Influence-based Twitter browsing with NavigTweet

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ABSTRACT

Directed links in social media determine the flow of information and, hence, indicate a user's influence. This paper proposes a novel visual framework to explore Twitter's '*Who Follows Who*' relationships, by browsing the friends' network to identify key influencers based on the actual influence of the content they share. We have developed NavigTweet, a visualization tool for the influence-based exploration of Twitter network. NavigTweet embeds a force-directed algorithm to display the graph in a multi-clustered way. To assess the user experience with NavigTweet, we have conducted a pre-release qualitative pilot study. We also report on the study and results of post-release user feedback survey.

1. Introduction

The existing literature indicates that many researchers endeavor to focus on the shared content provided by users in social networks [1–3], in order to provide a ranking based on the actual influence of the content that they share (e.g. ranking by number of followers). The social media literature makes a distinction between influencers and influence. Influencers are prominent social media users with a broad audience. For example, social users with a high number of followers on Twitter [4], or a multitude of friends on Facebook [5], or a broad network of connections on LinkedIn [6]. The term influence refers to the social impact of the content shared by social media users. If social media users seem to be interested in something, they normally show it by participating in the conversation with a variety of mechanisms, mostly by sharing the content that they have liked. In [7,8], it has been noted that a content that has an impact on a user's mind is usually shared. Influencers are prominent social media users, but we cannot be certain that their shared content has influence, as discussed by [9].

Social media have become pervasive and ubiquitous. There is a growing need for information visualization, which has recently become a popular subject of research [10,11,8]. In general, information visualization aims at showing information in an easy, user-friendly and graphical way. However visualizing information properly is not trivial and becomes a challenge for large social networks, such as Twitter. Twitter has been defined by many researches as the key role player of the change on how information dissemination is accom-plished. Its influence on information dissemination has led to research exploring how this is achieved. According to [12], the unicity of direction in Twitter connections provides the key driver of information dissemination via Word-of-Mouth (WoM) in retweets [13,14]. The ultimate goal of our research is to provide a novel visual framework to analyze, explore and interact with Twitter's '*Who Follows Who*' relationships by browsing the friends' network to identify the key influencers based on the actual influence of the content they share. In this paper, we exploit a modified power-law based force-directed algorithm [15–17] to clearly display the Twitter network graph in a multi-layered and multi-clustered way.

As part of this research, we have developed *NavigTweet* [18], a visual tool for the influence-based exploration of Twitter friends' network. It helps to identify the key players, and follow them directly through *NavigTweet*. The user can explore his/her own Friend-of-a-Friend (FOAF) network in order to find interesting people to be followed. The top-influencers are identified by both *user-level* (e.g. number of followers, number of tweets, etc.) and *content-based* (number of hashtags, number of URLs, etc.) parameters, thoroughly described in Section 2. Based upon these parameters, the tool adopts the Analytical Hierarchy Process (AHP) technique [19,20] to rank Twitter users. To gather a preliminary feedback on the *NavigTweet* user experience with a pilot release of *NavigTweet*, we have conducted a survey targeting a reference group of academic experts in the social media domain who have been asked to use the application in a real-time environment. This paper also presents the results of an extensive survey conducted to collect users' feedback (see Section 5.3).

In order to visualize twitter network in an aesthetically pleasant way, we exploit multi-layered and multi-clustered graph layout, by applying a modified power-law based force-directed graph drawing layout technique, as discussed in [21,15–17]. The layout technique is based on the idea that Twitter user nodes should be prioritized in

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laying out the overall network topology, but their placement should depend on the topology of their friends' network around them. In order to create a multi-layered hierarchy of peripheral friends' nodes around twitter user nodes, we use the metaphor of the k-shell decomposition analysis technique, as discussed in [22]. The details about the graph drawing layout technique are discussed in Section 3.

The remainder of this paper is structured as follows. Section 2 discusses network visualization techniques, intoduces the concept of influence and influencers in social media, and provides insights about Twitter analytics and visualization tools. Section 3 presents *NavigTweet* with its basic building blocks. Section 4 discusses the implementation aspects of *NavigTweet* along with interface controls. Section 5 presents the evaluation framework with results associated with pilot study and extensive survey, and also presents Web Analytics of *NavigTweet* Website. Conclusions are drawn in Section 6.

2. State of the art

In this section, we will discuss about the existing network visualization techniques, and will explore the concept of influencers and influence in social media. We also provide insights about Social Networks visualization tools.

2.1. Network visualization techniques

Several research efforts in network visualization have targeted power-law algorithms and their combination with the traditional force-directed techniques, as for example in [23–25]. Among these approaches, the most notable is the Out-Degree Layout (ODL) for the visualization of large-scale network topologies, presented by [26]. The core concept of the algorithm is the segmentation of network nodes into multiple layers based on their out-degree, i.e. the number of outgoing edges of each node. The positioning of network nodes starts from those with the highest out-degree, under the assumption that nodes with a lower out-degree have a lower impact on visual effective-ness.

The topology of the network plays an important role such that there are plausible circumstances under which nodes with a higher number of connections or greater betweenness have little effect on the range of a given spreading process. For example, if a hub exists at the end of a branch at the periphery of a network, it will have a minimal impact in the spreading process through the core of the network, whereas a less connected person who is strategically placed in the core of the network will have a significant effect that leads to dissemination through a large fraction of the population. To identify the core and the multi-layered periphery of the clustered network, we use a technique based on the metaphor of k-shell (also called k-core) decomposition of the network, as discussed in [21,16,22].

2.2. Influencers and influence in social networks

Traditionally, the literature characterizes a social media user as an influencer on the basis of structural properties. Centrality metrics are the most widely considered parameters for the structural evaluation of a user's social network. *Centrality* has been defined as the significance of an individual within a network [10]. Centrality has attracted a considerable attention as it clearly recalls concepts like social power, influence, and reputation. A node that is directly connected to a high number of other nodes is obviously central to the network and likely to play an important role [27]. In [28], the first centrality metric has been introduced, named as *degree centrality*, which is defined as *the number of links incident upon a node*. A distinction is made between in-degree and out-degree centrality, measuring the number of incom-ing and outgoing connections respectively. This distinction has also been considered important in social networks. For example, Twitter makes a distinction between friends and followers. Normally, on Twitter, users with a high in-degree centrality (i.e. with a high number of followers) are considered as influencers.

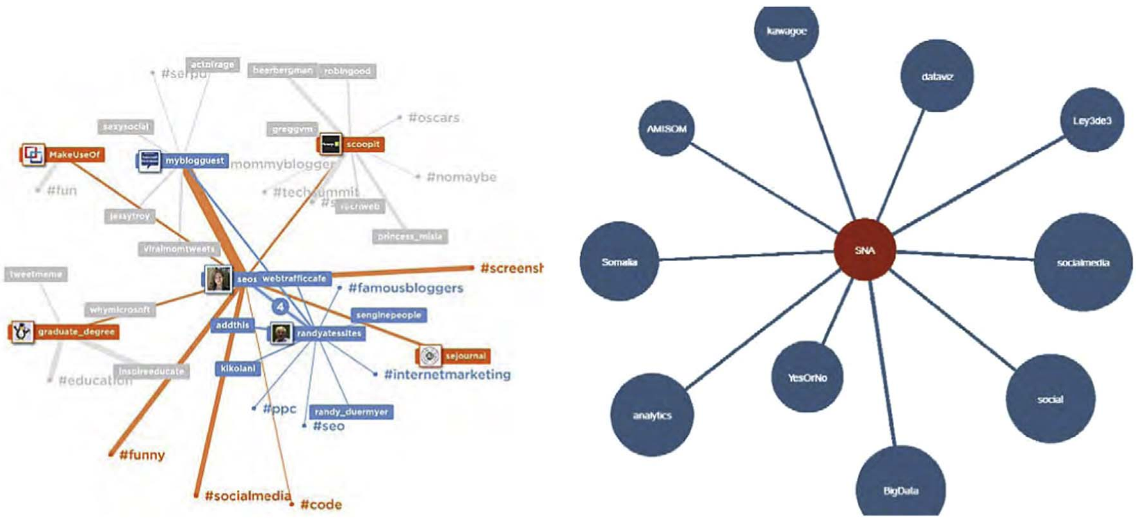
In addition to *degree centrality*, the literature also shows other structural metrics for the identification of influencers in social net-works. In [29], an approach is presented where users are identified as influencers based on their total number of retweets. Results highlight how the number of retweets are positively correlated with the level of users' activity (number of tweets) and their in-degree centrality (number of followers). The PageRank score [30] has also been frequently adopted to evaluate influencers. It has been empirically found that a tweet has a larger reach if its author has a higher PageRank score [31,32,12]. The authors' ranking provided by the PageRank algorithm has been proved to be similar to that obtained with the number of followers. However, it has been found to be different from the ranking provided by the volumes of retweets [12,33].

