. The approach employs the topic model to gradually detect keywords in a batch of messages in order to establish what the user truly desires. It then explores how time affects shifts in interest.

Kang et al. [28] LA-LDA, a model for hidden topics, was suggested. There is limited and unevenly distributed attention in the process of spreading views and data on the social network, and this model brings it all together.

Pennacchiotti et al. [29] Developed an innovative friend recommendation system employing Latent Dirichlet Allocation (LDA) to achieve exceptional recall rates, surpassing conventional approaches rooted in graph analysis. This cutting-edge system not only enhances the accuracy of friend suggestions but also outperforms existing strategies, setting a new standard for precision and effectiveness in social network recommendations.

Huang et al. [30] offered a new technique to integrate user feedback from various friend groups to make friend recommendations on social networks. Genomes are utilized as models of how friends see things, allowing researchers to gain a better understanding of what consumers prefer. The suggestion system takes a more personalized and situation-aware approach by considering how each friend in the group perceives things. This improves the accuracy and usefulness of suggested links on social networks.

Nguyen et al. [31] Introduced a novel friend recommendation method tailored to social networks that is based on the user's friend view within each friend group. In order to facilitate a more complex understanding of individual preferences, this method utilizes genomes as a metaphor for friend group perceptions. By putting this user-centered view into different friend groups, the recommendation system gives a more personalized and situationally-aware approach, which makes friend suggestions in social networks more accurate and useful.

Guo et al. [32] Developed a novel friend recommendation system for online social networks (OSNs) that is trust-based and respects users' privacy. Building on Huang et al.'s [33] work, As part of the strategy, several social role networks were connected to find connections and provide friend recommendation suggestions. With a focus on privacy and trust in online social interactions, this strategy, known as NC (Network Correlation)-based SFR, seeks to improve the precision and reliability of friend recommendations.

Therefore, based on the study, it can be seen that a lot of work has been done in the field of recommendation. Also, different researchers used different methods of finding similarities between users. Some recommend friends via a matching graph, others based on content, while some by analyzing profile. Lesser work has been done in recommending friends based on their interests. Hence, this paper recommends friend based on the common user interests which are elicited from the users' profile from Facebook.

3. Proposed Model

The proposed model finds the similarity between the users on the basis of their common interests. Here, for implementation the data has been collected from Facebook with the users’ data consisting of the following details: Name, DOB, Gender, Profile/work, Education, Current Place, Native Place, School, Graduation place, Friend Count, Social Links, Check-in, Visited Cities, Events, and Interests. The data being used is the synthetic dataset which is collected from Facebook manually. It is then followed by preprocessing the raw dataset for further operations.

After the extraction of data, convenience data sampling is performed. In the convenience sampling, the data is selected based on the availability and ability of the user or the participant. This leads to the extraction of useful results.

The system works in the following steps: Preprocessing, Indexing, Feature Generation, Training of dataset, Testing, and Evaluation.

1. Preprocessing: The data is extracted from Facebook, followed by the correction of data such as date format, gender format. After this, the multivalued data is merged.
2. Indexing: This is an effective data structure technique to productively recover records from the database files based on characteristics on which the indexing has been done. Here, we are assigning more frequent words as lower index; i.e. rare words are more interesting words and vice-a-versa.
3. Feature Generation: This is the means of creating new features from one or many features, for implied use in the statistical analysis
4. Training: In the training step, the training data is used to train an algorithm.
5. Testing and Evaluation: In this, the system is run and tested, and evaluated to get the results. The size of the partition of data considered here is 1000:200 i.e. 5:1. Also, to avoid overfitting in the system, more weight is assigned to the words that match contextual patterns, and less weight to those which do not match to which can also be called noise.

The system is run on 4 different platforms: TFIDF, LDA, SBA, and CDN. The first three are based on the existing methodologies and CDN is the proposed algorithm to find the similarity between users and ranking them accordingly. The algorithms are then compared on the basis of their results so as to evaluate.

1. USER CONTEXT BASED RECOMMENDATION SYSTEM

The proposed framework recommends a friend to a user based on the liking words extracted. The extraction of user interests or better known as Feature Extraction or Attribute Extraction is the key component of our framework. The system introduced is run on different algorithms and finally the accuracy of the systems is compared so as to find the best one.

