Analysing the Structure, Dynamics and Contents of Social Networks

Rohini Lokhande
Department of Information Technology, Thakur College of Engineering and Technology, Mumbai, India

Abstract: Social media permits its users to have numerous accounts in diverse social networking podiums. Popular social networking sites have billions of users that possess similar interests. The aim of this paper is to determine the identity of users and map those identities with those having similar interests. The developed system can be utilized for business intelligence that would help in creating a database of all users that possess specific interests. In this study, a system is developed wherein a user’s core interest is recognized in well-known social networking sites (i.e., Twitter and Plurk) by means of latent Dirichlet allocation (LDA) algorithm and Kullback–Leibler divergence method. In addition, in order to identify users across the abovementioned social networking sites, LDA will cogitate social network structure and article content of users. LDA initially establishes a user’s core interest. Next, it calculates similarity between target users. The results in this study prove to be quite promising, which reveal that LDA is an effective algorithm to map users across various platforms and efficient when compared with other methods.

Keywords: LDA, Twitter, Plurk, Social Network, KL Divergence

I. INTRODUCTION

Facebook, Twitter, LinkedIn, Plurk, etc. are some of the most prominent social networking sites that have billions of users who socialize with each other. Socializing in such sites means sharing of knowledge, ideas, and interests with the like-minded people. Enormous information is generated through such sites, and handling such information is a crucial factor so that business intelligence (BI) can be managed appropriately. For appropriate management of BI, user identification and mapping identified users from numerous sites are vital.

Social networking can be defined as the usage of internet-based programs to connect with acquaintances, relatives, colleagues, and clientele. Social networking sites can be used for not only social purposes but also business purposes. Social networking sites are one of the key areas for marketers or salespersons trying to engross users [1–3].

A social network consists of individuals known as nodes that are connected by a particular type of interdependency such as comradeship, similarity, common hobby or activity, and rapport of philosophies, learning, or stature.

Fig. 1 Structure of social network

Social network analyses relationships through network theory that contains nodes, edges, links, or connections [4]. Within a network, individual actors are called nodes, and relationships between the actors are called ties [5]. Ties can be of several types between nodes. It has been observed that social networking sites function at various levels (i.e., from family level to the level of nations) and portray an indispensable part in regulating the way how problems are solved, organizations are administered, and the extent to which an individual flourishes in attaining his/her goal. In other words, a social network is a map of specified ties. Accordingly, the nodes to which an individual is coupled are called social contacts of that individual. The value that an individual obtains from social network is called social capital.

Plenty of information and functions are present in social networks. User activities on social networks have turned out to be convoluted and impulsive. Determining core interests of users from superfluous data is one of the main objectives of this paper. In
order to determine the core interest of a user, it is necessary to first find target user’s core circle of friends. Figure 3 shows structure of matching users. There are two users, i.e., User X and User Y, who have friends in various social networking sites (e.g., User X can be User X1, User X4, User X3, and User X5 and User Y can be User Y1, User Y2, User Y3, User Y4, User Y5, and User Y6). If both these users be a member of same individual, then there would be analogous circle of friends, but the only problem would be that the circle of friends will not be of same size.

Finding similar circle of friends is not that easy because we are not aware of all identities of users. Therefore, in order to determine core interests of a user, the following assumptions have to be taken into account:

1) The more frequent is the communication between two users, the more closer they are.
2) There could be a possibility that similar circle of friends subsists in disparate social networks.

The remainder of this paper is organized as follows. Section II describes about the review of literature that is carried out in this domain. Section III focuses on the proposed system and the algorithm used in this study. Sections IV and V illustrates on the implementation details of the proposed system along with results and discussion. Section VI concludes the study with scope for future.
II. REVIEW OF LITERATURE