Besides structural metrics, the more recent literature has associated the complexity of the concept of influence with the variety of content. Several research works have addressed the need for considering content-based metrics of influence [32,34,35,8,11]. Content metrics such as the number of mentions [36], URLs [2,37], or hashtags [38,39] have been proved to increase the probability of retweeting [34,40]. Considering the domain of recommendation, [41] proposed an ap-proach by highlighting three properties: *recency of content*, *explicit interaction* among users and *user-generated content*. In studies on information propagation, inclusion of URLs or hashtags is extensively used to define models for predicting mentions [2], retweeting prob-ability [34,37] and topic adoption [42,38]. The dynamics of the retweeting process is also discussed in a few studies [40,43,39,44,45].

Twitter has been the most common dataset for research on user influence. For example, [46,12] measure the influence of Twitter users based on the sheer number of retweets spawned from the users' tweets. Recently, [47] have studied the elite users who control a significant portion of the production, flow, and consumption of information in the Twitter network. In [47], a top-down approach is used by identifying top users based on how frequently these appear in user-generated lists.

2.3. Social networks visualization tools

Social networks, more specifically, Twitter analytics tools generally aim at finding, analyzing and then optimizing a person's social growth. For example, *Twitonomy* [48] is an independent website, unaffiliated with Twitter that allows users to search for the Twitter history of accounts by entering a Twitter handle into a search box. Similarly, *Follower Wonk* [49] is a web application which helps a user explore and grow his social graph. As discussed in [50], *Klout* is a system-generated tool for measuring influence; in other words it is a powerful rating system that can be used as a measure of credibility. A user's Klout score is measured based on three components: *true reach* (how many people a user influences), *amplification* (how much the user influences them), and *network impact* (the influence of the user's network) [50]. *Klout* scores have a range of 1–100, with a higher score indicating a higher level of influence. [51] discusses additional analytics tools including *The Archivist*, *Social Bro*, *Twenty Feet*, *Tweet Stats*, *Twitter Counter*, *Tweet Stats*, and *Tweeps Maps*. Similarly, *Socilab* [52] is an open-source LinkedIn network visualiza-tion application which provides a cluster representation of the user's connections with multi-color modes, where the color indicates the category of the user (e.g. industry, country, or location). But the tool provides a basic graph representation, with a cluttered layout, limited to a maximum of 500 nodes due to LinkedIn API threshold. Network browsing is limited to 1-depth, i.e. a user can't browse his/her FOAF network but is limited to his/her own network only. In [53,54] authors also discuss about *NodeXL* tool which is a free, open-source template for Microsoft Excel that makes it easy to explore network graphs. With *NodeXL*, users can visualize and explore the graph of their input data in force-directed graph layout and calculate basic network metrics.



(a) Mentionmapp **(b)** Hashtagify

Fig. 1. Twitter visualization tools. (a) Mentionmapp (b) Hashtagify.

The literature on social network visualization tools indicates that there exist only a few visualization tools. [51,55] existing tools are reviewed, including *Touch Graph*, *Mentionmapp*, and *Hashtagify*. *Touch Graph* is a desktop and web application, where the user hosts visualizations on their server and views the visualization on a web browser. *TouchGraph Navigator* provides a cluster visualization of a user's Facebook network. This visualization solution reveals relationships between people, organizations, and ideas. *TouchGraph*'s *Facebook Browser* lets users visualize their Friends and Photos. It provides information for each friend and group of friends. The groups are clustered in different colors, but the representation is not friendly and a user cannot browse the network of other friends. Similarly, *Mentionmapp* provides a neat and interactive visualization, although sometimes it is hard to navigate due to ambiguous and cluttered graph layout, as shown in Fig. 1. It tends to discover the people who are more active in Twitter and the terms that they are talking about. The maximum depth of the graph is 2-level, as when a user browses another user's network, his/her own network disappears from the visualization. Finally, *Hashtagify* is Twitter Hashtags search engine, which allows users to find hashtags to reach a particular audience. Although the layout is not cluttered, as shown in Fig. 1b, as compared to *Mentionmapp* in Fig. 1a, the tool does not allow the browsing of users or their friends.

2.4. Literature gap

The literature mainly focuses on the concept of influencers, while the relationship between content and influence is rather unexplored. This paper takes a behavioral perspective by investigating characteristics of content, both at a structural and a content level, that are an outcome of behavioral decisions made by social media users. What we found missing from previous research is that generally content-based metrics of influence [35,11,8] do not measure influence by considering quantitative properties of a user's activity within a social networks e.g. Twitter [32,56,57]. We think that these numerical properties help to a great extent in the discovery of influential people. These “numbers” provide us a lot of information, which, if it is correctly processed, will help us complement network topology based metrics [58,59].

A further goal of this work is to design a scalable and robust power-law graph drawing technique in order to visualize complex social networks. We have discussed existing network visualization techniques. This paper will contribute to the quality of social network analysis by providing a visual framework to iteratively explore and interact with the network.

3. *NavigTweet* – visual exploration of twitter network

NavigTweet aims to provide a visual interface to interact and explore the Twitter network. It helps to identify the key players or prominent Twitter users among Twitter browsed network based upon the actual that content they share. The top-influencers are identified by both *user-level* (e.g. number of followers, number of tweets, etc.) and *content-based* (number of hashtags, number of URLs, etc.) influence parameters. The user can explore its own network and FOAF network in order to discover interesting people.

3.1. Application architecure

The work-flow of *NavigTweet* is provided in Fig. 2. The basic work-flow steps of the application are the following:

1. **Twitter Authentication**: *NavigTweet* uses the OAuth protocol for Twitter user authentication, using the pin-based mechanism provided by Twitter APIs. This module is responsible for handling user authentication for successful login.
2. **User Node**: After successful login, the application creates a user node on the graph canvas, corresponding to the user who has logged in.
3. **Twitter Data Streaming**: This module is responsible for fetching the data of a user's friends. Due to the rate-limit of Twitter APIs, we fetch a maximum number of 500 friend IDs and 100 User objects in one API call.
4. **Graph Model Processing**: This module creates nodes and edges for parsed friends on the graph canvas. As a result, a local neighborhood cluster of friend nodes around a user's node is created on graph canvas.
5. **AHP-Based Ranking**: This module provides each node's AHP-based score and rank, by using both *user-level* and *tweet-level* influence parameters provided by Twitter API, as discussed in Table 1. Due to the rate-limit of Twitter APIs, *NavigTweet* fetches the last 200 tweets of users in order to calculate their tweet-level rank.
6. **Graph Controller**: Finally, this module handles event-related functionalities (e.g. mouse double-click event) and applies the power-law based graph layout, discussed in Section 3.2. Whenever the user double-clicks on any node, the application repeats from step 3 and fetches the friends of the node on which the user has double clicked.

