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tweetStimuli: Discovering Social Structure of Influence

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Abstract. Social influence has become a field of study about how people might induce effect on others. Diffusion of information in large networks has been studied to analyze how the information flows over the network producing cascades as a main proxy of influence. For instance, microblogs such as Twitter has allowed to identify and rank influencers based on message propagation (retweets). Different factors of influence on Twitter have been identified such as: audience, interaction, users' actions and message content. In this paper, a new web application is presented. It allows to study these factors in a temporal order based on the perspective of local influence: given a target user, who influences the user as well as who has been influenced by the user. This application is able to retrieve all retweets and favorites to filter and rank them from different perspectives based on the type of tweets and attributes such as mentions or hashtags, as well as two kind of visualizations: clusters and networks which are the outcome of user behavior by retweeting and marking as favorites.

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1. Introduction

Different factors of influence metrics on Twitter have been studied such as Chat et al. [2] who analyze In-degree, Retweets and Mentions as well as centrality metrics or PageRank which find influencers [2, 3]. However, most of these studies found that In-degree or any other factor by itself does not reflect the influence of a user but a mixing of all of them. Other kind of factors has to be taken into account such as virality of users and items as well as users susceptibility [4].

Global influence has been introduced in [6] based on the number of channels between two individuals in the social network, while more paths exists between them, the greater is the capacity to influence. Although the global influence has been also tried to be measured, Bashky et al. [1] claim to focus on *local influence* given a target user A. It refers to who influenced A and who has been influenced by A focusing on diffusion cascades of depth 1 which are the most informative due to fact that the most non-trivial cascades have that depth. Some companies have tried to provide measurements in order to rank users influence on twitter such as: Klout[1], PeerIndex[2], Twitalyzer[3], Twitter grader[4], taking into account different user factors such as: number of followers, number of people that user influences, number of retweets, content and so on.

One problem with most of these approaches is that they only focus on the action of spreading information to find influencers and others influential effects are not considered. For instance, favorited tweets. They should be also considered since being favorite means some user A propagates information to B and B marks it as interesting. Besides, how social structure of influence is formed based on users behavior over time (retweets and favorites).

2. tweetStimuli

In this way, a new application has been deployed, named *tweetStimuli*, aimed to visualize, identify, rank and find the user's local influence on Twitter. The tool could also show how social structures of influence are formed and how they evolve over time. tweetStimuli has five main components: tweets reader, filtering module, ranking module, clustering and visualization module.

- *Tweets reader*: When user authenticates through twitter account, it

[1]http://klout.com
[2]http://www.peerindex.com/
[3]http://www.twitalyzer.com/
[4]http://tweet.grader.com/

retrieves the last 100 retweets and favorites, since tweetstimuli acts as a twitter client. A synchronization policy is applied to keep data up to date.

- *Filtering module*: Once tweets are retrieved, it performs a filter process based on content type (URLs, mentions) of the tweets (favorites or retweets).

- *Ranking module*: After the filtering process, it counts the number of tweets per user and the tweets are identified if user wants to request them to verify the content.

- *Clustering Module*: Before showing the visualization, it retrieves information about users followings to build the social network based on who follows whom and the proper cluster. It has been used the edge repulsion Linlog model [5] to provide the cluster visualization.

- *User search*: Any authenticated user is allowed to perform users search to visualize their influence and who has influenced them.

- *Ticket service*: This asynchronous service was created to enable users to analyse who of their followers (up to 1000) has been influenced by them.

The application can reveal valuable insights about user influence. For example, Figure 1, shows who has influenced the ex-president of Mexico: Felipe Calderon. Two clusters are observed: the cluster on the left side is mainly formed by people who presents TV Programs and the cluster on the right side are mainly formed by government departments and ministries. At this point, it can be concluded that ex-president of Mexico is mainly influenced by these two kind of twitter users.

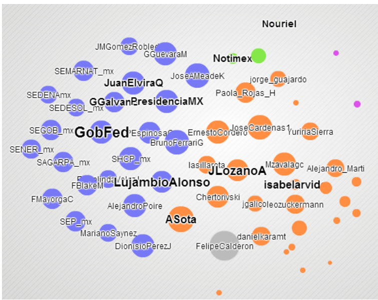

Figure 1: Ex-President of Mexico: Felipe Calderon retweets

3. Conclusions and further work

Through tweetstimuli, a list of users could be studied to analyse who are their social clusters of influence and how they evolve over time as well as users interest based on message content which it is hard to achieve, since it has to manage multiple requests to Twitter. Future efforts will be focused on modelling local influence in a formal way, studying the clusters from different type of tweets and users by applying graph measurements to identify possible patterns of influence and users behavior as well as the user content to develop a helpful profile recommendation on twitter as well as influence prediction based on item adoption. Provide a local influence score that allows to identify the user behavior to other users and message contents.

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