A great deal of literature review has been performed under this domain. Some of them are as follows. Zafarani Reza and Huan Liu [6] successfully showed that MOBIUS is helpful in recognizing users through social networking sites. The authors too created a path for scrutinizing and mining across social networking sites, which in turn lead to the establishment of innovative online services across sites. However, they were unable to analyze possibilities and discover features indigenous to specific sites beyond those constricted to usernames and incorporating them into MOBIUS for future needs. Stephen Paul Marsh [7] investigated philosophies of trust in diverse circumstances and developed an official narrative of its use with distributed and intelligent representatives. However, it was observed that Marsh’s model was convoluted, predominantly conjectural in nature, and strenuous during implementation. Abdul-Rahman Alfarez and Stephen Hailes [8] propositioned a model for strengthening trust in computer-generated communities on the basis of undeviating proficiencies and repute. Nonetheless, the proposed model was ad-hoc in nature, which restrain the applicability of the model in far-reaching scope. Schillo Michael, Petra Funk, and Michael Rovatsos [9] developed a trust model for situations where result of interaction is Boolean (i.e., good or bad) between trust relationship of two agents. A major disadvantage of their trust model was that they failed to contemplate on the degrees of satisfaction. Esfandiari Babak, and Sanjay Chandrasekharan [10] proposed two one-to-one trust acquisition mechanisms in their trust model. The first trust acquisition mechanism is based on observation. The authors also proposed the usage of Bayesian networks, and in order to accomplish trust acquisition, they suggested Bayesian learning. However, the proposed mechanism was unable to make a distinction between distrust and lack of knowledge about trust. Yu Bin and Munindar P. Singh [11] specified that information that is stored by an agent about direct interactions is a collection of values that replicate quality of these interactions. Moreover, they specified that only the most recent experiences with each counterpart are taken into account for calculations. However, the model failed to merge direct information with witness information. Mui Lik, Mojdeh Mohtashemi, and Ari Halberstadt [12] put forward a computational model grounded on sociological and biotic understanding. Their model not only calculated an agent’s trust score but also reputation score. However, the authors failed to observe the consequences of duplicity in their model. Nie Yuanping, Yan Jia, Shudong Li, Xiang Zhu, Aiping Li, and Bin Zhou [13] proposed a dynamic core interests mapping (DCIM) algorithm that takes into account not only a user’s social network structure but also the article content of a user to relate users across several social networking platforms. However, the authors were unable to improve the accuracy of user’s core topic analyses. Kumar Shamant, Reza Zafarani, and Huan Liu [14] insinuated a realistic approach to scrutinize migration patterns in social networking sites. They discovered patterns provided insights, which helped the authors in understanding social networking sites and estimating their attractiveness to improve BI and generating revenue by retaining users. However, they were unable to obtain the mapping of users across different social media sites.

Moreover, the authors were unable to determine if a user has moved to another site. Liu Siyuan, Shuhui Wang, Feida Zhu, Jinbo Zhang, and Ramayya Krishnan [15] proposed a solution named HYDRA—a framework that consists of the following steps: exhibiting mixed behavior by long-term behavior distribution investigation and multiresolution progressive information matching, forming physical steadiness graph to calculate high-order physical steadiness on users’ core social structures throughout dissimilar social networking platforms, realizing mapping function through multiobjective optimization comprising supervised learning as well as cross platform structure consistency maximization.

However, the authors considered only two real datasets (i.e., five popular Chinese social networks and two popular English social networks). More real datasets would be considered, which would have improved the accuracy of the proposed system. Cao Gaofeng, and Li Kuang [16] conducted experiments and the results of the experiments demonstrated the usefulness of extraction of core users and proved that ~20% core users permit recommender systems to attain >90% accuracy of top-N recommendation. However, the authors were unable to determine more approaches to define core users from different aspects (e.g., fusing similar relationships and trust relationships). Moreover, the authors were unable to find relatively stable approach to generate core users so as to reduce the frequency of updates.

Considering the abovementioned research gap limitations, this research work aims to propose and develop a unique approach to analyze the structure, dynamic, and content of social networking sites.

