NavigTweet: A Visual Tool for Influence-Based Twitter Browsing

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Abstract. Directed links in social media could represent anything from intimate friendships to common interests. Such directed links determine the flow of information and hence indicate a user's influence on others—a concept that plays a vital role in sociology and viral marketing. Identifying influencers is an important step towards understanding how information spreads within a network. Social networks follow a power-law degree distribution of nodes, with a few hub nodes and a long tail of peripheral nodes. This paper proposes a novel visual framework to analyze, explore and interact with Twitter '*Who Follows Who*' relationships, by browsing the friends' network to identify the key influencers based upon the actual influence of the content they share. We have developed NavigTweet, a novel visualization tool for the influence-based exploration of Twitter network. The core concept of the proposed approach is to identify influencers by browsing through a user's friends' network. Then, a power-law based modified force-directed method is applied to clearly display the graph in a multi-layered and multi-clustered way. To gather some insight into the user experience with the pilot release of NavigTweet, we have conducted a qualitative pilot user study. We report on the study and its results, with initial pilot release.

Keywords: Social Media Influencers · Social Media Influence · Twitter Analytics · Graph Visualization

1 Introduction

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 and retweets on Twitter, or a multitude of friends on Facebook, or a broad connections on LinkedIn. 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. (Anholt 2006; Myers & Leskovec 2014) has 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 the their shared content has influence, as discussed by (Benevenuto et al. 2010).

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Social media have become pervasive and ubiquitous. There is a growing need for information visualization, which has recently become a popular subject of research (Fan & Gordon 2014; Klotz et al. 2014; Myers & Leskovec 2014). 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 of challenge when the focus is 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 accomplished. Its influence on information dissemination has led to research exploring on how this is achieved. According to (Kwak et al. 2011) the unicity of direction in twitter connection provides the key driver of information dissemination via word of mouth (WoM) in retweets.

The ultimate goal of our research is to provide a novel visual framework to analyze, explore and interact with Twitter 'Who Follows Who' relationships, by browsing the friends' network to identify the key influencers upon the actual influence of the content they share. In this paper, we exploit a modified power-law based force-directed algorithm (Hussain et al. 2014) to clearly display the Twitter network graph in a multi-layered and multi-clustered way. 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 actual content they share and provides opportunity to follow them directly through application interface. 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.) influential parameters. The user can explore its own network and FOAF network in order to find out interesting people in the network and can directly follow or unfollow through application interface. The intended audience is people who want to find interesting information regarding their social network and empower them to enlarge their social network by providing interesting people to follow. The intended audience may find influencers among their own and as well as FOAF networks through a visual interface and can traverse the graph through visual interface to further explore networks at any depth level, to find out more influencers.

As part of this research, we have developed NavigTweet (Hussain 2015), a visual tool for the influence-based exploration of Twitter friends' network. It helps to identify the key players, and follow them directly through the NavigTweet. The user can explore its 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 3. Based upon these parameters, the tool adopts the Analytical Hierarchy Process (AHP) technique, to rank Twitter users, as our NavigTweet user explores his/her FOAF network. The NavigTweet users can find influencers within their friends' network through a visual interface and iteratively explore FOAF network to find more influencers. To gather a preliminary feedback on the NavigTweet user experience with a pilot release of NavigTweet, we have conducted a survey targeting reference group of academic experts in the social media domain who have been asked to use the application in real time environment. This paper presents the results of Table 4 questionnaire collected through the survey.

The remainder of this paper is structured as follows. Section 2 discusses influence and influencers in social media, and provides insights about Twitter analytics and visualization tools. Section 3 presents our methodology. Section 4 discusses implementation aspects of NavigTweet. Section 5 presents the evaluation framework with pilot study and results. Conclusions are drawn in Section 5.

2 State of the Art

In this section, we will discuss about the concept of influencers and influence in social media. We also discuss insights about Twitter analytics and visualization tools.

