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Image Content based Topological Analysis for Friend Recommendation on Twitter

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Abstract: ***Recently, there has been increase in usage of social media platform i.e., Twitter for sharing information, personal interests and breaking news during emergencies. One of the main challenges in twitter application is friend recommendation. In this paper, we propose a Novel Image Content based Topology Analysis for Friend Recommendation (IICTA-FR) for overcoming the challenges of finding the similar people. In IICTA-FR, we construct topology based tweet analysis and Image content analysis to find relevant friend for Twitter users. In this work, we provide a framework to compute relationship strength for ties based on directed interactions between users. The proposed ICTA-FR framework produces a directed and weighted graph where the nodes and edges represent Twitter users, and user interactions respectively. Further, each weight in the directed edge represents about the probability of any interaction going from the edge source to the edge destination in the future. This weight is based on both tweet analysis and image analysis. We used hierarchical generative model for understanding the images posted in twitter through a visual model. We used logistic regression based model for calculating the edge scores in the graph. The proposed methodology has been validated on real Twitter data and found to give better results than the existing state of art algorithms in terms success rate.***

Keywords: Twitter, Recommendation Systems, Image, Tweet, Topology.

I. INTRODUCTION

Recently, there is an exponential growth of number of users in social networks in the last decade. This statement is true in case of Twitter, where users share their opinions, photos, news, and videos every day to the like-minded people or friends. One of the important issues in these types of social networks is the recommendation of social friends efficiently. The main activities of social friends include tweets, retweets, response, likes, dislikes, sharing. These interactions provide a platform to share their feelings. These social friends share their working performance, habits, hobbies, preferences etc., In this point of view, Social friend recommendation has therefore become a hot research topic among research community and several methods have been proposed to conduct recommendation efficiently [1], [2].

One of the common technique used are Graph construction, in which nodes are taken as user, link edge are taken possible interaction among the users. In twitter, users (or nodes) are connected based on the quantitative value for each (directional) pair wise connection between user nodes. The calculation of edge value is based on interaction and image posted on the twitter. This work details a framework we have built at Twitter for computing tie strength.

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The effectiveness of the friend recommendation system depends on how well we understand the behavior of the user and his interaction. Typically understanding the behavior means analyzing the contents of tweets, retweets and image shared /posted on the twitter. All the above said factors lead to better user recommendations, improve the relevance of user search results, and provide enhanced performance on any task that can benefit from social recommendation systems. For example, Twitter users often search for a likeminded people with the chance of increasing their satisfaction to improve the relations and usage of the service.

The Computation for edge feature is having few points to note far. First, removing duplicate user accounts. Second millions of tweets of different users are to be analyzed. Finally, finding the preferences of users which matches with the current user. The matching criterion should be based on current topic interested in and images/video posted in the twitter. Ideally, we would like to make the computed weight a general and easily interpretable metric so that it is applicable for a variety of use cases. A major short coming in the current state of algorithms is analysis is done only on the posted tweets. But the interaction between two users is based on the posted images. Therefore a new category of Topological technique based on both tweet and image analysis is proposed.

In this paper, we present a framework named novel Content based Topology Analysis for Friend Recommendation (ICTA-FR) in Twitter. The constructed Graph is a directed, edge-labeled, weighted graph where the nodes are Twitter users, and the edges are labeled with interactions (from a fixed, extensible set) between a (directed) pair of users. The probability of user similarity via tweets & images is represented as edges. .This work is also based on Twiter’s user recommendation system, Who To Follow [3]. In [3] , a random walk algorithm is employed on the generated graph with weighted edges. The output of these algorithms will result in recommendations towards users that have similar interests with their followers. Our recommendation not only takes tweets into accounts, but also similar pictures posted on the timeline. This work can also be used as an effective pre-processing mechanism for finding the top-k connections of a end user, which can provide an easy scaling scheme for applications while minimizing the information loss. Finally, a variety of relevance products (such as search on Twitter, and Facebook) use the Graph weights for personalized scoring of results.