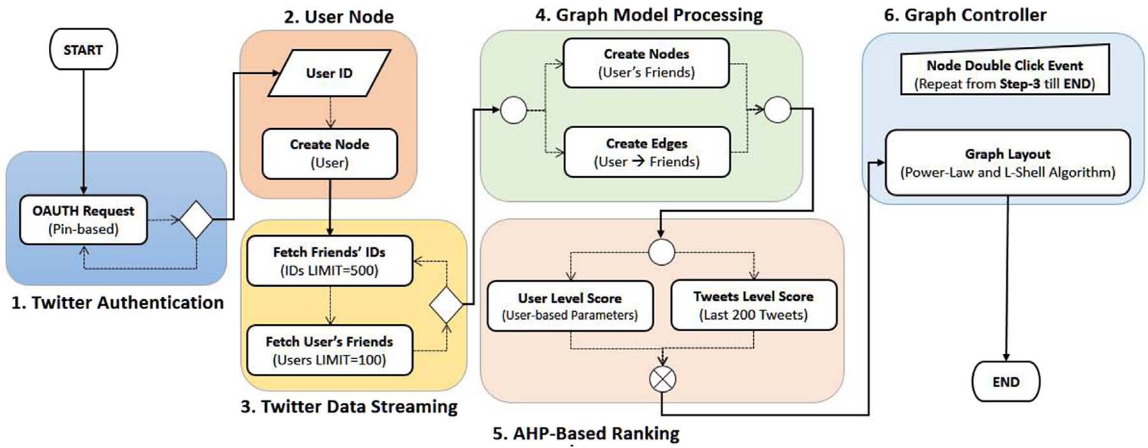


Fig. 2. *NavigTweet* Work-flow.

Table 1
Influence-based parameters of Twitter.

User-Level Resources	
Number of Following	"Following" someone means you will see their tweets (Twitter updates) in your personal timeline. Twitter lets you see who you follow and also who is following you.
Number of Favorites	Favoriting a tweet can let the original poster know that you liked their tweet. A user marks a tweet as favorite, in order to save it and have the possibility to check it later. We measure the volumes of tweets that have been marked as 'favorite'.
Number of Tweets	The total number of posts that the user has made since the time of Twitter sign-up.
Number of Lists	Lists are a shorter way of having information regarding a topic of interest. A user subscribes to such lists or creates them in Twitter.
Number of Followers	The number of users engaged in posts from the particular user, or subscribed to receive updates from that particular user.
Tweet-Level Resources (200 Recent Tweets)	
Number of URLs	We measure the number of web-links included in user tweets.
Number of Hashtags	We measure the number of hashtags used to mark keywords regarding specific topics of interest.
Number of Retweets	A retweet is used to share a post that someone else posted before. We measure the volume of the retweets that a user gets from other users.
Number of Favorited	A a tweet level, we measure the number of tweets of a user that have been marked as favorited by other users.
Number of Mentions	A user is mentioned in a tweet when the tweet is thought to be of his interest or just to be included in the message sharing. We measure such number of tweets where a user has been mentioned.

3.2. Basic building blocks of navigtweet

The basic building blocks of *NavigTweet* are the graph layout algorithm, the content-based user ranking methodology and the ranking algorithm. These modules are briefly described in the following.

3.2.1. Power-law algorithm (graph layout technique)

In order to draw the Twitter network in an aesthetically pleasant way, *NavigTweet* uses a modified force-directed graph layout, also presented earlier in [15,21,16]. The proposed approach is aimed at the exploitation of the power-law degree distribution of user nodes (N_s). Provided that the distribution of the degree of the nodes follows a power law, we can partition the network N into two disjoint sets of vertices, i.e. the set of Twitter users' nodes N_s, and the set of friends' nodes N_f, such that $N = N_s \cup N_f$ with $N_s \cap N_f = \phi$.

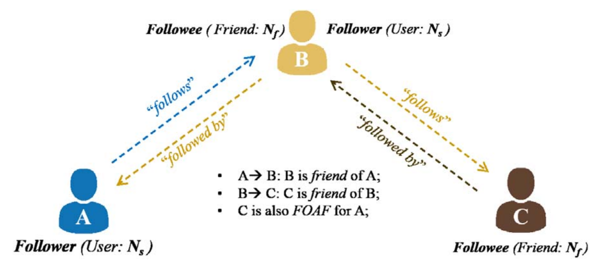


Fig. 3. Twitter network taxonomy.

Fig. 3 presents an example of Twitter network taxonomy, in which user *B* is *followee* (i.e. friend N_f) w.r.t user *A*, and also *follower* (i.e. user N_s) w.r.t. another user *C*, but *B* is not a *follower* w.r.t user *A*. Thus, in friendship connection, a user can not be both follower and followee w.r.t other users, unless both follow each other (e.g. *A follows B* and *B follows A*). Both N_s and N_f are two disjoint sets of vertices w.r.t their connections against distinct users.

We modeled the network as a one-mode directed graph G(*N*,*E*), where a user node in N_s is connected to a its friend node in N_f whenever there's a friendship connection (i.e. 'follows' relation) with them ('*Who Follows Who*' taxonomy). If two nodes do not have a *friendship* connection, then no directed edge is drawn between them.

The general work-flow of the power-law algorithm is presented in Fig. 4. The *Initialization and pre-processing* step is responsible for rescaling the size of each node in the graph, based upon their degree and AHP rank. The higher the degree and rank of a node, the greater the size and vice versa. This step is also responsible for partitioning the network into two disjoint sets of vertices, (i.e. users' nodes, and friends' nodes). The *Modified Force-Directed* step calculates attraction and repulsion forces, based upon the value of T_h, which is a threshold value that can be tuned to optimize the layout, by providing maximum forces exerted upon users' nodes N_s (*Adaptive Temperature Control*). The formulae of attraction and repulsion forces are similar to those used in traditional force-directed approaches, such as [24]. In this paper, the forces formulae have been taken from the power-law based modified force-directed algorithm presented in [60]. The *L-Shell Decomposition Analysis* step is responsible for the calculation of the l-shell value of friend nodes in N_f, in order to create a multi-layered hierarchy of friend nodes around the user nodes. This step also performs the final placement of nodes on graph canvas based on the computation of forces among nodes and the l-shell mechanism.

3.2.2. User ranking methodology

Our goal is to provide a ranking of users of Twitter, based on their influence parameters, as discussed in Table 1. We believe that each

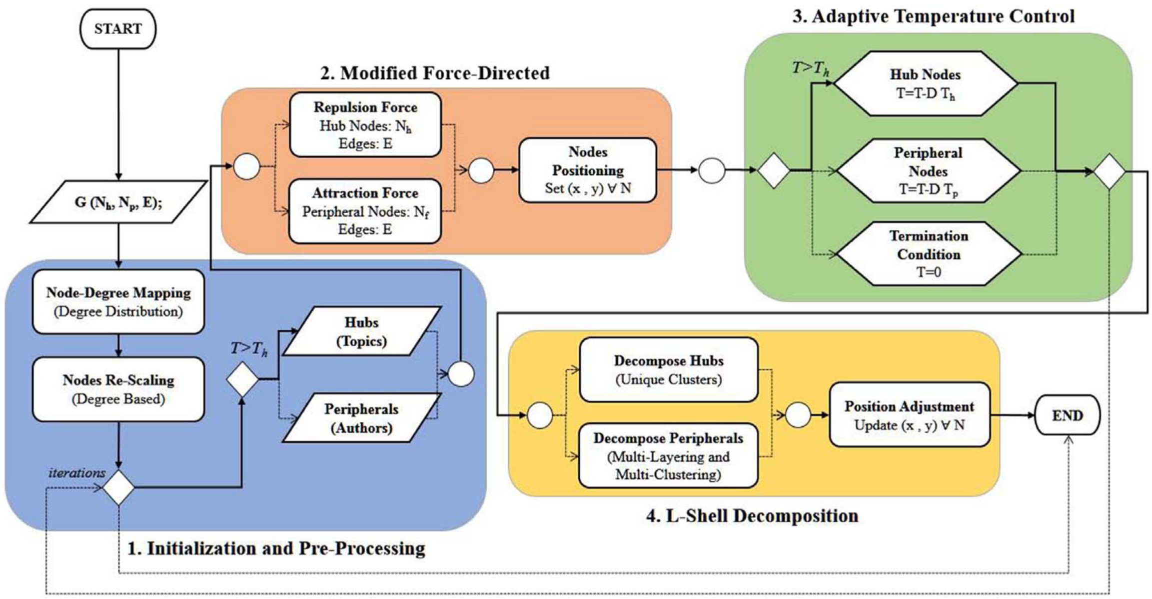


Fig. 4. Power-Law algorithm workflow.