1.1 TF-IDF

Tf-idf or TFIDF abbreviates for Term Frequency-Inverse Document Frequency. In Information Retrieval, when referring to TFIDF, it is a numerical statistic that is intended to manifest how significant a word is to a document in a corpus. In text mining, information retrieval, and user modeling; TFIDF is often used as a weighting factor. As per the study, a survey was conducted in 2015 that showed that 83% of text-based recommender system in digital libraries uses tf-idf [31]

a. Term Frequency: This refers to the count of a term in a document.

t- Term
d- Document
then, term frequency tf(t,d) = count of t in d/ number of words in d

b. Inverse Document Frequency: The specificity of a term can be quantified as an inverse function of the number of documents in which it occurs

t- term
d- document
D- total number of documents
Then, Inverse Document Frequency, idf (t, d) = log (D / { d ∈ D : t ∈ d })

{ d ∈ D : t ∈ d } depicts the totality of documents in which t occurs

Then, tf-idf can be calculated as:

tf-idf (t, d, D) = tf (t, d) * idf (t, D)

1.2 Latent Dirichlet Allocation (LDA)

LDA is an application of NLP. LDA is a generative statistical model that permits sets of observations to be interpreted by unobserved groups that explain why some parts of the data are related. . Latent Dirichlet Allocation (LDA) is a generative probabilistic topic model for automatically identifying topics from the corpus of the text documents. In social networks, a corpus is of different users (tuples) and consists of attributes (documents) like (location, interests, gender, age, etc.). It is a mixed membership model, based on the fact that a user might be recommended to a number of friends. The LDA is performed in the following steps:

Step 1: For each attribute, a dictionary and corpus of unigram and bigram is created. In our data, we have 4 numeric attributes and 11 text attributes.

Step 2: For each attribute, the LDA model is created to map words to topics (no. of topics here =10). This leads to a vectorized topic set for each attribute.

Step 3: For each training user, for each attribute, we have now topic values. For evaluation, a comparison is done between the topic vectors of the test user with each training user.

Step 4: Similarity between users is found out based on Euclidean distance.

A disadvantage for LDA is that with the increase in the number of users, the LDA's model would need retraining to create a new model.

1.3 Successive Bigram Association(SBA)

In NLP, the context analysis entails slicing down the sentences to extract the n-grams, noun phrases, themes, and facets present within. Lexalytics supports four methods of context analysis: N-grams, Noun phrases, Themes, and Facets. SBA, the proposed algorithm uses the following two steps for recommendation

a. *Using N-grams for Basic Context Analysis*: N-grams are combinations of one or more words. These words represent phrases, concepts, entities, and themes that arise in the text. There are three common levels of n-gram:

1 word = mono-gram
2 words = bi-gram
3 words = tri-gram
But, here in the proposed algorithm, we are dealing with quad-grams also.
4 words = quad-gram

b. *Using Stop Words to Clean up N-gram Analysis:* Stop words are the list of words that may appear in the document multiple times but also are of no use to use.

For eg., "ïs", "a", "an", "the", "of"
Therefore, to avoid unwanted entities, it becomes important to clean the stop words.

Hence, in SBA the pattern of words (N-grams) occurring in different documents is matched. The word is checked that in which user it had appeared. Then based on it, the weight is assigned to the user. If the test user lies nearby then it is likely to be matched.

The rating of the user if find out by the following:

$$ratingofwordw = N * log10\left(\frac{noofusers}{no.ofuserswithw}\right)$$

Where, N= N in N-grams

4.4 Context Driven Network(CDN)

Context-Driven Networks provide better observation and scalability for newer users on social networks. Classification of collection words as facet, theme, and phrase type of word pattern provides a piece of contextual information about attributes like interests, location of the user. The introduced model is a continuation of the n-gram network model using context analysis. This is the proposed algorithm to check the performance with other used existing algorithms (as in 4.1,4.2 and 4.3). The result of CDN is to be compared with TFIDF, LDA, and SBA results.