2.1 Influencers and Influence in Social Networks

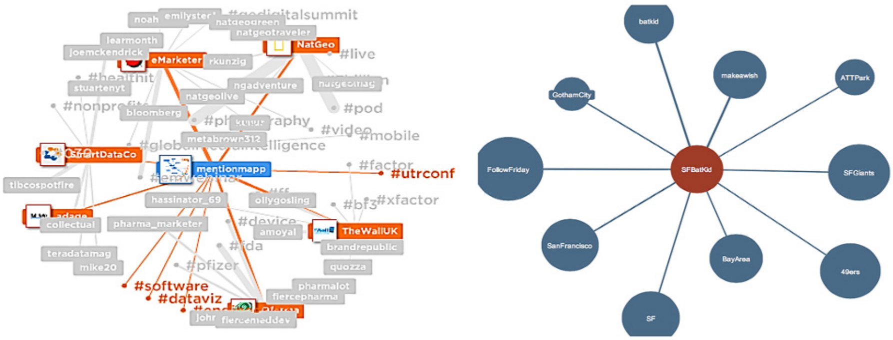
Traditionally, the literature characterizes a social media user as an influencer on the basis of structural properties. Centrality metrics are the most widely considered parameters for the structural evaluation of a user's social network. The centrality of a concept has been defined as the significance of an individual within a network (Fan & Gordon 2014). 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 (Barbagallo et al. 2012). In addition to degree centrality, the literature also shows other structural metrics for the identification of influencers in social networks. (Leavitt et al. 2009) presented an approach where users were identified as influencers based on their total number of retweets.

Several research works have addressed the need for considering content-based metrics of influence (Bigonha et al. 2012). Content metrics such as the number of mentions, URLs, or hashtags have been proved to increase the probability of retweeting (Bakshy et al. 2011). Twitter has been the most common dataset for researches on user influence. For example, (Chang 2014) and (Kwak et al. 2010) measure the influence of Twitter users based on the sheer number of retweets spawned from the users' tweets. Recently, (Wu et al. 2011) have studied the elite users who control a significant portion of the production, flow, and consumption of information in the Twitter network. In (Wu et al. 2011) a top-down approach is used by identifying top users based on how frequently these appear in user-generated lists.

2.2 Twitter Analytics and Visualization Tools

Twitter analytics tools generally aim at finding, analyzing and then optimizing a person's social growth. For example, `Twitonomy` (Twitonomy.com 2014) 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, `Followerwonk` (Followerwonk.com 2014) is a web application which helps a user explore and grow his social graph. As discussed in (Klout.com 2014), `Klout` is a system-generated tool for measuring influence; in other words it is a potential 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) (about Klout.com, 2012). `Klout` scores have a range of 1–100, with a higher score indicating a higher level of influence. (Kilpatrick 2015) discusses additional analytics tools including `The Archivist`, `SocialBro`, `Twenty Feet`, `TweetStats`, `Twitter Counter`, `Tweetstats`, and `TweepsMaps`.

The literature on social network visualization tools indicate that there exist only a few visualization tools. (Kilpatrick 2015; Kujawski 2014) reviews existing tools, including `TouchGraph`, `MentionMap`, and `Hashtagify`. `TouchGraph` is a real-time web application which provides a cluster visualization of a user's Facebook network. 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 navigate or browse the network of other friends. Similarly, `MentionMap` provides a neat and interactive visualization, although sometimes it is hard to navigate due to ambiguous and cluttered graph layout, as shown in Figure 1 (a). 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 visualization. Finally, `Hashtagify` allows a user to visualize a network based on a Twitter hashtag. Although the layout is not cluttered as compared to `MentionMap`, the tool does not allow the visualization of user's friends or followers.



(a) MentionMap (b) Hashtagify

Fig. 1. Twitter visualization tools

3 Design and Methodology

This section presents the network exploration approach and algorithms that are embedded in NavigTweet. First, we discuss the graph drawing algorithm that draws a Twitter network graph in an aesthetically pleasant and understandable way. Second, we discuss the ranking mechanism, that we adopted to identify influencers by using both user-level and content-based parameters.

3.1 Power – Law Algorithm (Graph Layout Technique)

This section summarizes the graph layout algorithm used in NavigTweet. Further details on the algorithm can be found in (Francalanci & Hussain 2014; Hussain et al. 2014). The power-law layout algorithm, shown in the following code snippet, belongs to the class of force-directed algorithms, see (Chan et al. 2004; Fruchterman & Reingold 1991). The proposed approach is aimed at the exploitation of the power-law degree distribution of Twitter users' nodes (N_s). Provided that the distribution of the degree of the nodes follows a power law, we partition the network into two disjoint sets of vertices N, 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 $N_s \cap N_f = \emptyset$.