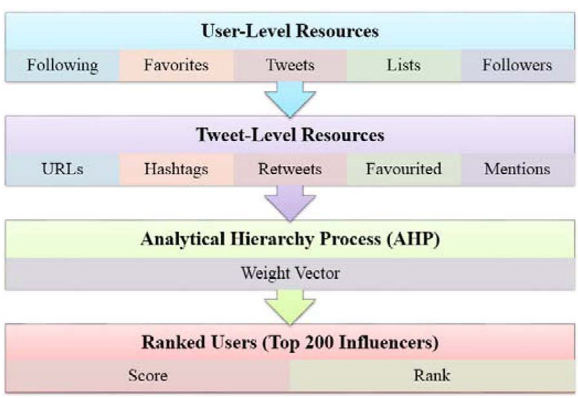


Fig. 5. Influence-based Ranking.

parameter plays an important role in identifying influencers within the network. The problem is to define how important each of these parameters is. For this purpose, we have used the method proposed by Saaty [19,20], called *Analytic Hierarchy Process* (AHP). This method has been used for decades and is widely accepted by the scientific community. We will explain how the method works in the next section. Our ranking methodology is shown in Fig. 5. The outcome of AHP is a vector of weights of parameters. *NavigTweet* provides an aggregate score of each user as a weighed sum of different parameters using the weights obtained from AHP. The higher the score the higher the rank, and vice versa.

3.2.3. User ranking algorithm

Algorithm 1 outlines the user ranking algorithm, adopted by *NavigTweet*. The algorithm calculates a ranking on the basis of both *tweet-level* and *user-level* influence parameters, as summarized in Table 1. The values against each influence parameter, are provided by Twitter API through pre-defined API methods. As an input, the algorithm takes a Twitter user node *N*, and as an output, it provides a final ranking value of *N*.

Algorithm 1. User ranking algorithm of *NavigTweet*.

Data:

N = Twitter user node;
U = Twitter user object, retrieved from Twitter API;
$U.Value_{parameter}$ = User-level parameter value, provided by Twitter API against each parameter of user object U;
$Tweet.Value_{parameter}$ = Tweet-level parameter value, provided by Twitter API against each parameter for a single Tweet;
$W_{parameter}$ = AHP based Weight Vectors against each parameter, calculated based upon priority matrix)

CONSTANT $W_{parameter}$ as DOUBLE;
Input : (N,U)
Output: Final Ranking value (Score) of each node $n \in N$.

begin
  function $UserBasedScore(u)$:= **do begin**
  (User-level influence parameters ranking)
  (Product sum of weight and values)
  $DOUBLE\ d \leftarrow \Sigma(W * U.Value) = (W_{favourites} * U.Value_{favourites}) + (W_{followers} * U.Value_{followers}) + (W_{following} * U.Value_{following})\ (W_{listed} * U.Value_{listed})\ (W_{tweets} * U.Value_{tweets});$
  $N.userRank \leftarrow d;$
  return d;
  end do
  function $TweetBasedScore(u)$:= **do begin**
  (Tweet-level influential parameters ranking)
  (Summing up values for each parameter for recent 200 tweets)
  for $i \Leftarrow 1 \rightarrow 200$ **do**
    $U.Value_{favourited} = U.Value_{favourited} + Tweet.Value_{favourited};$
    $U.Value_{retweets} = U.Value_{retweets} + Tweet.Value_{retweets};$
    $U.Value_{urls} = U.Value_{urls} + Tweet.Value_{urls};$
    $U.Value_{hashtags} = U.Value_{hashtags} + Tweet.Value_{hashtags};$
    $U.Value_{mentions} = U.Value_{mentions} + Tweet.Value_{mentions};$
  end
  $DOUBLE\ f \leftarrow \Sigma(W * U.Value) = (W_{favourited} * U.Value_{favourited}) + (W_{retweets} * U.Value_{retweets}) + (W_{urls} * U.Value_{urls})\ (W_{hashtags} * U.Value_{hashtags})\ (W_{mentions} * U.Value_{mentions});$
  $N.tweetsRank \leftarrow f;$
  return f;
  end do
  foreach $u \in U$ **do**
    $u.AHPScore = UserBasedScore(u) + TweetsBasedScore(u);$
  end
  (Descending sort of nodes by their AHP Score)
  (assign i^{th} indexed value as node's AHP Rank)
end

The *UserBasedScore(u)* method provides a score value of user-level parameters and returns a user-level score value. Similarly, the *TweetBasedScore(u)* method provides a score value of tweet-level

Table 2
Excerpt of *NavigTweet* node color scheme.

Type	Color	Stroke
Selected user	Blue	White and Thin
Influencer	Red	Green and Thick
User's friends	Random	Brown and Thin

parameters (last 200 fetched-tweets) and returns a tweet-level score value. After scoring each user, the algorithm provides a ranking value for each user by sorting all users based upon the score value.

3.3. Visual elements

The main visual elements of *NavigTweet* are the color-scheme, the graph layout and the node tool-tip. These are described in next sections.

3.3.1. Color scheme

NavigTweet uses a node color-scheme to distinguish different types of nodes (see excerpt in Table 2). There are two types of nodes, currently selected user nodes and the friend nodes. The nodes with a higher influence according to the AHP ranking are red with green bold stroke. Similarly, selected user nodes are represented in blue with white thin stroke and friend nodes are represented by any random color other than red and blue (with thin stroke).

3.3.2. Graph visualization

In order to create an aesthetically pleasant layout in the multi-clustered and multi-layered peripheral network, we apply the power-law based modified force-directed algorithm, discussed in Section 3.2. This algorithm arranges nodes in such a way that highly connected user nodes are placed in a more central position while less-connected friend nodes are placed in the periphery around their user node. In this way, each node has its own cluster of multi-layered friend nodes. Graph layouts generated with this technique are usually perceived as aesthetically pleasant, since all edges have roughly the same length and tend to avoid edge crossings.

Fig. 6 shows a small graph containing two different clusters of *user* nodes (i.e. ① and ②) around *friend* nodes (i.e. followees). *NavigTweet* identifies common friends, if any, who are '*followed by*' more than one user (e.g. node ④ in Fig. 6). In the example, the top users with the highest rank are highlighted by ③. The neighboring nodes in two distinct clusters of *user* nodes ① and ② are not connected, as these neighbors are not friends with each other. In the graph, the size of nodes varies, as shown in Figs. 6 and 7, based upon their relative rank within the local neighborhood of friends. The higher the node's rank, the larger the node size.

3.3.3. Node tool-tip

NavigTweet provides information for all nodes in a tool-tip. When the user brings the mouse over a particular node, the tool-tip shows the node information along with its rank, see annotation ① in Fig. 7. Additional user profile information, such as photo, screen name, location etc., is also displayed in the tool-tip.

4. Implementation

We have implemented *NavigTweet* as a desktop application. The application is written in JAVA using Twitter4j [61] – a JAVA-based library, and Piccolo 2D [62] – a JAVA based 2D Graphic library. The

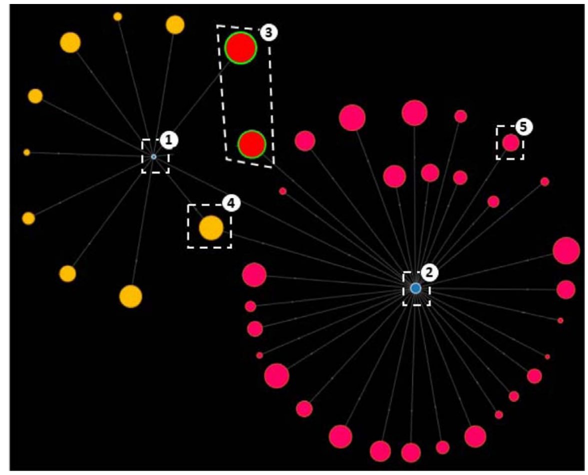


Fig. 6. Sample NavigTweet network graph.