These are the networks from Word Patterns to user representation in the form of a sparse matrix. These include Noun Phrase (NP), Theme and Facets

Noun Phrase: POS patterns incorporating noun phrases are versatile structures that enhance language expression. Common noun phrase patterns include:

- Noun
- Noun-Noun..… -Noun
- Adjective(s)-Noun
- Verb-(Adjectives-)Noun

Extraction of Noun Phrases helps restrict to phrases matching certain part of speech patterns

a. Theme: Themes constitute noun phrases characterized by contextual relevance scores. These thematic elements, identified and isolated based on speech patterns, inherently embody noun phrases.

b. Facets: These structures are designed to handle intricate scenarios where theme processing alone may not suffice. Occasionally, when the text lacks a suitable noun phrase despite harboring valuable meaning and intent, these elements come into play.

c. So, using CDN the word pattern is identified whether it is an NP, Theme, or a Facet. Using the analytic library, it is identified which word is Noun, adjective, etc. After identification, the N-grams are mapped to the patterns.

Here, the context matching is done based on which the weight is assigned. The context of the test user is matched with the context of our training user. The rating is then finally calculated to find the similarity. Rating is calculated by the below formula:

$$rating = \propto * \log 10\left(\frac{noofusers}{no.ofuserswithw}\right)$$

Where, $\propto$ = N/2 ….if context doesn't match

= No. of noun/verbs…….if context match

= 4………if it is a phrase

= 5………if it is a theme

= 6………if it is a facet

Algorithm 4 CDN Based Recommendations

Input: Training Data of 1000 Users, Test Data of 200 Users

Output: Distance vector of 1000 Users for 200 Users

```
Assumption: attributeList = { 'interests', 'dob', 'activities', ... }
uni, bi, tri, quad, context =  GET_CDN_MAP( 1000, TrainingSet )
FOR testId 1 to 200 do
   FOR attribute in  attributeList do
      sentence = DataSet[userId][attribute]
      tokens = tokenize(removeStopWords(sentence))
      FOR word IN tokens do
         FOR trainId IN uni[word], bi[word], tri[word], quad[word]
            Beta = GET_CDN_WEIGHT ( word, context[word] )
            rec[testId][trainId] = SUM( Beta * LOG ( 1000 / LEN( ngram[word] )
            distance[testUserId][trainingUserId] = 1000 - rec[testId][trainId]
RETURN distance
Function GET_CDN_MAP(  UserCount ,  DataSet ):
FOR userId 1 to UserCount do
   FOR attribute in  attributeList do
      sentence = DataSet[userId][attribute]
      tokens = tokenize(removeStopWords(sentence))
      FOR word in tokens do
         uni[word(i)] += userId
         bi[word(i-1)_word(i)] += userId
         tri[word(i-2)_word(i-1)_word(i)] += userId
         quad[word(i-3)_word(i-2)_word(i-1)_word(i)] += userId
         context = GET_CONTEXT(word(i-3)_word(i-2)_word(i-1)_word(i))
RETURN  uni, bi, tri, quad, context
Function GET_CONTEXT( word(i-3)_word(i-2)_word(i-1)_word(i)):
context = GET_VERB_NOUN_ADJ_USING_POSTAG( word(i-3), word(i-2),.. )
If context IN ('AN', 'ANN', 'AAN') THEN context = 'PHRASE'
If context IN ('NN', 'NNN') THEN context = 'THEME'
If context IN ('NVN', 'NVAN' , 'NVA') THEN context = 'FACET'
RETURN context
Function GET_CONTEXT_WEGHT( word, context ):
weight = NO_OF_TOKENS(word) / 2
IF  GET_CONTEXT(word) ==  context:
   IF context == 'FACET' THEN weight = 4.5
   ELSE IF context == 'THEME' THEN weight = 4
   ELSE IF context == 'PHRASE' THEN weight = 3.5
   ELSE weight = NO_OF_VERB(word) + NO_OF_NOUN(word)
RETURN weight
```

We are using two techniques for calculating impact of an attribute on a set of user i.e. Information Procure (IP) and Rating,

$$IP(An) = \frac{P\big(An(Ui) \cap An(Uj)\big)}{P\big(An(Ui)UAn(Uj)\big)}$$

Where

$IP(A_n)$ - Information Procure of Attribute(A_n)

$P(A_n(U_i) \cap A_n(U_j))$ - Probability of two users (U_i,U_j) being friend given A_n is common between them