Firstly, trust degree and interest similarity between all pairs of users are calculated and sorted from highest value to the lowest. Secondly, two strategies are used to select core users. This first strategy is to select users who appear the most in all other user’s nearest neighbor list. The second strategy is to select a user who has the highest weight of location in all other users’ nearest neighbor list. Thirdly, the effect of extracted core users in recommendation is validated.
III. PROPOSED SYSTEM

Figure 4 shows the block diagram of the proposed system that is used for identifying core users that possess similar interests in social networking sites (i.e., Twitter and Plurk).

![Block diagram of proposed system](image)

In this study, two social networking sites have been considered (i.e., Twitter and Plurk). In Twitter, there are as sequence of steps that need to be followed for identifying core users that possess similar interest. The first step involves searching Twitter users. In order to search Twitter users, we use Twitter application programming interface (API). For instance, Twitter API is able to provide names of 1000 Twitter users. The next step involves reading the timelines of those 1000 Twitter users and identifying their followings. In other words, for a particular Twitter user, we try to determine the total number of followers that user has. Once the total number of followers have been identified, the next step is to apply LDA algorithm that provides a list of core users that possess similar interests.

Similarly, for Plurk, the first step involves searching Plurk users. In order to search Plurk users, we use Plurk API. For instance, Plurk API is able to provide names of 1000 Plurk users. The next step involves reading the timelines of those 1000 Plurk users and identifying their followings. In other words, for a particular Plurk user, we try to determine the total number of followers that user has. Once the total number of followers have been identified, the next step is to apply LDA algorithm that provides a list of core users that possess similar interests. Finally, a comparison can be made between the two social networking sites that identify core users possessing similar interests.

A. Latent Dirichlet Algorithm

Blei et al. [17] proposed LDA that can be used for topic modeling. It is used for understanding topics across documents (humans vs. machines). The main intention of using LDA is mainly to detect underlying topics in text documents. LDA can be used for a variety of purposes like sentiment analysis, object localization for images, automatic harmonic analysis for music, and bioinformatics. In LDA, the first assumption is that documents with similar topics will use similar groups of words. LDA suggests that words carry strong semantic information and documents discussing similar topics will use similar words. Latent topics are therefore discovered by identifying groups in the corpus that will currently occur together within documents. In addition, the second assumption is about document definitions/modeling. For instance, documents are probability distributions over latent topics, and topics are probability distributions over words. This means that according to LDA every different document contains a number of topics, each topic has a distribution of words associated with it. Note that in LDA, probability distributions are used instead of strict word frequencies. So, while other bag-of-words models may focus on the most frequently occurring words in a document, in this study, a holistic approach is used wherein a lot of concentration is given on the distribution of words across topics.
Figure 5 shows several documents (i.e., Doc1 and Doc2) that comprise distribution of topics.

![Fig. 5 Documents (Doc1 and Doc2) comprising distribution of topics](image1)

Figure 6 shows several topics (i.e., Topic A and Topic B) that comprise distribution of words.

![Fig. 6 Topics (Topic A and Topic B) comprising distribution of words](image2)

B. Generative Process

LDA assumes that new documents are created in the following manner:

1) Determine the number of words in a document.
2) Choose a topic mixture for the document over a fixed set of topics (i.e., 20% topic A, 30% topic B, and 50% topic C).
3) Generate words in the document by:
   a) First, select a topic based on the document’s multinomial distribution.
   b) Second, select a word based on the topic’s multinomial distribution.

C. LDA as a Topic Model

LDA is a topic model that generates topics based on word frequency from a set of documents. It is specifically useful for finding reasonably accurate mixtures of topics within a given document.

Steps involved in performing LDA:

1) Create a collection of documents from news articles.
2) Each document represents a news article.
3) Data cleaning is the next step:
   a) Tokenizing: Converting a document to its atomic elements.
   b) Stopping: Removing meaningless words.
   c) Stemming: Merging words that are equivalent in meaning.

LDA assigns a random topic to each word in the corpus of documents that have been provided. It starts by randomly assigning topics.

