A Visual Approach to the Empirical Analysis of Social Influence

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Abstract: This paper starts from the observation that social networks follow a power-law degree distribution of nodes, with a few hub nodes and a long tail of peripheral nodes. While there exist consolidated approaches supporting the identification and characterization of hub nodes, research on the analysis of the multi-layered distribution of peripheral nodes is limited. In social media, hub nodes represent social influencers. However, the literature provides evidence of the multi-layered structure of influence networks, emphasizing the distinction between influencers and influence. The latter seems to spread following multi-hop paths across nodes in peripheral network layers. This paper proposes a visual approach to the graphical representation and exploration of peripheral layers and clusters to exploit underlying concept of k-shell decomposition analysis. The core concept of our approach is to partition the node set of a graph into hub and peripheral nodes. Then, a power-law based modified force-directed method is applied to clearly display local multi-layered neighbourhood clusters around hub nodes. Our approach is tested on a large sample of tweets from the tourism domain. Empirical results indicate that peripheral nodes have a greater probability of being retweeted and, thus, play a critical role in determining the influence of content. Our visualization technique helps us highlight peripheral nodes and, thus, seems an interesting tool to the visual analysis of social influence.

1 INTRODUCTION

The literature on social media makes a distinction between influencers and influence. The former are social media users with a broad audience. For example, influencers can have a high number of followers on `Twitter`, or a multitude of friends on `Facebook`, or a broad array of connections on `LinkedIn`. The term influence is instead used to refer to the social impact of the content shared by social media users. The breadth of the audience was considered the first and foremost indicator of influence for traditional media, such as television or radio. However, traditional media are based on broadcasting rather than communication, while social media are truly interactive. It is very common that influencers say something totally uninteresting and, as a consequence, they obtain little or no attention. On the contrary, if social media users are interested in something, they typically show it by participating in the conversation with a variety of mechanisms and, most commonly, by sharing the content that they have liked. (Boyd et al., 2010) has noted that a content that has had an impact on a user's mind is shared. Influencers are prominent social media users, but we cannot expect that the content that they share is bound to have high influence, as discussed by (Benevenuto et al., 2010).

In previous research, (Bruni et al., 2013; Klotz et al., 2014) has shown how the content of messages can play a critical role and can be a determinant of the social influence of a message irrespective of the centrality of the message's author. Results suggest that peripheral nodes can be influential: this paper starts from the observation made by (Chan et al., 2004) that social networks of influence follow a power-law distribution function, with a few hub nodes and a long tail of peripheral nodes, consistent with the so-called small-world phenomenon as noted by (Xu et al., 2007). In social media, hub nodes represent social influencers, but influential content can be generated by peripheral nodes and spread along possibly multi-hop paths originated in peripheral network layers. The ultimate goal of our research is to understand how influential content spreads across the network. For this purpose, identifying and positioning hub nodes is not sufficient, while we need an approach that supports the exploration of peripheral nodes and of their mutual connections.

In this paper, we exploit a modified power-law based force-directed algorithm (Hussain et al., 2014) to highlight the local multi-layered neighborhood clusters around hub nodes. The algorithm is based on

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the idea that hub nodes should be prioritized in laying out the overall network topology, but their placement should depend on the topology of peripheral nodes around them. In our approach, the topology of periphery is defined by grouping peripheral nodes based on the strength of their link to hub nodes, as well as the strength of their mutual interconnections, which is metaphor of k-shell decomposition analysis (Kitsak et al., 2010; Carmi et al., 2007).

The ultimate goal of our research is to understand how influential content spreads across the network. For this purpose, identifying and positioning hub nodes is not sufficient, while we need an approach that supports the exploration of peripheral nodes and of their mutual connections. In this paper, we exploit a modified force-directed algorithm (Hussain et al., 2014) to highlight the local multi-layered neighborhood clusters around hub nodes. The algorithm is based on the idea that hub nodes should be prioritized in laying out the overall network topology, but their placement should depend on the topology of peripheral nodes around them. In our approach, the topology of the periphery is defined by grouping peripheral nodes based on the strength of their link to hub nodes, as well as the strength of their mutual interconnections.