The main contribution lies in two aspects:

1. A novel graph representation with tweet similarity and posted image similarity.
2. A a Novel Content based Topology Analysis (ICTA-

FR) for effective friend Recommendation.

The rest of the paper is organized as follows. Section II gives an overview of the recent works. In Section III, the proposed methodology for Novel Content based Topology Analysis for Friend Recommendation is presented. Finally, Section IV describes the experiments and analysis of the real twitter data set. Conclusions are drawn in Section V.

II. RELATED WORKS

In social media, we are stuck with different types of user. What should I tweet? Which user should I choose to become follower? Which news should be shared? Or before choosing a friend, we feel the need for asking other people's opinions. Recommender systems fill this gap by helping twitter users to find the most suitable followee (or personality) for them. Recommender Systems are widely used in web applications in e-commerce. But slowly , recommender systems also finds in social media platforms like Twitter, Facebook, Youtube etc., In e–commerce, recommender systems [5] is introduced to predict customer's next action & sell items for increasing the customer satisfaction. These recommender systems are trained with customer's previous data like past preferences, messages, images, videos. For example, at youtube.com, videos are recommended to YouTube users [4] based on the past history, subscription, comments section, user's location and user's search history. In online networking, (for example, Twitter) client's attributes are expected to be broke down for suggestion comparable occasions or clients [6, 7]. What's more, Facebook has a companion recommender framework in light of system structure. At YouTube, video proposals for every client depend on client's most recent exercises [24]

In this section, we review some of the text content analysis techniques: [8] considers client produced content on Twitter and builds up a quick calculation for constant client to-client similitude for adherent/followee suggestion. It has been produced just for content comparability. [9] Concentrates on versatile applications and makes companion proposals by considering the impact of various social angles, for example, areas and normal fascinating words. It characterizes change likelihood for kinship proposal in light of area neighborhood and intriguing word co-event. Crafted by [10] additionally consolidates social data from various layers. It takes both setting and substance data and partners it with space learning. It takes client's verifiable input to join various types of data. A current investigate course called versatile suggestion [11] likewise joins diverse systems by presenting inert components and amplifying the back dispersion.

We discuss some of the image analysis techniques here: The greater part of the prior question also, scene acknowledgment work offers a solitary name to a picture, e.g. a picture of a panda, an auto or a shoreline. Some go further in doling out a rundown of comments without confining where in the picture every comment has a place (e.g. [13]). A couple of simultaneous division and acknowledgment approaches have recommended more gritty decay of a picture into frontal area question and foundation mess. Be that as it may, every one of them as it were apply to a solitary protest or a solitary kind of question (e.g. [12]). The work [14] show catches the co-events of items furthermore, abnormal state scene classes. Acknowledgment turns out to be more exact when distinctive semantic segments of a picture are at the same time perceived, enabling every segment to give relevant limitations to encourage the acknowledgment of the others. Moreover, both protest acknowledgment inside a scene and in addition scene order can profit by understanding the spatial degrees of each semantic idea. Our model can perceive and portion numerous items also as arrange scenes in one intelligible system.

Now we see some scene analysis techniques: A few past works have adopted on a more all encompassing strategy in scene translation [15, 16, 17, 18]. In every one of these works, worldwide scene level data is fused in the model for enhancing better protest acknowledgment or recognition. Scientifically, our approach is nearest in soul with Sudderth et al [17]. We both take in a generative model to name the pictures. Our occasion understanding model, nonetheless, vary essentially from the past works by giving an arrangement of integrative and various leveled names of a picture, playing out the what(event), where(scene) and who(object) acknowledgment of a whole scene. What's more, our aggregate scene understanding demonstrate stretches out this to more comprehensive picture understanding including concurrent protest acknowledgment, picture comment and division.