$P(A_n(U_i)U\ A_n(U_j))$ - Probability of two users (U_i,U_j) being friends at random

Thus, Information Procure (A_n) captures impact of the attribute in dataset and filter words having sufficient information gain then Calculate context of those words

For example: "who.com": ORGANIZATION
"dhoni": "PERSON"
"indore mumbai": "LOCATION"

Use information procure and context to give more weight during recommendation. Here, the context matching is done based on which the weight is assigned. The rating is then finally calculated to find the similarity. Rating is calculated by the below formula:

$$rating = N * math.\log 10\left(\frac{no_{users}}{no_{words}}\right) + INFO_{GAIN_{WEIGHT}} * information_{gain(word)} + Context_{based_{weight}}$$

Human beings generated recommendations considering the actual context of words common between users.

On the same lines, Context-Based system detects the context of words and gives more weight to words that point to unique location, occupation, education, people, or organization.

Hence, Results suggested by Context-Based system are found to be better than normal algorithms that consider only common words among recommendations.

4. Result

A total of 1000 users' data was collected from Facebook. The partitioning data was considered to be 1000:200 i.e.

5:1. The system yields result by comparing the similarity factor between two users. Based on the similarity, ranking is assigned to each user and by the use of which a friend is recommended to a user.

Based on the work done, this is seen that CDN yields better outcomes compared to other algorithms. The Root Mean Square (RMS) error of CDN is showed in Table 1 when examined with TFIDF, LDA, and SBA.

Table 1 Accuracy

Algorithm	RMS Error Count	RMS Error
CDN vs TFIDF	994	335.3625879
CDN vs LDA	994	690.3117122
CDN vs SBA	994	43.97179672

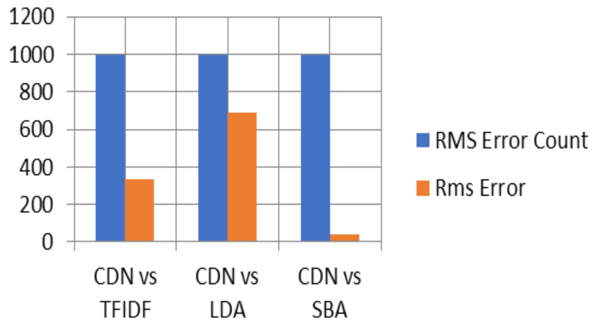

Figure 1. Graph showing CDN accuracy

Figure 1 is the graphical representation of Table 1, which shows that the RMS error with RMS Error Count as 994 is least with SBA and highest with LDA. Figure 5 shows the graph of Log (Error) with the size of dataset for different size of test data.

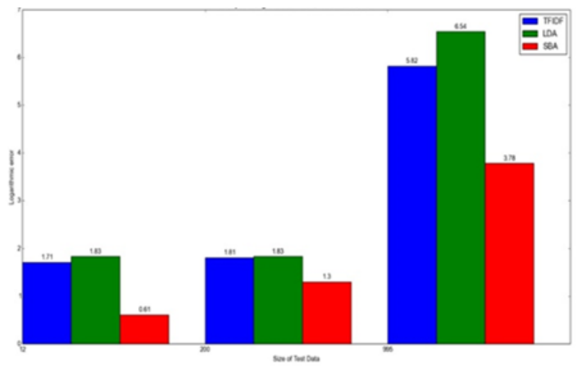

Figure 2. Graph of Logarithmic RMS Error of Test Data

Some of the screen-shots are there to understand the result as follows :