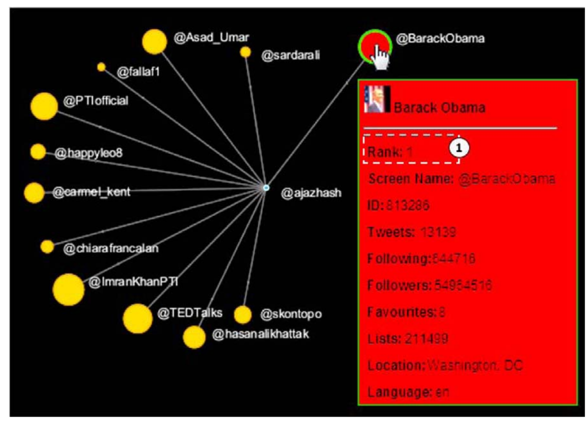


Fig. 7. Node tool-tip.

application has a GUI compatible with multiple operating systems (Windows, MAC OS, and Linux / Unix) and contains a runnable JRE file. The only pre-requisite of *NavigTweet* is the JAVA Runtime Environment. During installation, the setup will automatically install the JRE Bundle package, if missing. *NavigTweet* uses OAuth-based protocol for user authentication provided by Twitter API. The OAuth protocol allows Twitter users to approve the application and allow it to act on their behalf without sharing their password. Then, *NavigTweet* can require an Access Token from Twitter. This initial configuration is a one-time process. Further details can be found on *NavigTweet* website [63].

4.1. Application interface

Fig. 8 shows the main screen of *NavigTweet*. The user interface consists of three panels: left, center and bottom. The left panel shows the influencers, as well as Twitter and control options. The center panel shows the graph canvas, where the user can explore and interact with the graph. The bottom panel provides the timeline and console panes for the currently selected node.

4.1.1. Left panel

The *Left Panel* provides three further sub-panels: *Influencers Panel*, *Twitter Panel* and *Control Panel*. The *Influencers Panel* is dedicated to show both graph-level and user-level top-20 influencer list, as shown in Fig. 8. A user can directly follow or un-follow Twitter users from the top-20 influencer list. The *Twitter Panel* displays the user's timeline and provides a bird-eye view of the whole graph. Moreover a user can post tweets directly to his or her timeline and

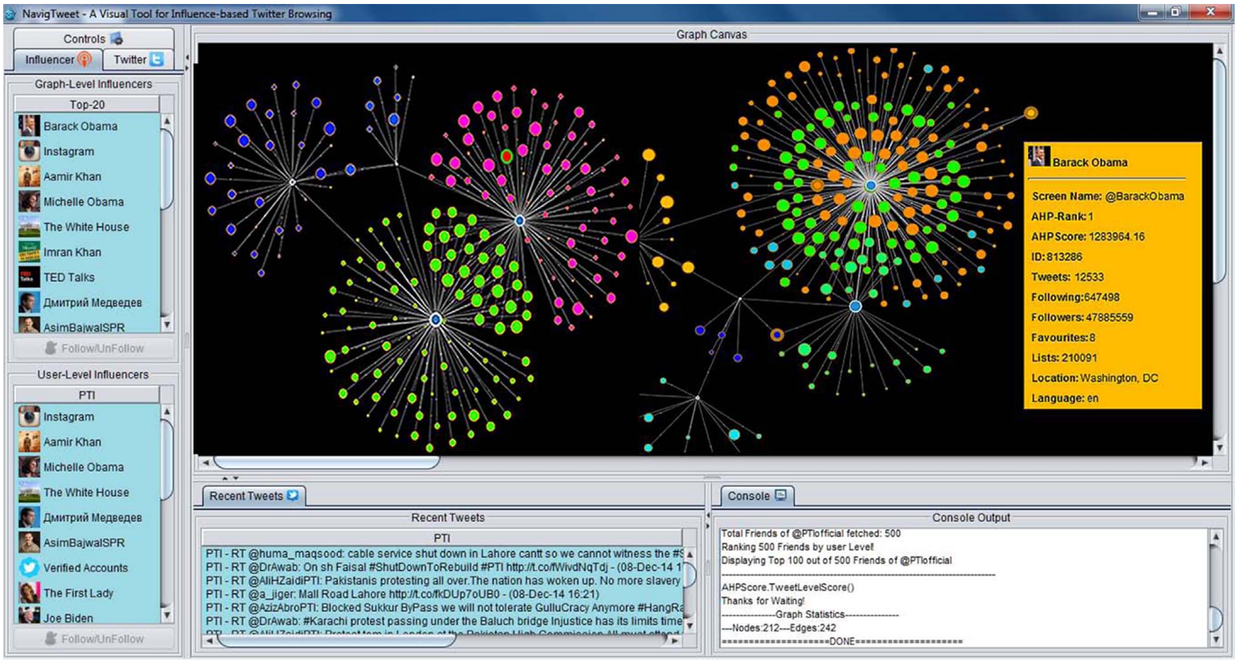


Fig. 8. Main Screen of *NavigTweet* Interface.

can also send a direct message to his or her followees. The *Control Panel* provides various button controls for print, data export, and show / hide node labels.

4.1.2. Center panel

The *Center Panel* of *NavigTweet* shows the graph canvas, where a user can explore and interact with the graph. Users can zoom in to explore network topology. They can pan the background and move elements around via drag and drop, to further optimize the graph visualization and adapt it to their needs. Whenever a node is dragged and released, the rest of the nodes are repositioned with animated transitions according to the power-law based force-directed algorithm. When a user double-clicks on any node, the application fetches the node's friends in real-time and shows them on the graph.

4.1.3. Bottom panel

The Bottom Panel of *NavigTweet* displays the most recent 20 tweets of the currently selected user. When a user selects a different node, the recent tweets of new selected user will be dynamically displayed.

4.2. Application functionalities - summary

The main functionalities of *NavigTweet* are outlined in Table 3. NavigTweet is available to download from the website[1].

Table 3
Main functionalities of *NavigTweet*.

Categories	Features
User Profile Management	• User authentication • OAuth protocol • Access token generation for login • Profile information access
Interaction with Twitter	• Follow / unfollow user • Display friend network graph • View timeline • Post a tweet • Explore social network at any depth. • User search • Top-20 user-level influencers (i.e. influencers that are selected among any node on canvas.) • Top-20 graph-level influencers (i.e. influencers that are selected among users connected with a followee relation with currently selected users) • View user analytics • Send direct messages
Influence-based Social Network	• Perform AHP-based ranking of users • Show mutual-follower(s) • Browse FOAF network • Identify top-100 influencers among each user's browsed network
Interface and Controls	• Zoomable user interface • Node tooltip • Show/hide node labels • Bird's eye View of Graph Canvas • Print graph • Apply power-layout • Console output/log • Multi-color clusters • Export data (CSV) • Mouse events (drag, scroll, over, click, etc.)

5. Evaluation and results

In this section, we present a qualitative comparison between *NavigTweet* and existing applications.

5.1. Comparison with existing applications

As noted in Section 2.3, there exist a few visualization tools supporting the exploration of Twitter's network. Table 4 shows the highlights of the comparison between *NavigTweet* and the tools that we have been able to test. Some tools are cited in previous literature, but have not been mentioned and can not be used anymore. We have considered various features in the comparison related to performance, service, support, interface, and scalability.

Table 5 provides a qualitative analysis of the usability of tools, including *NavigTweet*. We have considered several factors related to

[1] http://bit.ly/1sBRDxq

Table 4
Quantitative comparison between *NavigTweet* and similar tools.

Criteria x Tool	TouchGraph	Mentionmapp	Socilab	Hashtagify	NavigTweet
Real-time	No	Yes	No	Yes	Yes
Graph depth	1	2	1	2	n-level
Response time	<5 s	<5 s	>5 s	<5 s	>5 s
Initial load time	>5 s	<5 s	>5 s	>5 s	>5 s
Open source	No	No	Yes	No	TODO
Free / Freemium	Both	Freemium	Freemium	Freemium	Free
Social Network	Facebook	Twitter	LinkedIn	Twitter	Twitter
Platform	Web	Web	Web	Web	Currently Desktop
Help & support	Feedback	Feedback	Feedback	Tutorials	Feedback & Tutorial

Table 5
Qualitative comparison between *NavigTweet* and similar tools.