Recently video scene analysis techniques are also proposed. In [19], the content analysis on traffic video are analyzed with the help of object trajectories, where as in [20] semantic rules are extracted to understand the content present in the video. These two techniques can be used for short videos posted on the twitter. One famous approach to fuse fleeting data is to process Structure from Motion (SfM) between sequential outlines with a specific end goal to register geometric/movement based highlights [21,22] One downside of this approach is that precise SfM calculation might be moderate as well as may require a substantial cushion of past casings to process. Then again, as well as likewise, a huge graphical model can be characterized among various edges, where edges between outlines spread forecasts after some time [23,24]. Performing limited, estimated induction over such extensive models remains a testing issue. Besides, with a specific end goal to productively process inexact arrangements, just a gauge of the MAP conveyance is returned, i.e., there is no vulnerability in the naming or minor disseminations.

The main idea behind this approach is to consider posted tweets, customer preferences and posted images. In this method, we provide a framework to compute relationship strength for ties based on directed interactions between users. The proposed work produces a directed, weighted graph where

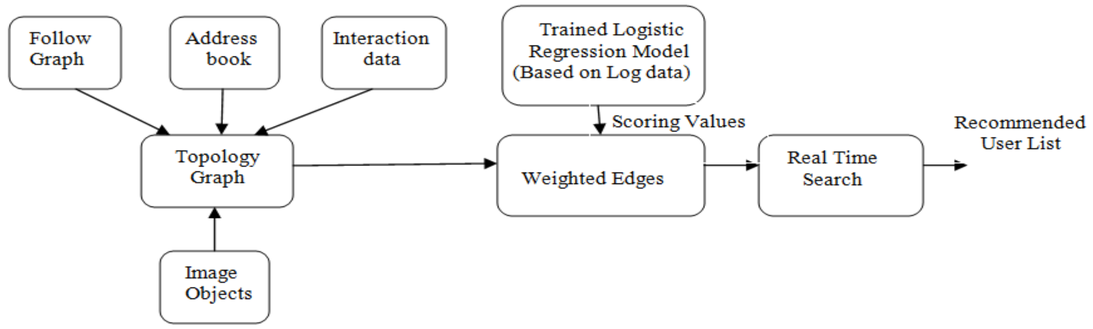

Fig. 1 Shows the proposed framework for a Novel Content based Topology Analysis for Friend Recommendation (ICTA-FR)

the nodes and edges represent Twitter users, and user interactions respectively. Further, each weight in the directed edge represents about the probability of any interaction going from the edge source to the edge destination in the future. This weight is based on both tweet analysis and image analysis. We used hierarchical generative model for understanding the images posted in twitter through a visual model. Finally, list of users recommended for each type of users.

III. PROPOSED NOVEL IMAGE CONTENT BASED TOPOLOGY ANALYSIS FOR FRIEND RECOMMENDATION APPROACH

Overview

Recently Twitter has become popular platform to convey information in the form short messages, images, videos. But users do not follow all the users in the twitter. These systems provide information about follower, followee to recommend new type of users. But it is found that there is still there is room for improvement by considering images and text messages. We proposed a Novel Content based Topology Analysis for Friend Recommendation (ICTA-FR)(as shown in fig 1) , which consists of graph construction, feature calculation and applications. The graph nodes represent end users. A set of links in the graph connecting nodes are obtained with the help of address book and their personal interaction. Each link is labeled with weight feature, representing the type & frequency of interaction from source to destination user. Logistic regression model is trained with aggregated edge feature. This trained model is used to calculate the probability of user interactions in the graph.

Graph Generation

In this Graph Generation, edge is linked between users when ever follow event occurs, phone or email address book, interaction event occurs. The follow event refers to one user follows other user. The address book event refers to one user is present in other user book or vice versa. Finally the interaction event refers to the user actions like re-tweeting, like, sharing etc., In addition to this, we maintain time-stamp to each edge links. This graph computation is done routinely to incorporate the latest edge features and old edge links are pruned to old interaction based on time stamp attribute. More information about graph edge features, user features and image features are presented in the next sections.