IV. IMPLEMENTATION

A. Installation of Twitter Library

![Fig. 7 Twitter library installation](image3)
B. Installation of Tweepy Library

Fig. 8 Tweepy library installation

C. Installation of LDA Library

Fig. 9 LDA library installation

D. Installation of NLTK Library

Fig. 10 NLTK library installation

E. Installation of stop-words Library

Fig. 11 Stop-words library installation
F. Installation of Gensim Library

![Gensim library installation](image1)

**Fig. 12** Gensim library installation

G. Installation of Pyldavis Library

![Pyldavis library installation](image2)

**Fig. 13** Pyldavis library installation

H. Installation Of ipython Library

![IPython library installation](image3)

**Fig. 14** IPython library installation
1) For Twitter: To search Twitter users and find followers of a Twitter user

### TABLE I
Twitter Users and Their Respective Followers

| @realDonaldTrump | @DonalDJTrump | @MarConibio | @Mike_Pence |
|-------------------|--------------|------------|-------------|
| @JoeBiden        | @POTUS       | @AlyssaNahm | @RyanAFournier |
| @VP              | @FirstLady   | @VP        | @SecondLady |
| @POTUS           | @VP         | @VP        | @VP         |

| @FLOTUSMelaniaTrump | @BarackObama | @MelaniaTrump | @LaraLeaTrump |
|----------------------|--------------|--------------|--------------|
| @WhiteHouse         | @WhiteHouse  | @MELANIATrump| @TaraTrump   |
| @WhiteHouseHstry    | @Barack      | @Melania     | @Lara        |
| @FLOTUS             | @Barack      | @Melania     | @Lara        |

| @EricTrump         | @POTUS       | @EricTrump   | @POTUS       |
|-------------------|--------------|--------------|--------------|
| @POTUS             | @EricTrump   | @POTUS       | @EricTrump   |

| @POTUS             | @EricTrump   | @POTUS       | @EricTrump   |
|-------------------|--------------|--------------|--------------|
| @POTUS             | @EricTrump   | @POTUS       | @EricTrump   |

| @POTUS             | @EricTrump   | @POTUS       | @EricTrump   |
|-------------------|--------------|--------------|--------------|
| @POTUS             | @EricTrump   | @POTUS       | @EricTrump   |

| @POTUS             | @EricTrump   | @POTUS       | @EricTrump   |
|-------------------|--------------|--------------|--------------|
| @POTUS             | @EricTrump   | @POTUS       | @EricTrump   |
2) For Twitter: To get timelines of the followers

| Twitter users      | Followers |
|--------------------|-----------|
| DonaldTrumpJr      | 1. @kaguracin  
                     2. @Jeff_Mandy  
                     3. @alt  
                     4. @DonaldJU  
                     5. @RickSema  
                     6. @dougstafford  
                     7. @RobMorrison  
                     8. @DevonNexa  
                     9. @AndrewCMcCarthy  
                     10. @SeeHernardt |
| ErikTrump          | 1. @ParasahbrahCNN  
                     2. @EmersonPolling  
                     3. @AndrewMNelson  
                     4. @HillSchoolYiA  
                     5. @ColbyComSA  
                     6. @AviBerkow  
                     7. @BillsBlasio  
                     8. @Lonzie2Engel  
                     9. @VAKruta  
                     10. @mhocyah |
| FLOTUS             | 1. @WhiteHouse  
                     2. @WhiteHouseRoy  
                     3. @BarackObama  
                     4. @realDonaldTrump  
                     5. @VP  
                     6. @SecondLady  
                     7. @POTUS  
                     8. @theGiBsummit  
                     9. @RepMcCaul  
                     10. @ONESAmerica  
                     11. @chicago mayor  
                     12. @SecArmy  
                     13. @Smartwomen  
                     14. @SenatorShaheen  
                     15. @Jacquelyn_M  
                     16. @Sambos  
                     17. @DEShigian  |
| IvankaTrump        | 1. @Wald2Pearce  
                     2. @amaroknik  
                     3. @CuomoPrimetime  
                     4. @JenSauders  
                     5. @PressSec  
                     6. @TuckerCarlson  
                     7. @JesseBWatters  
                     8. @WhiteHouse  
                     9. @Scavino45  |
| kimigulfoyle       | 1. @kimgulfoyle  
                     2. @thehamashajane  
                     3. @RNCLatinos  
                     4. @GaryCoby  
                     5. @RNCRsearch  
                     6. @AZachParkinson  
                     7. @MattWolking  
                     8. @EoinAPomer  
                     9. @TrumpWarRoom  
                     10. @marcorubio  |
| TeamTrump          | 4. @MailOnline  
                     5. @DailyMail  
                     6. @SecondLady  
                     7. @AviBerkow  
                     8. @RealWalkAway  
                     9. @usminority  
                     10. @greggufeld  |
| TiffanyATrump      | 1. @Feminist  
                     2. @DailyCaller  
                     3. @DailyMailUK  |
3) For Twitter: LDA application