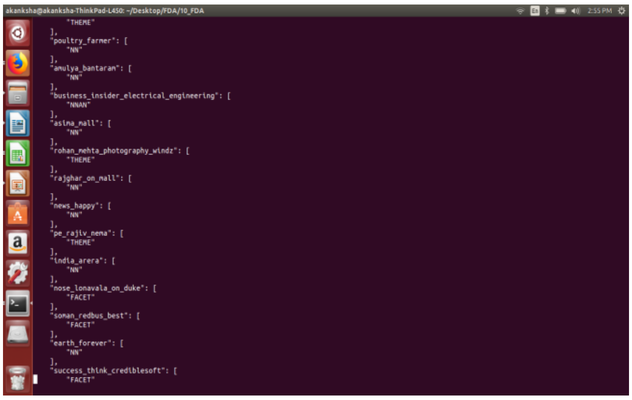

Figure 3. Word Patterns

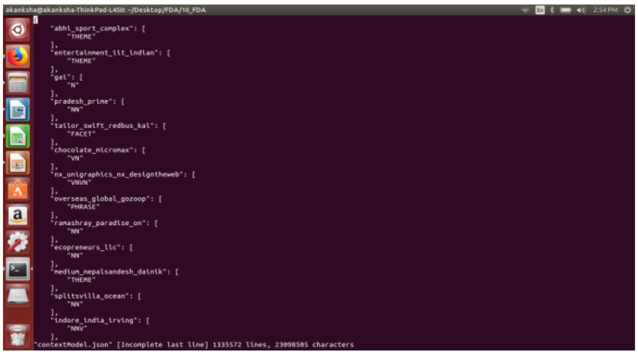

Figure 4. Word Patterns and context

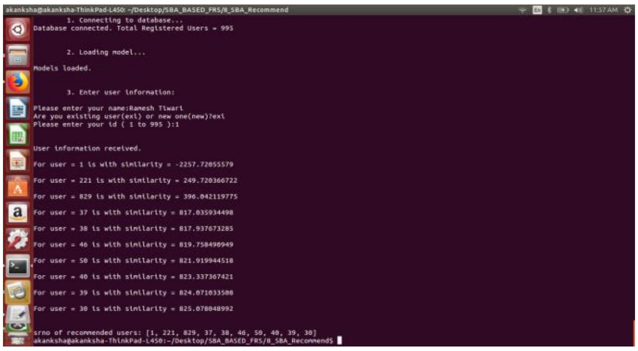

Figure 5. Similarity Index

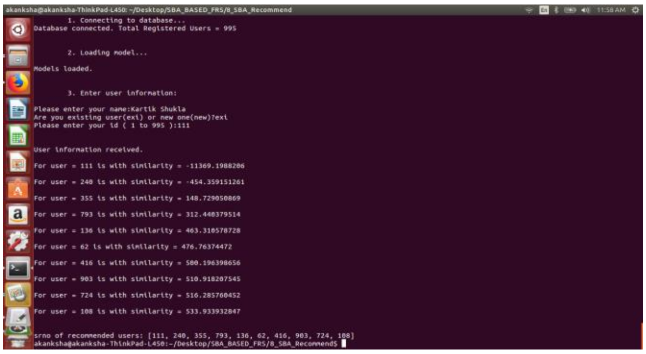

Figure 6. Similarity Index and Recommendations

5. Conclusion and future scope

With the growth of the internet, the exponential rise in online social networking platforms such as Facebook has delighted one's concentration. As a result, many researchers have put a lot of effort into trying to find more reliable methods to recommend a user with the closest similarity. In this paper, we implemented four different methods for the recommendation purpose for the social network Facebook. Distinct from the previous recommendation mechanisms which mostly rely on social graphs in existing social networking services, the proposed model used the interests of users to find the similarity between two users. The existing methods (TFIDF, LDA, and SBA) are compared with the proposed methodology CDN. CDN gave better results from the rest of the algorithms, giving better similarity and recommendation. Also, it can be concluded that common interests between users can help in getting a better recommendation.

Past the present model, the proposed model can be expanded to new levels. We would like to evaluate our system on other new attributes apart from interest. Also, we intend to acquire other social media platforms apart from Facebook. This would help the system to be scalable to large-scale. The system can be integrated with latest machine learning, deep learning and meta-heuristic approaches for efficient, effective and robust search and improve their performance in terms of solution quality, robustness etc. The following could be the nearest points of action as future scope:

Scalability : The system can be made scalable to handle huge amounts of data with increasing resources. This when considered with economic context can use very helpful for a scalable business which implies that a company can increase sales with increasing resources. A scalable system helps also helps in improving the performance and cost of a system. The proposed system can be made scalable in different terms including increased user data, increased factors for a recommendation, or any other.