Edge Features

We considered Uni-direction message follow, Bi-directional follow and SMS follow. In Uni-directional follow, only one user follows the other. In bi-directional follow, both users follow each other. In SMS follow, one user (follower) receives all of the messages from other user(followee). These follows are collected from address book of each particular user, along with the time stamp. Besides, we not just store a Boolean incentive on every one of these highlights yet in addition store a number of amounts. For take after edges, we store the number of days since the edge was made. The address book edge is likewise explained with this amount. The collaboration edges are dealt with in a somewhat extraordinary way. We gather two sorts of collaborations from a client A to B: (1) Visible collaborations (from B's perspective): A retweets B's tweet, A top picks B's tweet, A notices B (by means of their handle), or A messages B, and (2) Implicit collaborations: A ticks on B's tweet or on a connection inside the tweet, A visits B's profile page. For every one of these connections, we gather a few time arrangement related esteems that mean to catch the recurrence, force and regency of every cooperation when it happens:

• Non-zero days: the quantity of days when such a connection happens

• Mean and difference: the mean and change of collaboration checks (figured over non-zero collaboration days)

• Decayed tally: an everyday exponentially-rotted association checks (EWMA).

• Days since last association: number of days since the last association of this write

• Elapsed days: number of days since the primary communication of this write happened

At last, we say a couple of other edge includes that are in expansion to the above. To begin with, we have an element for the quantity of various non-zero connections composes for an edge as we have discovered assorted variety of recorded co-operations between two clients to be a decent pointer.

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We likewise have an element for the quantity of basic companions (clients that both take after and are trailed by both users) to quantify closeness as far as the diagram. We likewise include a couple of point related edge includes on each edge. For processing these, we utilize the 300 theme scientific categorization and high accuracy subject displaying framework to dole out inspired by and referred to for themes for every client as portray in [10]. This outcome in a few edge highlights, for example, the number of basic points between source client's keen on and goal client's known-for and so forth.

User Features

For each edge include type depicted in past segment, we total the qualities and utilize it for the source client as sending highlight and for the goal client as got include. For instance, the EWMA of a client's aggregate retweets is the whole of EWMA of re-tweet co-operations on all its active edges. Then again, the mean of notices is the day by day normal of tweets containing the client's name. We likewise incorporate a few highlights for every client's action and notoriety. These incorporate number of tweets in the most recent week, dialect, nation, and number of supporters, number of individuals they take after, and Page Rank on the take after chart.

Image Features

The various leveled generative model[14] depicts the scene of a picture through two noteworthy parts. In the visual part, a scene comprises of articles that are thus portrayed by an accumulation of patches and a few area highlights. The second part manages boisterous labels of the picture by presenting a twofold switch variable. This variable empowers the model to choose whether a tag is outwardly spoken to by objects in the scene or whether it speaks to all the more outwardly insignificant data of the scene. Consequently, the switch variable empowers a principled joint demonstrating of pictures and message and an intelligible expectation of what labels are outwardly significant. The various leveled portrayal of picture highlights, protest districts, outwardly pertinent and unessential labels, and general scene gives both best down and bottom up logical data to parts of the model. Keeping in mind the end goal to clarify the generative procedure of our model scientifically, we initially present the detectable factors. Each picture d ∈ D is over-sectioned into little reasonable areas by utilizing Felzenszwalb et al [9]. For every area, we remove NF = 4 kinds of highlights, where F = {shape, shading, area, texture}1. We advance vector quantize area highlights into locale code words, signified by the variable R in the model (see case of the delegate areas for 'horse' in Fig.1). We utilize 100, 30, 50, 120 code words for each component write, separately. Furthermore, the arrangement of patches X is acquired by isolating the picture into squares. Essentially, patches are spoken to as 500 code words acquired by vector quantizing the SIFT [20] highlights removed from them (see case of the agent patches for 'horse' in Fig.1). Boisterous labels are spoken to by the variable T , which is seen in preparing. To create a picture and its comparing comments, a scene class C is examined from a settled uniform earlier appropriation. Given a scene, we are currently prepared to produce both the visual and literary segments of the scene.

Given the scene class C, the likelihood of articles in such scenes is represented by a multinomial dispersion. For every one of the picture districts signified by the left interior box, we to start with test a protest $O \sim Mult(\eta_c)$.