Algorithm 1: High-level structure of power-law layout algorithm.

```
DATA:
  Ns = User Nodes (Selected Users);
  Nf = Friend Nodes;
  E = Edges connecting user and friend nodes.
  d = Node Degree, representing the number of connected friends;
  T = Energy / Temperature Variable;
  Th = Temperature threshold, to control simulation.
BEGIN
1. NodePartition();
2. resetNodesSizes(Nf ,d);
3. InitialLayout();
      IF (T>Th) DO
           AttractionForce(Ns,Nf);
           RepulsionForce(Ns,E);
      ELSE
           AttractionForce(Nf,Ns);
           RepulsionForce(Nf,E);
4. LShellDecomposition(Ns,Nf);
5. NodesPlacement (Ns,Nf);
6. TempCoolDown(T);
END
```

The `resetNodesSizes(Np,Nt,d)` method is responsible for resetting the size of each node in the graph, based upon their degree. The higher the degree of a node, the greater the size and vice versa. The `InitialLayout()` 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 hub-nodes N_h. The formulae of attraction and repulsion forces are similar to those used in traditional force-directed approaches, such as (Chan et al. 2004). In this paper, the forces formulae have been taken from the power-law based modified force-directed algorithm presented in (Hussain et al. 2014). The `LShellDecomposition(Ns,Nf)` method 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 friends nodes around the user nodes. The `NodePlacement(N_s,N_f)` step performs the placement of nodes on graph canvas based on the computation of forces among nodes. Finally, the `TempCooldown(T)` step is responsible for the control of the overall iteration mechanism. This step is responsible for cooling down the system temperature, in order to make the algorithm converge. Moreover, the general workflow of the power-law algorithm is presented in Figure 2.

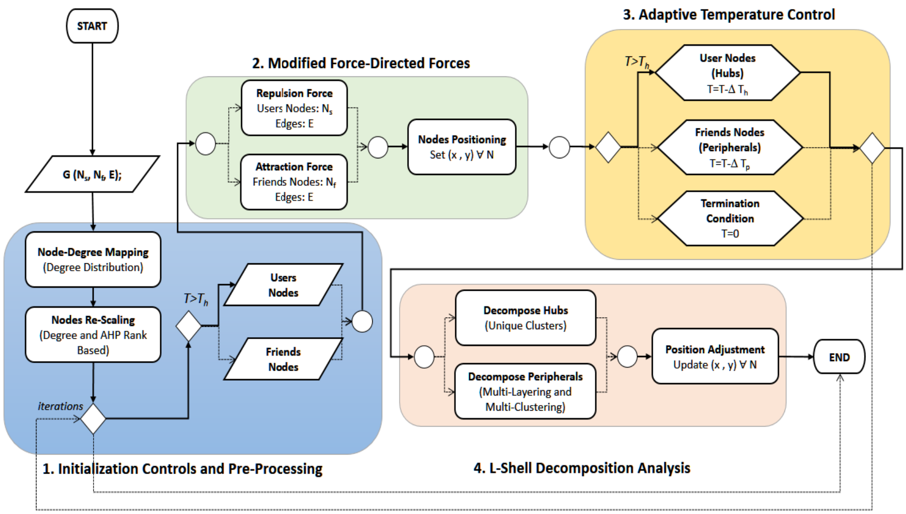


Fig. 2. Power–Law algorithm workflow

3.2 User Ranking Methodology

The ranking methodology that we have adopted in NavigTweet, is summarized in Figure 3. NavigTweet initially collects influence parameters, at both user-level and tweet-level. To weigh different parameters, based upon their relative importance, we have adopted the Analytical Hierarchy Process (AHP) method proposed by (Saaty 1990; Saaty & Vargas 2001), which is widely used in the scientific community.

The outcome of AHP is a vector of weights of parameters. NavigTweet provides aggregated 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. Figure 3 summarizes the methodology framework of user ranking adopted by NavigTweet.

3.3 User Ranking Algorithm

Algorithm 2 outlines the user ranking algorithm adopted by NavigTweet. As an input, the algorithm takes Twitter user node N, and object U provided by Twitter API, and, as an output, it provides final ranking value of U.