The approach is tested on a large sample of tweets expressing opinions on a selection of Italian locations relevant to the tourism domain. Tweets have been semantically processed and tagged with information on *a)* the location to which they refer, *b)* the location's brand driver (or category) on which authors express an opinion, *c)* the number of retweets, and *d)* the identifier of the retweeting author. With this information, we draw corresponding multi-mode networks highlighting the connections among authors (retweeting) and their interests (brand, category, and sentiment) by aesthetically pleasant layouts. By visually exploring and understanding multi-layered periphery of nodes in clusters, we also propose few content related hypothesis in order to understand network behaviour and relationship among *frequency*, *specificity*, *retweets* and expressed sentiments in tweets. Insights on the relationship among would help social media users make their behavioural decisions. Social media users are aware that a post is influential if it raises attention from other users (Anger and Kittl, 2011). Results highlight the effectiveness of our approach, providing interesting visual insights on how unveiling the structure of the periphery of the network can visually show the potential of peripheral nodes in determining influence and content relationship.

The remainder of this paper is structured as follows. Section 2 discusses limitations of existing semantic network drawing techniques and tools, and influence in social media. Section 3 briefs about the implementation aspects of our work. Section 4 presents the experimental methodology, performance evaluation, results and benchmark comparison. Conclusions are drawn in Section 5.

2 STATE OF THE ART

In this section, we will discuss about limitations of existing network visualization techniques. We will also briefly highlights few aspects of influencers and influence in social media.

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 (Chan et al., 2004; Andersen et al., 2004; Boutin et al., 2006; Andersen et al., 2007). Among these approaches, the most notable is the Out-Degree Layout (ODL) for the visualization of large-scale network topologies, presented by (Chan et al., 2004; Perline, 2005). The core concept of the algorithm is the segmentation of the 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 effectiveness. The topology of the network organization plays an important role such that there are plausible circumstances under which the highly connected nodes or the highest-betweenness nodes 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 technique which is metaphor of the *k-shell* (also called *k-core*) decomposition of the network, as discussed in (Kitsak et al., 2010). Examining this quantity in a number of social networks enables us to identify the best individual spreaders in the multi-layered periphery of clustered network when the spreading originates in a single hub node.

2.2 Influencers and Influence in Social Networks

Centrality metrics are the most widely used parameters for the structural evaluation of a user's social network. The concept of centrality has been defined as the importance of an individual within a network (Freeman, 1979). Centrality has attracted a considerable attention as it clearly recalls notions like social power, influence, and prestige. 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 (Sparrowe et al., 2001; Renoust et al., 2013). A node with a high degree centrality has been found to be more actively involved in the network's activities (Hossain et al., 2006).

The more recent literature has associated the complexity of the concept of influence with the diversity of content. Several research works have addressed the need for considering content-based metrics of influence ((Bakshy et al., 2011; Naaman et al., 2010) and (Suh et al., 2010). Clearly, this view involves a significant change in perspective, as assessing influence does not provide a static and general ranking of influencers as a result. However, there is a need for effective visualization technique in social networks, which enable user to visually explore large-scale complex social networks to identify influencers in social networks. The layout should be aesthetically pleasant and provide multi-layered periphery of the nodes in clustered networks to exploit spread of influence in social networks.

In this paper, we propose a power-law based modified force-directed technique, as an earlier version discussed in (Hussain et al., 2014) which also metaphorically exploit k-shell decomposition analysis technique (Kitsak et al., 2010). Our proposed approach enables us to visually explore large-scale complex social networks, and visually identifies social influencers among network. The influence seems to spread across multi-layered periphery of nodes in clustered and aesthetically pleasant graph layouts.

3 THE POWER - LAW ALGORITHM

This section provides a high-level description of the graph layout algorithm used in this paper. An early version of the algorithm has been presented by (Hussain et al., 2014). This paper improves the initial algorithm by identifying multiple layers of peripheral nodes around hub nodes. The power-law layout algorithm belongs to the class of force-directed algorithms, such as the one by (Fruchterman and Reingold, 1991).

The base mechanism is that of starting from an initial placement of graph nodes, and then iteratively refining the position of the nodes according to a force model. The iteration mechanism is controlled by means of an innovative temperature *cooldown* step. Algorithm 1 provides a high-level overview of the whole algorithm by showing its main building blocks. In order to re-produce the results and further study, the detailed outlined methods can be found in earlier version, presented by (Hussain et al., 2014).