Extended platforms : The system can be extended to multiple other platforms too in near future such as Instagram, LinkedIn, and many. The recommendation could help them recommend a common friend, contact, or colleague. Not only in terms of friends or a contact, but this can also be used for other recommendations too such as clothes on a shopping website, or grocery on a grocery online website based on previous search or buy history.

Good for Business Models : This recommendation system can give new heights to businesses too. This can help many businesses in growing their sales and profit along with saving time. Businesses could use this technology in different dimensions as user can convert in consumer by providing good recommendation.

Discerning the Emotional state of a user : Effective computing can help the RS to identify the emotional state of a user that can be used to recommend the services accordingly. This can be used in different fields such as music, whereby sensing the current mood of the user, the RS will recommend songs accordingly. Similarly, for books, places to visit, etc.

Benefits in Healthcare Industry : The context-based RS can also prove very helpful in the Healthcare industry where a patient can be recommended different options such as medicine, a nearby hospital, doctor, dispensary, etc. This can prove to be a great success in life saving if applied. Based on the patients' context of illness, medication, and other factors, it can produce good results.

Education and Career fields : Context-based RS can also bring great changes to the field of education and career. The proposed method if applied in the field of education can use to recommend books, courses, colleges to students based on their interest in different subjects and fields.

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Conflicts of interest

The authors declare no conflicts of interest.

References

[1] https://www.statista.com/topics/1164/social-networks/

[2] Facebook statistics. http://www.digitalbuzzblog.com/facebook-statistics-stats-facts-2011/.

[3] G. Spaargaren and B. Van Vliet. Lifestyles, Consumption and the Environment: The Ecological Modernization of Domestic Consumption. Environmental Politics, 9(1):50-76, 2000.

[4] M. Tomlinson. Lifestyle and Social Class. European Sociological Review, 19(1):97-111, 2003.

[5] Chen J, Geyer W, Dugan C, Muller M, Guy I (2009) Make new friends, but keep the old recommending people on social networking sites. In: Proceedings of ACM conference on human factors in computer systems (CHI 09). ACM Press, New York, pp 201–210. doi: 10.1145/1518701.1518735

[6] Silva NB, Tsang I-R, Cavalcanti GDC, Tsang I-J (2010) A graph-based friend recommendation system using genetic algorithm. In: Proceedings of IEEE congress on evolutionary computation (CEC 10). IEEE Computer Society, pp 1–7. doi: 10.1109/CEC.2010.5586144

[7] Tofik R. Kacchi, Prof. Anil V. Deoranker," friend Recommendation system based on Lifestyles of Users" International Conference on Advances in Electrical, Electronics, Information, Communication and Bioinformatics (AEEICB16)2016, pp.01–04.

[8] Peter Zhibo Wang, Hairong Qi,"Friendbook: A Semantic-Based Friend Recommendation System for Social Networks," IEEE Transactions on Mobile Computing, Vol. 14, No. 3, MARCH 2015, pp. 01–14.

[9] Bian and H. Holtzman, "Online friend recommendation through Personality matching and collaborative filtering," in Proc. 5th Int. Conf. Mobile Ubiquitous Compute, Syst., Services Technol., 2011, pp.230- 235.

[10] J. Kwon and S. Kim, "Friend recommendation method using physical and social context," Int. J. Comput. Sci. Netw. Security, vol. 10, no. 11, pp. 116–120, 2010.

[11] Zhao Du, Lantao Hu, Xiaolong Fu and Yongqi Liu, "Scalable and Explainable Firend Recommendation in Campus Social Network System", Springer Science+Buisness Media Dordrecht 2014.

[12] Liangbin Yang, Binyang Li, Xinli Zhou and Yanmei Kang, "Micro-blog Friend Recommendation Algorithms Based on Content and Social Relationship", Springer Nature Singapore Pte.Ltd. 2018.

[13] Yan Zhao, Jia Zhu, MengdiJia, Wenyan Yang and Kai Zheng,"A Novel Hybrid Friend Recommendation Framework for Twitter", Springer International Publishing AG 2017.

[14] Rachana Raghuwanshi and G.L. Prajapati, "An Approach for Friend Recommendation Based on Selected Attributes", Proceedings of the World Congress on Engineering 2017 Vol II WCE 2017, July 5-7, 2017, London, U.K.