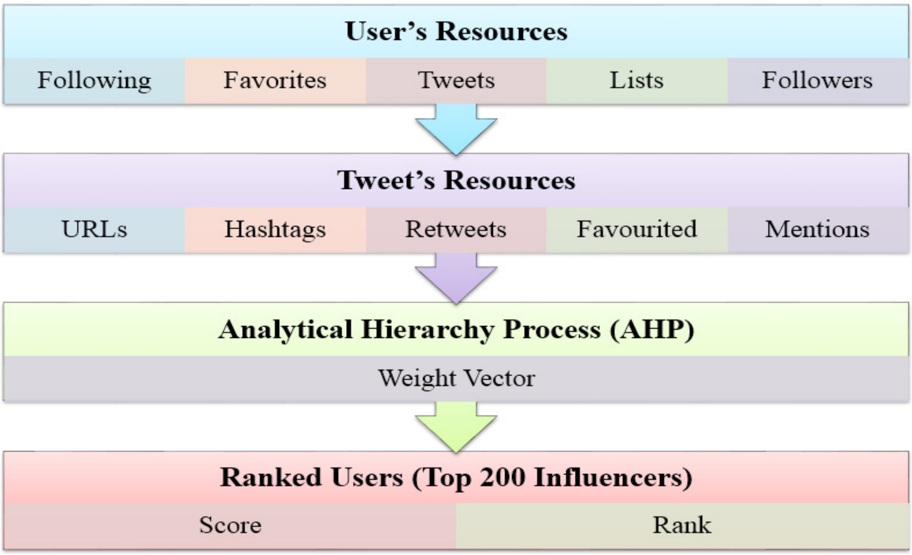


Fig. 3. User ranking methodology/workflow

Algorithm 2: User ranking algorithm of NavigTweet.

DATA
N = Twitter User Node
U = Twitter User Object, retrieved from Twitter API.
(AHP based Weight Vectors)
CONSTANT $W_{parameter}$ as DOUBLE

INPUT
(N, U)

OUTPUT
Final Ranking value (Score) of each node n ∈ N.

BEGIN
1. **function** UserBasedScore(u) := **do begin**
2. (User-based influence parameters ranking)
3. (Product sum of weight and values)
4. $DOUBLE\ d \leftarrow \sum(W * U.Value) = (W_{favourites} * U.Value_{favourites}) + (W_{followers} * U.Value_{followers}) + (W_{following} * U.Value_{following}) + (W_{listed} * U.Value_{listed}) + (W_{tweets} * U.Value_{tweets})$;
5. N.userRank ← d;
6. **return** d;
7. **end do**
8. **function** TweetBasedScore(u) := **do begin**
9. (Tweet-based influential parameters ranking)
10. (Summing up values for last 200 fetched-tweets)
11. **for** i:=1 **to** 200 **do begin**
12. $U.Value_{favourited} = U.Value_{favourited} + Tweet_i.favourited$;
13. $U.Value_{retweets} = U.Value_{retweets} + Tweet_i.retweets$;
14. $U.Value_{urls} = U.Value_{urls} + Tweet_i.urls$;

$U.Value_{hashtags} = U.Value_{hashtags} + Tweet_i.hashtags$;
$U.Value_{mentions} = U.Value_{mentions} + Tweet_i.mentions$;
end for
$DOUBLE\ f \leftarrow \sum(W * U.Value) = (W_{favourited} * U.Value_{favourited}) + (W_{retweets} * U.Value_{retweets}) + (W_{urls} * U.Value_{urls}) + (W_{hashtags} * U.Value_{hashtags}) + (W_{mentions} * U.Value_{mentions})$;
`N.tweetsRank ← f;`
return f;
end do
∀ u in U **do begin**
`u.AHPScore = UserBasedScore(u)+TweetsBasedScore(u);`
end for
`( Descending sort of nodes by their AHPScore )`
(assign i^{th} indexed-value as node's AHPRank)

END

The `UserBasedScore(u)` method provides a score value of user-level parameters and returns a user-level score value. Similarly, `TweetBasedScore(u)` method provides a score value of tweets-level parameters (last 200 fetched-tweets) and returns a tweet-level score value. After scoring each user, the algorithm provides a rank value of each user by sorting all users based upon score value.

3.4 Application Workflow Architecture

The workflow of NavigTweet is provided in Figure 4. The basic building of the application are the following:

1. **Twitter Authentication:** NavigTweet uses OAuth protocol for Twitter user authentication, using the Pin-based mechanism provided by Twitter API. This module is responsible for handling user authentication for successful login.
2. **User Node:** After successful login, the application creates a user node on graph canvas, corresponding to the user who has logged in.
3. **Twitter Data Streaming:** This module is responsible for fetching the user's friends' data. Due to the rate-limit of Twitter APIs, we fetch a maximum number of 500 friend IDs and 100 User objects in once 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 friends' 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 shown in Figure 3.
6. **Graph Controller:** Finally, this module handles event related functionalities (e.g. mouse double-click event), and applies power-law based graph layout over graph nodes. Whenever, the user double-clicks on any node, the application repeats from the 3rd module of Twitter Data Streaming, in order to fetch clicked node's friends, and position them on the canvas.