Algorithm 1: Abstract power-law layout algorithm structure.

```
begin
    call NodeCharacterization();
    call InitialLayout();
    while Temperature > 0 do
        if Temperature > T_h then
            call NodePlacement(N_h, E_h);
        else
            call NodePlacement(N_p, E_p);
        end
        call
        TemperatureCooldown(Temperature);
    end
end
```

The proposed approach is aimed at the exploitation of the power-law degree distribution of data. Provided that the distribution of the degree of the nodes follows a power law, we partition the set of nodes N into the set of hub nodes N_h and the set of peripheral nodes N_p, such that $N = N_h \cup N_p$, with $N_h \cap N_p = \varnothing$. As a consequence, the set of edges E is also partitioned in the set of edges E_h for which at least one of the two nodes is a hub node, and the set E_p which contains all the edges connecting only peripheral nodes, with $E = E_h \cup E_p$, and $E_h \cap E_p = \varnothing$. The distinction of a node n as a hub node or as a peripheral node is based on the evaluation of its degree $\rho(n)$ against the constant ρ_h, which is a threshold defined as the value of degree that identifies the top i^{th} percentile of nodes, sorted by decreasing value of degree. Since the power-law is supposed to hold in the degree distribution, we have assumed $i = 20$ and consequently ρ_h as the 20^{th} percentile, thus considering as hub nodes the 20% of the nodes with the highest values of degree - the Pareto's 80-20 Rule, as suggested by (Koch, 1999).

The *NodeCharacterization* step is a preprocessing phase aimed at distinguishing hub nodes from peripheral nodes, so that in the following steps it is possible to leverage the power-law distribution of nodes and assigning level value (l_s) using k-shell decomposition analysis technique. The *InitialLayout* step provides the initial placement of nodes (either a random placement or another graph layout algorithm). The *NodePlacement(N, E)* step performs the placement of nodes based on the computation of forces among nodes; its inputs are a node set N and an edge set E, such that the placement of nodes can be selectively applied to chosen subsets of nodes/edges at each step. The *TemperatureCooldown* step is responsible for the control of the overall iteration mechanism.

We tuned this algorithm by means of the metaphor of k-shell decomposition analysis (Kitsak et al., 2010; Carmi et al., 2007; Alvarez-Hamelin et al., 2006; Abello and Queyroi, 2013), in order to define the concept of level of each node in the multi-layered periphery of our graphs. This process assigns an integer as level index (l_s) to each node, representing its location according to successive layers (l shells) in the network. Small values of (l_s) define the periphery of the network, while the innermost network levels correspond to greater values of (l_s), as shown in Figure 1.

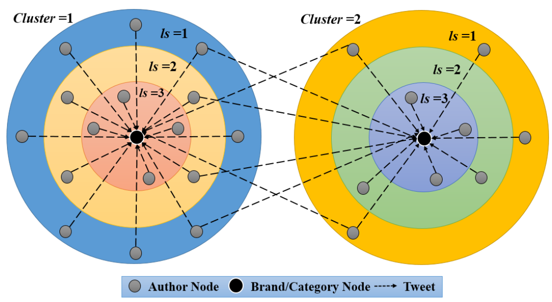


Figure 1: Metaphor of k-shell decomposition analysis.

4 EXPERIMENTAL RESULTS

In this section, we will discuss about dataset that we used in our experiment, and the network models that we built from the dataset. We further will discuss the obtained visualization results. Hypotheses pertaining to visualization stand point have also been discussed and empirically evaluated in this section.

4.1 Data Sample

We collected a sample of tweets over a two-month period (December 2012 - January 2013). For the collection of tweets, we queried the public Twitter APIs by means of an automated collection tool developed ad-hoc. Twitter APIs have been queried with the following crawling keywords, representing tourism destinations (i.e. brands): *Amalfi*, *Amalfi Coast*, *Lecce*, *Lucca*, *Naples*,*Palermo* and *Rome*. Two languages have been considered, English and Italian. Collected tweets have been first analysed with a proprietary semantic engine in order to tag each tweet with information about *a)* the location to which it refers, *b)* the location's brand driver (or category) on which authors express an opinion, *c)* the number of retweets (if any), and *d)* the identifier of the retweeting author.