Criteria x Tool	TouchGraph	Mentionmapp	Socilab	Hashtagify	NavigTweet
Network browsing	Self & Others	Self & Others	Self	Self	Self & Others
Friendly colors	Somehow	Yes	Yes	Somehow	Somehow
Clusters clarity	Yes	Yes	Somehow	Somehow	Yes
Multi-color cluster	No	No	Yes	Yes	Yes
Zoom-able Interface	Yes	Yes	Yes	Yes	Yes
Pan & drag	Yes	Yes	Yes	Yes	Yes
Information quantity	A lot	Normal	Normal	Normal	Normal
Information placement	ToolTip	None	Tooltip	Tooltip	Tooltip
Default information	Name + Photo	Name + Photo	Name	Name	Screen Name

aesthetics, such as color-scheme, distance between nodes, information amount displayed per node, zoom-ability of graph canvas, node shapes, mouse controls, etc. The evaluation is subjective and has been performed by the authors of this article.

5.1.1. Summary of comparison

The following summarizes the main points of our comparison between *NavigTweet* and similar tools:

- *NavigTweet* provides visual exploration functionalities, with identification of influencers based on both content-level and tweet-level influence parameters.
- *NavigTweet* algorithm allow minimum node-cluttering and edge-overlaps. It is robust and scalable beyond 500 nodes.
- NavigTweet considers a broad range of influence parameters(e.g. *Klout* considers 3 parameters only - reach, amplification, and network impact).
- Almost all tools explore networks up to maximum 2-level depth. In contrast, *NavigTweet* provides a highly scalable exploration experience up to n-depth level.

5.2. Pilot test execution and results

The pilot activity aimed to target expert user opinion, in order to get feedback and suggestions on the usability of *NavigTweet* and the degree of user satisfaction. Insights from pilot have been used to improve *NavigTweet* before extensive testing.

5.2.1. Pilot team

We targeted a reference group of 8 people from academia. All participants were familiar with the idea of graph visualization and had knowledge in social network analysis. Table 6 provides details about pilot participants. The participants could interact with *NavigTweet*, while they were gradually told about interactive features. We intended to demonstrate the application in a real-time environment, to gather their feedback about the usability and general effectiveness of the application.

Table 6
Pilot Participants.

Resource	Role	Research Line
Participant 1	Full Professor	Information Systems
Participant 2	Full Professor	Dynamics of Complex Systems
Participant 3	Full Professor	Graph Theory, Information Visualization
Participant 4	Associate Professor	Data, Web and Society
Participant 5	Associate Professor	Information Systems
Participant 6	Associate Professor	Data, Web and Society
Participant 7	Associate Professor	Information Systems
Participant 8	Associate Professor	Advanced Software Architecture

5.2.2. Pilot phases

The methods through which we assessed the quality of *NavigTweet* are described below:

- **Phase 1: Face-to-Face Interviews** – During the pilot, we have performed one-to-one, face-to-face interviews. We had the opportunity to brief the interviewees about the application scenario, installation, and application flow. With each participant, we obtained real-time feedback while using the application. The discussion sessions with each participant took around 1 hour. To provide some rough guidance through the features of *NavigTweet* and ensure touching upon a wide range of visualization aspects, a number of questions were asked. Participants were asked these questions to give them an incentive to look at *NavigTweet* features and aspects of the visualization and interface, and to induce suggestions on missing or desired features. Results are summarized in Table 7 which provides the pilot summary response from all participants.
- **Phase 2: Feedback Survey** – The pilot activity also involved a structured feedback survey, provided in Table 8, which we have administered after the face-to-face meeting. The questionnaire was designed to cover the qualitative aspects of *NavigTweet* user interface. Each participant was encouraged to provide us his/her opinion and remarks by answering these questions.

Table 7
Summary of pilot responses.

GENERAL FEEDBACK	• Application functionality is acceptable. • Application performs with acceptable speed and response. • Application interface is user-friendly. • Browse FOAF networks is useful. • Notify any Twitter Rate-Limit Exceed Exception is useful. • Follow / Unfollow user in real time is effective.
TWITTER-SPECIFIC FEEDBACK	Each participant randomly tested every feature of the *NavigTweet*. The test response was satisfactory. Summary about each set of requirements is as follows: • **User Profile Management**: Successful user authentication via OAuth protocol, along with request token generation. After successful login, user profile was accessible. • **Direct Interface with Twitter**: Successful working of each feature, Top-20 Influencers, Time-Line view. Tweet posting was speedy and responsive. • **Influence-based Social Network**: User ranking and Twitter score found to be accurate. Mutual friends also been found by exploring FOAF networks. • **Interfaces and Controls**: All application interfaces worked perfectly, no Twitter API related exception thrown by application. Tested graph print feature as well.
IMPROVEMENT SUGGESTIONS	• Graph Nodes' Legend panel. • Display Top-20 graph-level influencers panel, to highlight influencers. • Export graph data into CSV. • Graph Nodes' Legend. • Follow / unfollow any user at run-time. • Web-Interface of *NavigTweet*.

5.2.3. Pilot tasks

Each participant was involved in testing all application features and provided his/her qualitative feedback. Suggestions were classified according to following categories:

- **User Profile Management**: The set of requirements which fall under this category are related to application interfaces like *user-authentication*, *OAuth based Token generation* and *user profile information*.
- **Direct Interface with Twitter**: This includes functionalities such as *posting a tweet*, *showing user-time line*, *sending direction messages* to the user, and *viewing top-20 influencers* fall under this category.
- **Influence-based Social Network**: The set of requirements which fall under this category are related to *ranking of users*, *identification of mutual follower(s)*, and *browsing of FOAF networks*.
- **Application Control Interfaces**: The control options or features like *node tool-tip*, *ZUI*, *Bird's eye view* [64], *Print Graph* and *Export data* fall under this category.

5.2.4. Pilot results

Overall, the survey results were positive, as shown in Fig. 9, which presents the summary evaluation of different functional areas of *NavigTweet*. Each pilot participant evaluated existing features of the application and proposed new requirements, both functional and non-functional. The only technical issue identified during pilot activity was the *Installer Problem on MAC OS* (the application failed to install on MAC OS).

Comments were generally favorable towards *NavigTweet* ("*Really useful, and aesthetically pleasant graphs with nice color-scheme*", "*Innovative and Informative tool*", "*User Ranking and Influencers Identification over graphs is quite wonderful!*"), which was especially praised for *User Interface*, *Graph Animated Layout*, *Multi-colored Clustering Scheme*, *Dynamic Top-20*, *User- and Graph-Level panel*, *Browsing Friends' List*, *Mutual-Friends Identification*. Several participants pointed out that the tool identifies actual influencers that are visualized in a novel and easy-to-understand way.

Some participants were not happy with Twitter rate-limit, which is beyond our control as per Twitter API policy, although Participants appreciated the exception handling feature of *NavigTweet*. A pilot participant advised to reduce tool-tip contents and to eliminate some information panels, as the tool itself is self-explanatory and provides an understandable work flow. Three pilot participants insisted about web-based interface, which we are considering for the next release of *NavigTweet*. Another pilot participant advised to introduce a new

Table 8
Pilot Feedback Survey.

QUESTIONS	ANSWER CRITERIA
QUALITATIVE ANALYSIS	
Do you find *NavigTweet* interesting? (User Interest)	• Funny • Boring • Helpful • Informative • Innovative • Useful • Usable
How would you rate the effectiveness of *NavigTweet*, as an interactive tool to explore your Twitter social network? (User Interaction)	Low/High 5 point scale.
How would you rate the clarity for *NavigTweet*? (Clarity Perception)	Low/High 5 point scale.
Do you find *NavigTweet* helpful in exploring and identifying the influencers (prominent Twitter users)? (Influencers Identification)	Yes/No/Somehow
Would you browse other users' friend networks via *NavigTweet*? (Network Browsing Level)	Yes/No/Somehow
How would you rate *NavigTweet* overall? (User Satisfaction)	Low/High 5 point scale.
USER INTERFACE	
Do you like interface of *NavigTweet? (Graphical User Interface)*	Low/High 5 point scale on: • Graph representation • Friendly color-scheme • Cluster clarity • Informative node tool-tip
Which color scheme in clusters you prefer? (Clusters color-scheme)	Same/Different
How much information is displayed per user node? (User Information Quality)	Too little/Normal/Too much

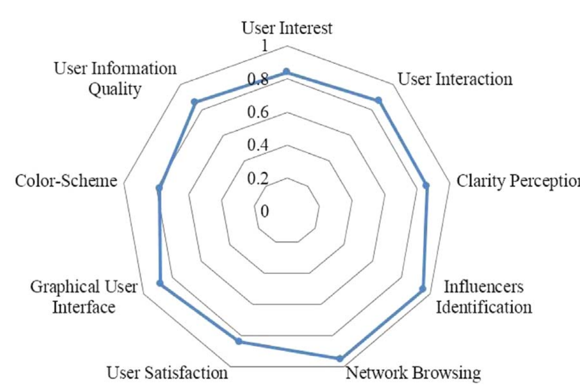


Fig. 9. Rating of *NavigTweet* based on qualitative criteria.