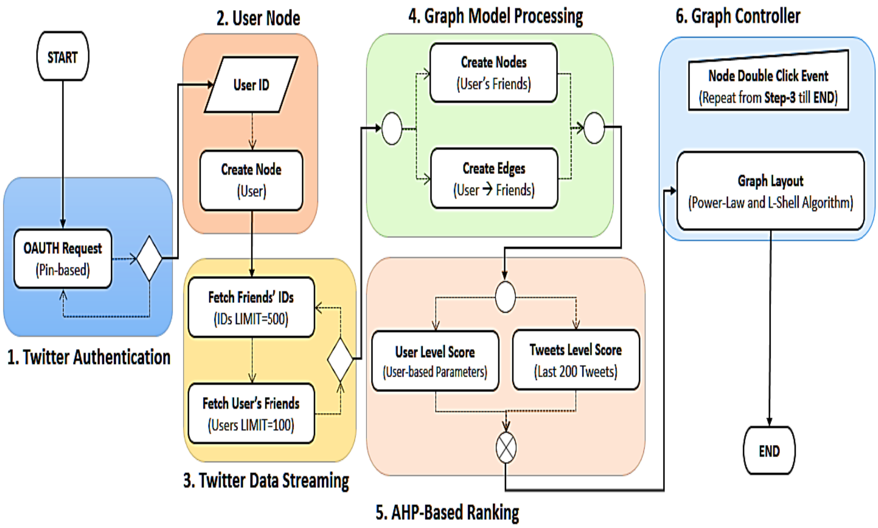


Fig. 4. NavigTweet Workflow

4 Implementation

We have implemented NavigTweet as a desktop application. The application is written in JAVA using Twitter4j (Twitter4j.org 2010) – a JAVA based Twitter Streaming API, and Piccolo 2D (Bederson et al. 2004) – a JAVA based 2D Graphics API. The 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

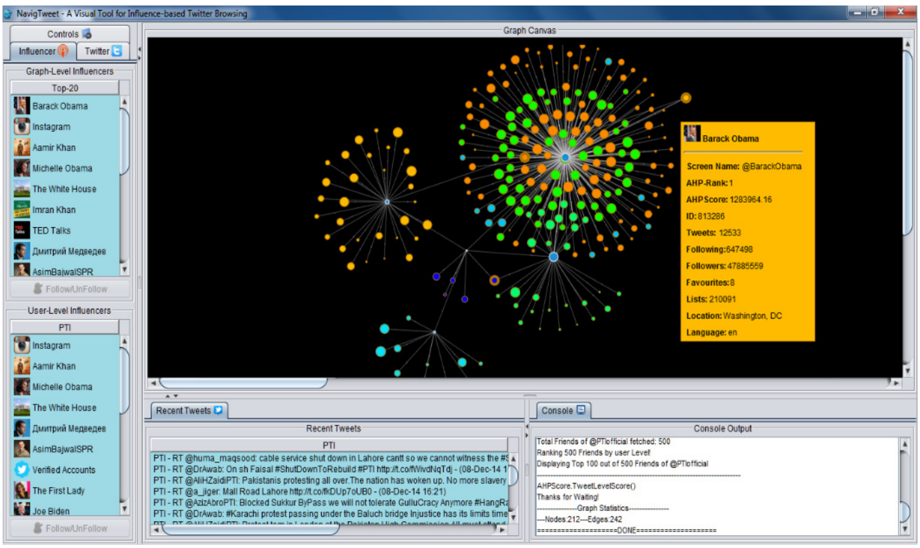


Fig. 5. Screenshot of NavigTweet Interface

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 official website (Hussain 2015).

Figure 5 shows the main screen-shot of NavigTweet. The interface consist of three panels, left, center and bottom. The left panel shows the influencers, as well as Twitter and control options. The influencers-pane shows the top-20 influencers. The Twitter-pane shows user-timeline and a button to send direct message to followees. The control–pane provides button controls, node search, and graph legend panel. The center panel of NavigTweet shows the graph canvas, where the user can explore and interact with the graph. The bottom panel of NavigTweet provides timeline and console panes for the currently selected node.
The main functionalities of NavigTweet are summarized in Table 1.