[15] Zhiwei Deng, Bowei He, Chengchi Yu and YuxiangChen,"Personalized Friend Recommendation in Social Network Based on Clustering Method", Springer-Verlag Berlin Heidelberg 2012.

[16] Mohamed Farikha, Mohamed Mhiri and FaiezGargouri,"A User Interest Ontology Based on Trusted Friend Preferences for Personalized Recommendation" Springer International Publishing AG, EMCIS 2017, LNBIP 299, pp. 54-67

[17] Fei Yu, Nan Che, Zhijun Li, Kai Li and Shouxu Jiang, "Friend Recommendation Considering Preference Coverage in Location-Based Social Networks" Springer International Publishing AG, PAKDD 2017, Part II, LNAI 10235, pp. 91-105.

[18] Zhen Zhang, Xiangguo Zhao and Gouren Wang, "FE-ELM: A New Friend Recommendation Model with Extreme Learning Machine" Springer Science+Buisness Media New York 2017.

[19] Zhou Zhang, Yuewen Liu, Wei Ding and Wei Wayne Huang, "A Friend Recommendation System Using Users' Information of Total Attributes" Springer International Publishing ICDS 2015, LNCS 9208, pp. 34-41.

[20] Fizza Abbas, Ubaidullah Rajput, HasooEun, Dongsoo Ha, Taeseon Moon, Wenhui Jin, Hyunjun Back, Honglae Jo, Sul Bang, Seung-ho Ryu and Heekuck, "Trust Evaluation Based Friend Recommendation in Proximity Based Mobile Social Network" Springer International Publishing CSoNet 2016, LNCS 9795, pp. 158-169.

[21] Praveen Kumar and G. Ram Mohana Reddy, "Friendship Recommendation System Using Topological Structure of Social Network" Springer Nature Singapore Pte Ltd. 2018.

[22] Pankaj L. Pingate, S. M. Rokade, "A Survey of Friendbook Recommendation Services", International Journal of Science and Research (IJSR), ISSN (Online): 2319-7064, Vol 3, Issue 11, November 2014.

[23]Facebookstatistics.http://www.digitalbuzzblog.com/Facebook-statistics-stats-facts-2011/.

[24] Wei Jiang, Ruijin Wang, ZhiyuanXu, Yaodong Huang, Shuo Chang, and Zhiguang Qin, "PRUB: A Privacy Protection Friend Recommendation System Based on User Behavior" Hindawi Publishing Corporation 2016.

[25] Pooja N. Dharmale, P. L. Ramteke, "An Efficient Method for Friend Recommendation on Social Networks" International Research Journal of Engineering and Technology (IRJET) Vol. 3, June-2016.

[26] Ido Guy, NaamaZwerdling, Inbal Ronen, David Carmel, ErelUziel, "Social Media Recommendation based on People and Tags" SIGIR ACM 2010.

[27] Nan Zheng, Shuangyong Song and HongyunBao,"A Temporal-Topic Model for Friend Recommendations in Chinese MicrobloggingSystem"IEEE 2015.

[28] Jeon-Hyung Kang, Kristina Lerman, LiseGetoor,"LA-LDA: A Limited Attention Topic Model for Social Recommendation" cs.SI 2013.

[29] Marco Pennacchiotti, Siva Gurumurthy,"Investigating Topic Models for Social Media User Recommendation"WWW ACM 2011.

[30] Shangrong Huang, Jian Zhang, Dan Schonfeld, Lei Wang, Xian-Sheng Hua,"Two-Stage Friend Recommendation based on Network Alignment and Series Expansion of Probablistic Topic Model"IEEE Transaction 2017.

[31] Trung L.T. Nguyen and Tru H. Cao, "Multi-group-based User Perceptions for Friend Recommendation in Social Networks" Springer International Publishing PAKDD 2014, LNAI 8643, pp. 525-534.

[32] Linke Guo, Chi Zhang, Yuguang Fang and a fellow, "A Trust-based Privacy-Preserving Friend Recommendation Scheme for Online Social Networks" 1545-5971 (c) 2013 IEEE

[33] Shangrong Huang and team "Social Friend Recommendation Based on Multiple Network Correlation" 1520-9210 (c) 2015 IEEE