Table 9
Feature Updates Summary.

Requirement/Feature	Update Status	Remarks
Display Top-20 Graph-Level Influencers	YES	Added in left Influencers Panel.
Data export feature	YES	Button provided in left Control Panel to export the CSV file.
Graph node legend	YES	The graph legend panel is added in left Control Panel.
Node tool-tip content update	YES	Revised contents for clear user understanding.
Application stand-alone JRE file	YES	The Runnable JRE can be downloaded from *NavigTweet* website.
User guide in installer package	YES	PDF file is added in installer package.
Webpages of user-guide	YES	User Guide webpage created.
Web-based interface	NO	Will be considered in next version.
Influencers Graphs/Pie charts	NO	Will be considered in next version.
Twitter Analytics	NO	Will be considered in next version.

panel with graph-level influencers among all selected users and their connections. We also received advice on introducing a data export feature prior to public release.

The detailed summary of feature updates, based on pilot feedback are provided in Table 9. Prior to the public release, we implemented most of the recommended changes.

5.3. Extensive survey: summary of responses

We created an online survey[2], as shown in Table 8, which is available on *NavigTweet* website [63]. In order to get real-time feedback from end users, we circulated information within communities by engaging in online conversation. We targeted social networks like Facebook, LinkedIn and posted on various blogs,and communities and groups. We also targeted a variety of forums.

5.3.1. Rollout strategy

We circulated the survey via different communication channels and targeted various end-user segments. The communication channels which we adopted for *NavigTweet* survey rollout are listed below:

- **Emails**: Direct release notification emails sent to the user base, along with survey.
- **Social Media**: *NavigTweet* release news are posted on social media like FB, Twitter, LinkedIn, Google+. Additionally, various technology blogs (Twitter, FB, Linkedin, etc.) are also targeted.
- **Direct Communication**: Release information circulated directly to social circle including friends, co-workers, etc. which they further circulated within their social circle.

5.3.2. Target market and segmentation

The market segmentation which is targeted for *NavigTweet* survey roll-out is described as follows:

- **Students**: University students at bachelor, Masters and PhD-level. Emails were sent to mailing lists of students in universities in multiple countries.
- **Academic Faculty**: We targeted faculty members of various universities, and sent release notification to their mailing lists.
- **Industry segment**: Industry related people were also notified via email.

[2] http://goo.gl/azdMZ5

5.3.3. Demographics

In order to understand user demographics (e.g. age, gender, education, job profile, etc.), we asked a few questions in the questionnaire, which helped us to know our interviewees. Among all users, 64 % are male under age of 31–35 years (27.2%) with a Master's degree qualification (41%). Most respondents were active and regular Twitter users, who normally use Twitter on a daily basis (41.3 %) or twice per week (21.7 %). Fig. 10 shows a summary of the demographics of our sample.

5.3.4. Questionnaire results

So far, we have collected 103 questionnaires from end-users. A summary of their responses is shown in Fig. 11. The questionnaire survey, as provided in Table 8, was categorized into three parts: 1) *Qualitative Analysis* 2) *User Interface* and 3) *Comments and Suggestions*. Fig. 11a shows a summary of the *Qualitative Analysis* answers. Likewise, Fig. 11b presents a summary of the overall rating of *NavigTweet*. Fig. 11c shows a summary of the *User Interface* section. Finally, Fig. 11d shows the *daily response rate* to the survey during first 3-month period. Peak responses occurred when we sent our reminders.

- **Qualitative Assessment** – More than 80 % of the respondents found *NavigTweet* as an interesting tool (helpful, informative, innovative, easy to use, etc.), 82.6 % of users rated the effectiveness of *NavigTweet* by scoring 4 or 5 on a 1–5 scale. Overall, 86.9 %users seems to be satisfied with *NavigTweet*.
- **User Interface** – More than 80 % of users like the user interface of *NavigTweet* including graph representation, multi-clustering with distinct coloring nodes, functional clarity, tool-tip, pan & drag, zoom-ability, and color-scheme; 81.5 % of users prefer different color scheme in graph clusters; 93.5 % of users found information displayed per user node as normal.
- **Comments & Suggestions** – Comments received through survey responses were generally favorable. 54.6 % of users were *Satisfied* and 25.3 % of users were *Very Satisfied*. The overall rating of *NavigTweet* is presented in Fig. 11b.

5.4. Web analytics (navigtweet *website)*

Although collecting feedback questionnaires has proved a cumbersome activity, *NavigTweet* site has had over 5000 visits within a 3-months period – To analyze their behaviors we used Google Analytics [65] for *NavigTweet* website [63].

Fig. 12 shows a snapshot of the Google analytics dashboard for the *NavigTweet* website.

Fig. 12 also shows a geographical map of the users who have accessed *NavigTweet* website. Users from different countries visited the website. The main continents are Europe (55.3 % sessions), Asia (26.6 % sessions), Americas (10.61 %). In total, *NavigTweet* website has been accessed from 54 different countries. 4909 were the total unique visitors of the websites, and 5,609 visit sessions were created on website.

6. Discussion and conclusions

The objective of this study was to investigate the relationship between content and influence on social media. As per previous studies [3,10,11,8], the content of messages can play a critical role and can be a determinant of the social influence. We focused on behavioral perspective of content-based influence and designed a software tool – *NavigTweet* to leverage the concept of content-based exploration of Twitter network.

NavigTweet allows users to analyze, explore and interact with

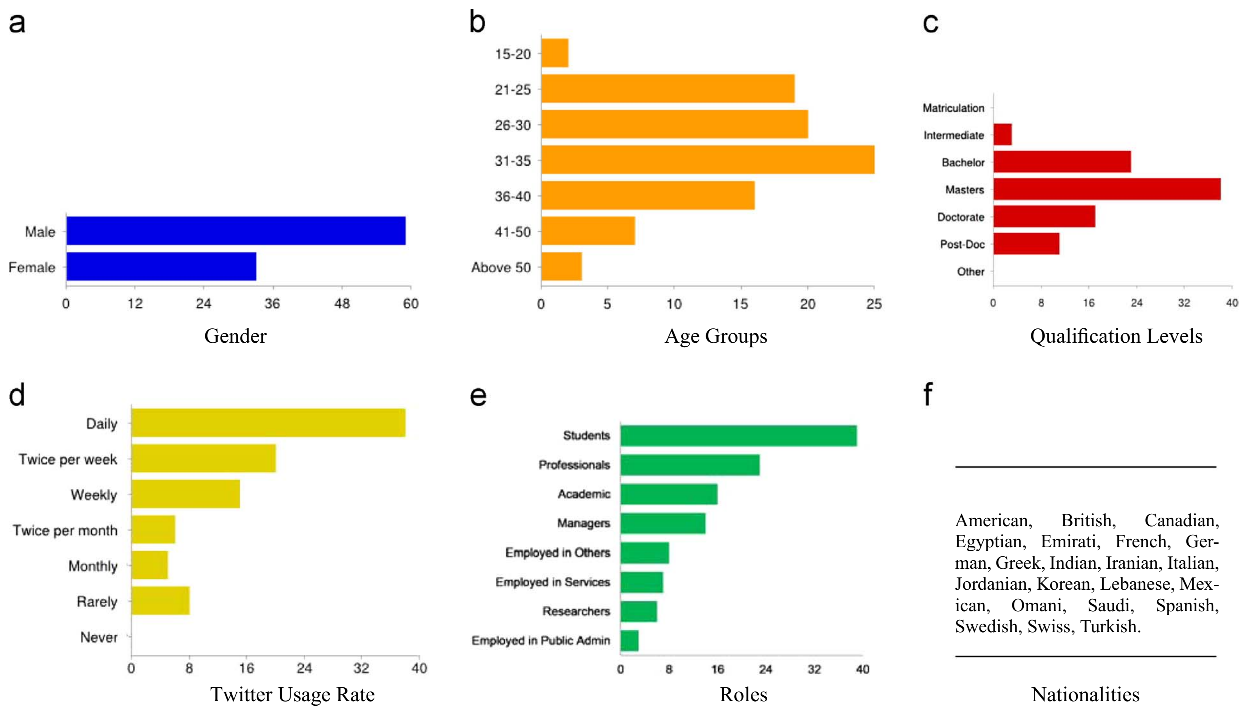


Fig. 10. Users' Demographics. (a) Gender (b) Age Groups (c) Qualification Levels (d) Twitter Usage Rate (e) Roles (f) Nationalities.