Table 1. Main functionalities of NavigTweet

Categories	Features
• **User Profile Management**	— User Authentication — Access Token Generation for Login. — Profile information access
• **Interaction with Twitter**	— Follow / Unfollow user — Display friends' 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 ranking of each user — Show mutual-Follower(s) — Browse FOAF network.
• **Interface and Controls**	— Zoomable user interface — Node Tooltip and Show/Hide node labels — Bird's Eye View of Graph Canvas. — Print Graph. — Apply Power-Layout — Console Output/Log — Multi-Colour Clusters — Export Data (CSV) — Mouse Events (Drag, Scroll, Over, Click)

5 Evaluation and Results

In this section, we present a qualitative comparison between NavigTweet and existing applications. Later, we present the pilot execution and results.

5.1 Comparison Between NavigTweet and Existing Applications

As noted in Section 2, there exist a few visualization tools. Twitter changes its API periodically, which enforces developers to continuously update their tools. This represents the main reason why the number of tools are practically limited. Table 2 shows the highlights of the comparison between NavigTweet and the tools that we have been able to test.

Table 2. Features comparison

Features x Tool	TouchGraph	MentionMap	InMaps	NavigTweet
Real-time	No	Yes	No	No
Graph depth	1	2	1	Many
Response time	<5s	<5s	<5s	>5s
Initial load time	>5s	<5s	<5s	>5s
Open source	No	No	No	TODO
Pre/freemium	Both	Freemium	Freemium	Currently Freemium
Social Network	Facebook	Twitter	LinkedIn	Twitter
Platform	Web	Web	Web	Currently Desktop
Help and support	Feedback	Feedback	FAQ/Feedback	Feedback/Tutorial

Table 3 provides a more qualitative analysis of the usability of different tools, including NavigTweet. Note that clarity can be defined as the percentage of the amount of information displayed as perceived by human mind. The main difference among the tools is their ability to represent graphs. We have considered several aesthetics factors, such as color-scheme, distance between the nodes displayed, information amount displayed per node, zoom ability of graph canvas, node shapes, mouse controls, etc.

5.2 Pilot User Feedback Survey

The pilot activity aims to target expert user opinion, in order to get feedback and suggestions. Our goal was to finalize the application by incorporating their feedback, prior to an extensive survey research step which is still ongoing. The pilot was also meant as a technical test of NavigTweet multi-platform compatibility features.

Table 3. Clarity comparison

Clarity x Tool	TouchGraph	MentionMap	InMaps	NavigTweet
Network browsing	Self & Others	Self & Others	Self	Self & Others
Friendly colors	Somehow	Yes	Yes	Somehow
Clusters clarity	Yes	Yes	Somehow	Yes
Multi-color cluster	No	No	Yes	Yes
Zoom-able Interface	Yes	Yes	Yes	Yes
Pan & drag	Yes	Yes	Yes	Yes
Information quantity	A lot	Normal	Normal	Normal
Information placement	ToolTip	None	ToolTip	Tooltip
Default information	Name + Photo	Name + Photo	Name	Screen Name
Node shape	Circular	Rectangular	Circular	Circular

Pilot Participants: Initially, we targeted a reference group of 8 people from academia, who are expert in the domains of *Data, Web and Security*, *Information Systems*, *Advanced Software Architecture and Methodologies*, and *Social Network Analysis*. We intended to demonstrate the application in a real-time environment, to gather their feedback about the application.

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. We obtained real-time feedback from each participant who was asked to run and use the application. The discussion and test sessions with each participant took around 1 – 1.5 hours. During each session, each participant tested the application thoroughly and provided us with open-ended feedback.

Feedback Survey: The pilot activity also involved a structured feedback survey, provided in Table 4, which have administered after the face-to-face meetings.

Pilot Results: We conducted briefing sessions with each pilot participant, where we discussed in detail the application scenarios. Each pilot participant evaluated existing requirements and features of the application and also proposed new requirements, including both functional and non-functional requirements. A technical issue identified during pilot activity was the *Installer Problem on MAC OS* (the application failed to install on MAC OS). Overall, the survey results were positive, as shown in Figure 6. 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. A pilot participant advised to reduce tool-tip contents, and to reduce some information panels, as the tool itself is self-explanatory and provides an understandable work-flow. Another pilot participant advised to introduce new panel of graph-level influencers, i.e. tool should show top influencers from overall graph of currently selected users and their followee relation connections. We also received advises on introducing other features like Data export, refined node search, and hence we also implemented these features prior to public release.