Given the object O , we sample the image appearance:

1. For each $i \in F$, sample global appearance features: $R_i \sim Mult(\alpha_i \mid O)$, where there is a unique α_i for each object and each type of region feature.
2. Sample A_r many patches: $X \sim Mult(\beta \mid O)$.

Graph Traversal

We tried a random walk approach(as shown in Table-1). We used the random walk with jumps with the following transition probabilities:

$$p_i = \begin{cases} \dfrac{\alpha / n+1}{d_i + \alpha}, & \text{if i has a link to j} \\ \dfrac{\alpha / n}{d_i + \alpha}, & \text{if i does not have link to j} \end{cases} \qquad \text{Eq(1)}$$

where d_i is the degree of node i and α is a parameter.

Table. 1 Novel Random Walk Algorithm
The following is used for detecting the top k list of largest degree nodes: 1. Set k, α and m. 2. Execute a random walk step according to (1). If it is the first step, start from the uniform distribution. 3. Check if the current node has a > degree than one of the nodes in the current top k candidate list. Add new node in the top-k candidate list and Delete the worst node out of the list. 4. If the number of random walk steps is < m, return to Step 2 of the algorithm. 5. Else Stop, otherwise.

IV. RESULTS AND DISCUSION

In this section, we provide an evaluation for the performance of ICTA-FR. We performed two kinds of evaluation for the ICTA-FR: (i) a self-evaluation that measures the effectiveness of Topology Graph in its own learning task, and (ii) an evaluation from an application standpoint in measuring the effectiveness of the Topology Graph in enhancing quality for the metric. We present results from both of these evaluations. First, we evaluate these generated Graph learning effectiveness by splitting the features into several groups and then computing the area under curve (AUC) for each group. Then, we evaluate the quality of the Topology Graph by conducting a small user survey for the application of determining precision of top-L edges.

Self-evaluation

In this self-assessment, we utilize verifiable connections to construct Graph models and after that utilization the AUC metric to assess these models. Given seven days of communication information we manufacture a Graph show utilizing highlights portrayed before with accumulated Graph edges for the main day of the week. As previously, we split the day by day co-operations for the rest of the times of the week into two sorts: (i) obvious communications (counting retweet, top pick, specify, coordinate message) and; (ii) certain associations (counting tweet clicks, connect rings, profile clicks). Review that every one of the edges in the accumulated Graph for the main day are marked as 1 if the edge saw any cooperation in the next week and - 1 on the off chance that it didn't. We don't play out any unequivocal adjusting of positive and negative preparing cases. Utilizing this information we prepare a model utilizing stochastic gradient descent logistic regression with L2 regularization and decide the AUC for the model.

The results of this evaluation are shown in Table 2. The initial two gatherings utilize diverse time arrangement for recorded highlights like Retweets, Favorites and Messages. The following gathering includes certain association and edge write (take after edge, bidirectional, or SMS). We at that point utilized highlights in view of the notoriety of the client and the highlights separated from the system like aggregate takes after, and add up to adherents. We likewise assessed the effect of adding highlights identified with points that a client is related with. For a given edge we utilized the number of covering subjects as the element esteem. Next we utilized highlights acquired from the outline of client's movement like number of posted tweets, number of sent top choices and client's nation. The last arrangement of highlights is acquired from client's address books. The change of AUC as we included new highlights is appeared in the second section. As is clear, including vertex highlights has been very important. Further, we note that consistency of edge highlights (reflect by non-zero-days) is likewise a decent indicator of future communications. At long last, client movement is positively identified with improved client action, so the probability of co-operations additionally goes up.