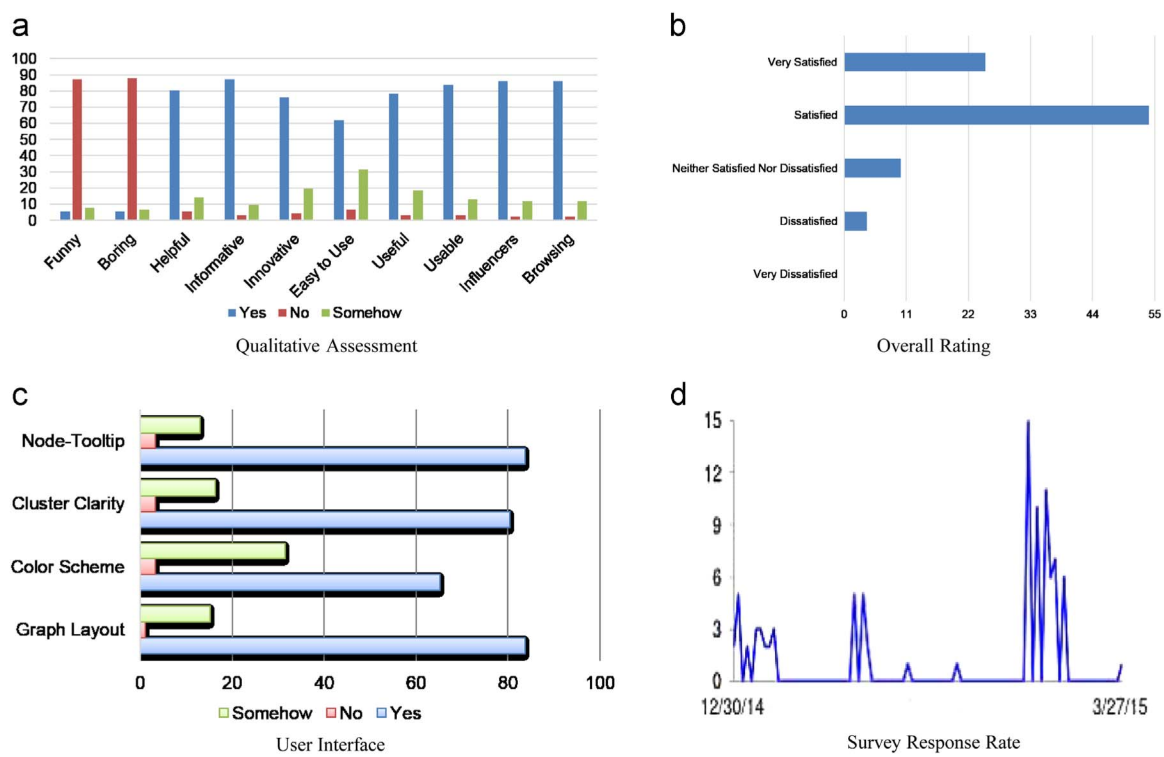


Fig. 11. Summary of Responses. (a) Qualitative assessment (b) Overall rating (c) User interface (d) Survey response rate.

Twitter '*Who Follows Who*' relationship, by browsing a user's friends' network to identify the key influencers based upon the influential content that they share on Twitter. *NavigTweet* helps to identify the key players, and follow them directly through the *NavigTweet*.

We have reported on a qualitative and quantitative analysis of our tool compared to other similar tools. We also reported on a pre-launch pilot test execution, involving a qualitative user study to assess user experience. We found that pilot participants were positive about the functionalities and features of the tools and with novelty of the idea itself, and received favorable comments concerning *NavigTweet*. We have addressed the pilot comments by modifying and updating the tool, accordingly. We have conducted an extensive survey, and, so far, we have collected 103 questionnaires from end-users. The preliminary feedback that we have obtained suggests that *NavigTweet* is both viable and useful. *NavigTweet* can help general users in order to understand the influence dynamics by providing a visual exploration platform, by which users can browse through their own and FOAF networks at unlimited depth-level friends' network. This represents an

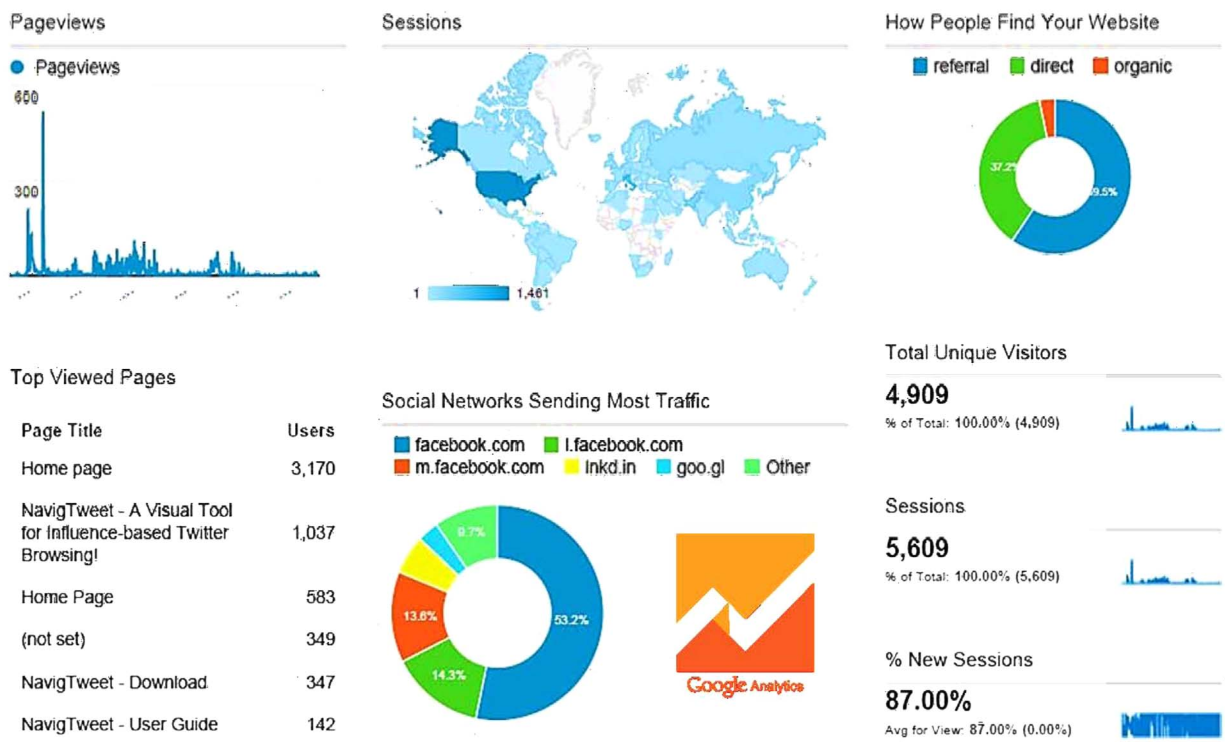


Fig. 12. *NavigTweet* website dashboard. Recorded Period: *Dec 1, 2014 – June 22, 2016*.

important novel feature of *NavigTweet* as per our pilot and extensive survey results.

Future work will consider implementation of web-based interface of *NavigTweet*, with additional navigation and analysis features. This will broaden our potential user base and allow for a broader study of users behavior when exploiting Twitter with a content-based approach.

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