Table 4. 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 networks? *(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' friends' 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 the User Interface of NavigTweet? *(Graphical User Interface)*	• Graph Representation. • Friendly color-scheme. • Cluster Clarity. • Informative node tooltip
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

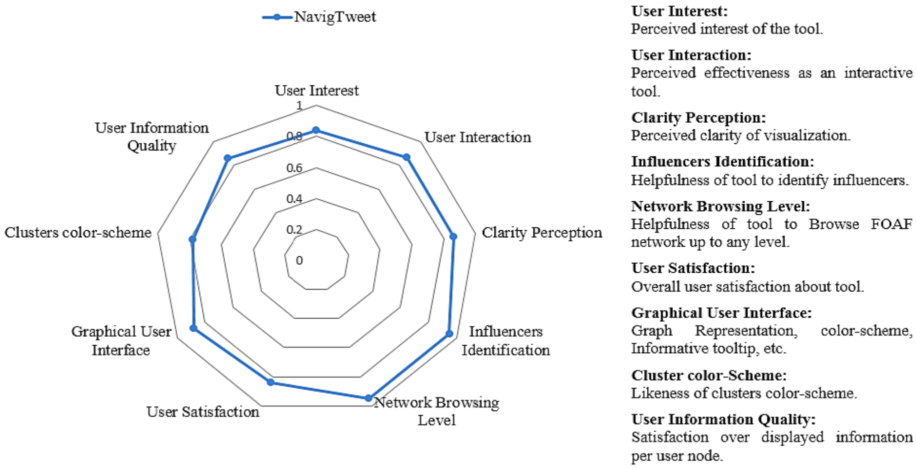


Fig. 6. User rating of the NavigTweet based on different criteria

6 Discussion

Identifying the most efficient 'influencers' in a network is an important step to-wards optimizing the use of available resources and ensuring the more efficient spread of information. Social media influencers are prominent users who share important contents and are most likely to be followed by intended audience, e.g. in Twitter, people with high number of followers seems to be prominent active users. The ultimate goal of our research is to provide a visualization framework to analyze, explore and interact with social network, specifically Twitter. We presented a power-law based modified force-directed algorithm to draw aesthetically pleasant multi-clustered and multi-layered graphs.

Moreover, we intend to identify prominent users in Twitter network, by investigating the influence of the actual content that social media users share. For that purpose, we collected both user-level and content-level (tweet-based) influence parameters provided by Twitter API and applied AHP technique in order to determine the score and rank of each user. We developed NavigTweet – a visual tool for exploring influence based Twitter browsing, in which user can explore and interact with his own and FOAF networks. NavigTweet identifies top-100 influencers among friends' network and provides users an opportunity to directly follow them via application interface.

The intended audience is people who want to find interesting information regarding their social network and empower them to enlarge their social network by providing interesting people to follow. User can explore his own and FOAF network at any depth-level to find influencers. NavigTweet provides a novel research dimension towards visualizing and exploring social networks to identify most prominent users, based upon the influence of their actual shared content, in the network.

We conducted pre-launch pilot activity via qualitative user-study, in order to get real-time feedback and suggestions. Comments from pilot were generally favorable.

We incorporated pilot comments by updating functionalities in NavigTweet, which is officially released and available to public users.

7 Conclusion and Future Work

This paper proposes a novel visual framework to analyze, explore and interact with 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. We developed NavigTweet, which is able to visualize Twitter FOAF networks in aesthetically pleasant multi-clustered and multi-layered graphs, and helps to identify prominent users or top influencers from the network. We have reported on a qualitative analysis of our tool. We also reported on a pre-launch pilot test execution, by involving a qualitative user study, to get a feedback via survey. We found that pilot participants were positive about the functionalities and features of the tools along 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 are currently conducting an extensive survey.

Future work will consider detailed evaluation and implementation of web-based interface of NavigTweet, in which we intend to incorporate additional navigation and analysis features. Any suggestions or reviews received from end-users, as part of the ongoing extensive survey, will also be considered in this second release.