### TABLE III

| Sr. no. | Twitter users and their respective followers |
|---------|---------------------------------------------|
| 1.      | DonaldJTrump Jr. csv                         |
|         | ['user', 'DonaldJTrump Jr', 'allahpundit', 'JeffLaundry', 'ahk', 'Doraminated', 'RichSemenas', 'dougstafford', 'RobManess', 'DevinNunes', 'AndrewCMcCafferty', 'SecBernardt'] |
| 2.      | EricTrump.csv                                |
|         | ['user', 'EricTrump', 'PamelaBrownCNN', 'EmersonPolling', 'Andrew_M_Nelson', 'HillSchoolYA', 'ColsyConMMA', 'AriBerman', 'BillDeBlasio', 'Lewandowskill', 'VAKruta', 'mehronah'] |
| 3.      | FLOTUS.csv                                   |
|         | ['user', 'FLOTUS', 'WhiteHouse', 'WhiteHouseHry', 'BarackObama', 'realDonaldTrump', 'VP', 'SecondLady', 'FLOTUS'] |

**a) Users discussing about same topic**

### TABLE IV

| Sr. no. | Twitter user and their followers | Probabilities |
|---------|----------------------------------|---------------|
| 1.      | jimmyroyle, 'TimRumHisMouth'     | -0.02146692E+01 |
| 2.      | Trump, 'Surabees'                 | -0.83159912E+01 |
| 3.      | DonaldTrump, 'dougstafford'      | -0.35654437E+01 |
| 4.      | jimmyroyle, 'ValidPharos'        | -0.36065067E+01 |
| 5.      | jimmyroyle, 'RajaFibres'         | -0.26790760E+01 |
| 6.      | DonaldTrump, 'DevinNunes'        | -0.74059325E+01 |
| 7.      | mike_palmer, 'RyanAFomer'         | -0.16606169E+01 |
| 8.      | mike_palmer, 'VP'                 | -0.77912439E+01 |
| 9.      |realDonaldTrump, 'Scravo45'       | -0.06052120E+01 |
| 10.     | Trump, 'sурсkim'                 | -0.10202761E+01 |
| 11.     | Trump, 'GlashTRUMPtvNN'          | -0.21453873E+01 |
| 12.     | jimmyroyle, 'JanitaKam'          | -0.23366879E+01 |
| 13.     | DonaldTrump, 'Doraminated'       | -0.25841686E+01 |
| 14.     | LaraLeeTrump, 'JoeTalkShow'      | 0.26856178E+01 |
| 15.     | FLOTUS, 'VP'                     | 0.26873442E+01 |
| 16.     | Trump, 'SenatorShahsen'          | 0.29096311E+01 |
| 17.     | jimmyroyle, 'Servercal'          | 0.29591366E+01 |
| 18.     | FLOTUS, 'WhiteHouseHry'          | 0.30911366E+01 |
| 19.     | Trump, 'SecArmy'                 | 0.33515232E+01 |
| 20.     | Trump, 'theCBSsmoother'          | 0.34590699E+01 |

4) Installation of plurk_oauth library

Fig. 15 Plurk_oauth library installation
5) For Plurk: To search Plurk users and find followers of a Plurk user