User-evaluation

In this area, we give comes about because of a little study of Twitter clients that assesses the execution of Topology Graph on the accuracy of distinguishing their best followings. For this review we enrolled 2300 clients who got to Twitter on web and utilized English as their essential tweeting dialect. We too chosen just those clients who utilized the administration frequently and henceforth knew clients that they are following great

Table. 2 User Evaluation in terms of Accuracy

Evaluation	No: of Twitter Users	Accuracy (%)
Satisfied	1879	81.6
Partially Satisfied	190	8.2
Not Satisfied	121	5.2
Not Applicable	110	4.7

Comparison

For comparison purposes, we used state of art algorithms like: 1) Relational Domain Recommendation (RDR), 2) SVM, 3) On-Line Collaborative filtering (OLCF), 4) random tag similarity. In Fig.2, we had drawn graph between Accuracy vs Number of twitter users for the proposed ICTA-FR approach and Text based Recommendation approach. We used RDR approach in text based recommendation system. We steadily increased the opinion of twitter users and accuracy was calculated based on the subjective evaluation done by each individual user. This whole process was experimented with results shown in Fig.2. Clearly, there was an improvement of accuracy over the traditional systems because of the analysis of tweet images content similarity.

Similarly, for comparison purposes, we first performed tag similarity for every pair of twitter users to find the recommended user. We performed another work based on SVM for classification of recommended or not recommended labels for each set of users based on the set of group comparison method. We took another work based on collaborative filtering method(OLCF) to find recommend friends. This work was based on finding the cosine similarity of feature of two users. Finally we performed Relational Domain Recommendation (RDR) based on consideration of different networks, connecting the links in different network with specific probability. All the experiment results with comparison were shown in figure 3. In this figure 3, x-axis represents the comparison for different sets of recommendation group(i.e., 10,20,30,40,50). For all these cases, we found our methodology outperforms all the state of art algorithms. The main reason behind this is the consideration of tweet images and text images simultaneously for enhancing the overall accuracy of the recommender systems.

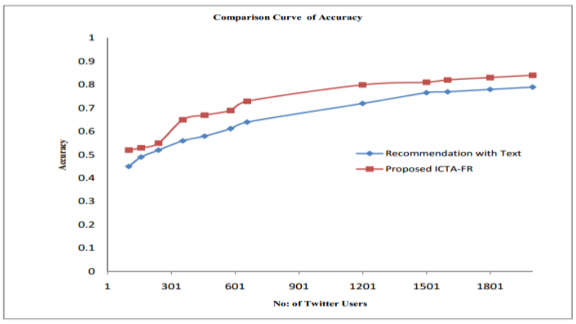

Fig. 2 Comparison Curve of Accuracy of the Proposed ICTA-FR with Text based Recommender system

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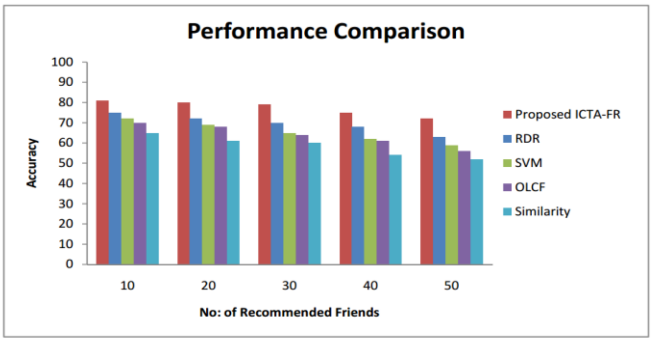

Fig. 3 Comparison Curve of Accuracy of the Proposed ICTA-FR with state of art algorithms

Table 2 demonstrates the conveyance of number of twitter content worth suggesting among clients' assessment decisions, satisfied, partially satisfied, not satisfied, and Not Applicable. About 81% of fulfilled twitter users what's more, 8% in part fulfilled twitter users were suggested by recommender. About 5.2% of not fulfilled twitter users were really discovered not worth suggesting by recommender systems. We think this is low and the circumstance needs to be examined.

V. CONCLUSION

This paper has proposed a Novel Content based Topology Analysis for Friend Recommendation (ICTA-FR) to identify similar people using user information parameters & tweet images from network of twitter users. The main contribution of this work includes a A novel graph representation with tweet similarity and posted image similarity. This graph models both the co-occurrence of visual words of tweet images and also the textual information similarity in which they appear. Experimental results are conducted on real Twitter data and found to give better results than the existing state of art algorithms in terms success rate. Results are qualitatively consistent with the user evaluation. In future, this work will be extended to include the twitter video also to enhance overall performance in different video scenes.

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