References

1. Anholt, S.: Competitive identity: The new brand management for nations, cities and regions. Palgrave Macmillan (2006)
2. Bakshy, E., Hofman, J.M., Mason, W.A., Watts, D.J.: Everyone's an influencer: quantifying influence on twitter. Paper presented at the Proceedings of the Fourth ACM International Conference on Web Search and Data Mining (2011)
3. Barbagallo, D., Bruni, L., Francalanci, C., Giacomazzi, P.: An empirical study on the relationship between twitter sentiment and influence in the tourism domain. In: Information and Communication Technologies in Tourism 2012, pp. 506–516. Springer (2012)
4. Bederson, B.B., Grosjean, J., Meyer, J.: Toolkit design for interactive structured graphics. IEEE Transactions on Software Engineering 30(8), 535–546 (2004)
5. Benevenuto, F., Cha, M., Gummadi, K.P., Haddadi, H.: Measuring User Influence in Twitter: The Million Follower Fallacy. Paper presented at the International AAAI Conference on Weblogs and Social, ICWSM 2010 (2010)
6. Bigonha, C., Cardoso, T.N.C., Moro, M.M., Gonçalves, M.A., Almeida, V.A.F.: Sentiment-based influence detection on Twitter. Journal of the Brazilian Computer Society 18(3), 169–183 (2012)
7. Chan, D.S.M., Chua, K.S., Leckie, C., Parhar, A.: Visualisation of power-law network topologies. The 11th IEEE International Conference on Paper presented at the Networks, ICON 2003 (2004)
8. Chang, J.-Y.: An Evaluation of Twitter Ranking Using the Retweet Information. Journal of Society for e-Business Studies 17(2) (2014)

9. Fan, W., Gordon, M.D.: The power of social media analytics. Communications of the ACM 57(6), 74–81 (2014)
10. Followerwonk.com (2014), https://followerwonk.com/
11. Francalanci, C., Hussain, A.: A Visual Approach to the Empirical Analysis of Social Influence. Paper presented at the DATA, - Proceedings of 3rd International Conference on Data Management Technologies and Applications (2014), http://dx.doi.org/10.5220/0004992803190330
12. Fruchterman, T.M.J., Reingold, E.M.: Graph drawing by force-directed placement. Software: Practice and Experience 21(11), 1129–1164 (1991)
13. Hussain, A.: NavigTweet (2015), http://home.deib.polimi.it/hussain/navigtweet/
14. Hussain, A., Latif, K., Rextin, A., Hayat, A., Alam, M.: Scalable Visualization of Semantic Nets using Power-Law Graphs. Applied Mathematics & Information Sciences 8(1), 355–367 (2014)
15. Kilpatrick, G.:(January 2, 2015), http://twittertoolsbook.com/10-awesome-twitter-analytics-visualization-tools/
16. Klotz, C., Ross, A., Clark, E., Martell, C.: Tweet! – and I can tell how many followers you have. In: Boonkrong, S., Unger, H., Meesad, P. (eds.) Recent Advances in Information and Communication Technology. AISC, vol. 265, pp. 245–253. Springer, Heidelberg (2014)
17. Klout.com (2014), https://klout.com/home
18. Kujawski, M.: (August 13, 2014), http://www.mikekujawski.ca/2014/08/13/two-free-twitter-network-visualization-tools/
19. Kwak, H., Lee, C., Park, H., Chun, H., Moon, S.: Novel Aspects Coming From the Directionality of Online Relationships: A Case Study of Twitter. ACM SIGWEB Newsletter (Summer 2011)
20. Kwak, H., Lee, C., Park, H., Moon, S.: What is Twitter, a social network or a news media? Paper presented at the Proceedings of the 19th International Conference on World Wide Web (2010)
21. Leavitt, A., Burchard, E., Fisher, D., Gilbert, S.: The influentials: New approaches for analyzing influence on twitter. Web Ecology Project 4(2), 1–18 (2009)
22. Myers, S.A., Leskovec, J.: The bursty dynamics of the Twitter information network. Paper presented at the Proceedings of the 23rd International Conference on World Wide Web (2014)
23. Saaty, T.L.: How to make a decision: the analytic hierarchy process. European Journal of Operational Research 48(1), 9–26 (1990)
24. Saaty, T.L., Vargas, L.G.: Models, methods, concepts & applications of the analytic hierarchy process, vol. 1. Springer (2001)
25. Twitonomy.com (2014), http://www.twitonomy.com/
26. Twitter4j.org (2010), http://twitter4j.org/en/index.html
27. Wu, S., Hofman, J.M., Mason, W.A., Watts, D.J.: Who says what to whom on twitter. Paper presented at the Proceedings of the 20th International Conference on World Wide Web (2011)