### TABLE V

| Plurk ID | Plurk users       | Count of friends | IDs & names of friends |
|----------|-------------------|------------------|------------------------|
| 5079107  | Trumpy            | found 0 friends  | 3677232 cat-bat!      |
|          |                   |                  | 3307543 \_ A\_I\_O    |
|          |                   |                  | 4283097 clupper        |
|          |                   |                  | 3395776 Evelyn         |
| 3604685  | Trampoline        | found 0 friends  | 4958887 banohi         |
|          |                   |                  | 4174104 honeydais06    |
|          |                   |                  | 4038644 SUPERgirl      |
| 4689522  | trump805          | found 2 friends  | 3958776 Evelyn         |
| 14119959 | TrumpAndConquer   | found 0 friends  | 6412150 Omi\_pLin     |
| 14070064 | Trumpyte          | found 0 friends  | 13885687 Astrology     |
|          |                   |                  | 13811611 Maryasu       |
|          |                   |                  | 13811608 aacosmotic85  |
|          |                   |                  | 3677232 cat-bat!      |
| 11510640 | Trampoline4d2     | found 9 friends  | 4283097 clupper        |
|          |                   |                  | 3395776 Evelyn         |

6) For Plurk: To get timelines of the followers

### TABLE VI

| Sr. no. | Plurk ID |
|---------|----------|
| 1.      | 11510640 |
| 2.      | 13811608 |
| 3.      | 3604685  |
| 4.      | 4038644  |
| 5.      | 4428202  |
| 6.      | 3948291  |

7) For Plurk: LDA application

### TABLE VII

| Sr. no | Plurk ID and their respective followers |
|--------|----------------------------------------|
| 1.     | 11510640 ['user: '11510640', '13811608'] |
| 2.     | 3604685 ['user: '3604685', '4038644'] |
| 3.     | 4428202 ['user: '4428202', '3948291'] |
| 4.     | 6155566 ['user: '6155566', '3457487'] |
| 5.     | 7305924 ['user: '7305924', '5437339'] |
| 6.     | 4484868 ['user: '7448468', '3779245'] |

a) Users discussing about same topic:
V. RESULTS AND DISCUSSION

Figure 16 shows graphical representation of core users possessing similar interests with probabilities on y-axis. As evident from the figure, Twitter usernames are plotted on x-axis such as CLewandowski, realDonanldTrump, Scavino45, DanScavino, FoxNews, seanspicer, KeithSchiller45, amongst others. Users discussing about the same topic are shown by lines of various colors.

Figure 17 shows graphical representation of core users possessing similar interests with probabilities on x-axis. As evident from the figure, Twitter usernames are plotted on y-axis such as CLewandowski, realDonanldTrump, Scavino45, FDRLST, Heminator, EricTrump, Discovery, BenLecomteSwim, amongst others. Users discussing about the same topic are shown by lines of various colors.
VI. CONCLUSION AND FUTURE SCOPE

The developed system proves to be an applicable technique for analyzing the dynamics, structure, and content of two well-known social networking sites, i.e., Twitter and Plurk. The system helps in understanding and identifying core users that possess similar interests in the abovementioned social networking sites through the application of LDA algorithm and KL divergence technique. Identifying core users possessing similar interests will help social analysts to a large extent to understand the patterns of core users and their interests so that suitable decisions can be taken by them in near future. While this research work has demonstrated the potential of efficiently analyzing the dynamics, structure, and content of two well-known social networking sites, i.e., Twitter and Plurk, many opportunities for extending the scope of this research work remain. In future, we plan to use some other algorithms such as DCIM algorithm and JS technique. We also plan to implement the developed system keeping in mind some other factors such as we will consider only those Tweets and Plurk messages that are tweeted by popular users, which means only those Tweets and Plurk messages will be considered for analyzing the dynamics, structure, and content of Twitter and Plurk users who have maximum number of followers. Also, in the near future, we plan to fetch Tweets and Plurk messages for a particular Twitter and Plurk user on the basis of location so that we can efficiently analyze the dynamics, structure, and content of Twitter and Plurk. Moreover, we would include a few more social networking sites such as Facebook, Instagram, and Netlog for analysis purposes.

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