Our data sample is referred to the tourism domain. We have adopted a modified version of the Anholt Nation Brand index model to define a set of categories of content referring to specific brand drivers of a destination's brand (Anholt, 2006). Examples of brand drivers are *Art & Culture*, *Food & Drinks*, *Events & Sport*, *Services & Transports*, etc. A tweet is considered *Generic* if it does not refer to any Specific brand driver, while it is considered *Specific* if it refers to at least one of Anholt's brand drivers. Tweets have been categorized by using an automatic semantic text processing engine that has been developed as part of this research. The semantic engine can analyse a tweet and assign it to one or more semantic categories. The engine has been instructed to categorize according to the brand drivers of Anholt's model, by associating each brand driver with a specific content category described by means of a network of keywords. Each tweet can be assigned to multiple categories. We denote with N_C the number of categories each tweet w is assigned to; the specificity $S(w)$ of a given tweet w is defined in Equation 1 as follows:

$$S(w) = \left\{ \begin{array}{l} 0, N_c = 0 \\ 1, N_c > 0 \end{array} \right\} \tag{1}$$

The data collection step has been followed by a preliminary data analysis aimed to the statistical exploration of the characteristics of data distribution. Results highlighted that all variables follow a power-law distribution (Newman, 2005). Since the SEM tool adopted for model verification provides only linear regression to model variable relationships, each variable has been represented on a logarithmic scale and standardized. For the sake of clarity, the values reported in Table 1 refer to the descriptive statistics of the original non-linear variables.

4.2 Network Models

In order to verify the effectiveness of the proposed algorithm with respect to the goal of our research, we have defined different network models based on the

Table 1: Basic descriptive statistics of our data set.

Variable	Value
Number of tweets	957,632
Number of retweeted tweets	79,691
Number of tweeting authors	52,175
Number of retweets	235,790

data set described in the previous section. Figure 2 provides an overview of the adopted network models.

- *Author → Brand (N_1)*: This model considers the relationship among authors and domain brands, i.e., touristic destinations in our data set. The network is modelled as an undirected affiliation two-mode network, where an author node n_a is connected to a brand node n_b whenever author a has mentioned brand b in at least one of his/her tweets. The weight of the edge connecting n_a to n_b is proportional to the number of times that author a has named brand b in his/her tweets.
- *Author → Category (N_2)*: This model considers the relationship among authors and domain brand drivers (categories), i.e., city brand drivers in our data set (namely, *Arts & Culture*, *Events & Sports*, *Fares & Tickets*, *Fashion & Shopping*, *Food & Drink*, *Life & Entertainment*, *Night & Music*, *Services & Transport*, and *Weather & Environmental*). The network is modelled as an undirected affiliation two-mode network, where an author node n_a is connected to a category node n_c whenever author a has mentioned a subject belonging to category c in at least one of his/her tweets. The weight of the edge connecting n_a to n_c is proportional to the number of times that author a has named category c in his/her tweets.

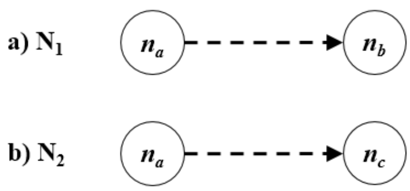


Figure 2: Network Models a) N1: Author → Brand, b) N2: Author → Category.

4.3 Discussion on Network Visualization Results

Table 2 provides descriptive statistics on the size of the N_1 and N_2 networks built with our data sample, based on the models described in Section 4.2. The dataset contains network models with 7 distinct brands representing tourism destinations and 10 domain brand drivers (i.e. categories), consistent with Anholt's model (Anholt, 2006).

The discussion on the results of network visualization will adopt network N_1 network (i.e. Author → Brand) as reference example. Figure 3 provides an enlarged view of network N_1 visualized by means of the proposed power-law layout algorithm. A summary description for all the remaining networks N_1 and N_2 will follow at the end of this section.

The network visualization depicted in Figure 3 adopts multicoloured nodes to represent authors, and highlighted encircled blue (dark) nodes to represent the tourism destinations (i.e. brands) on which authors have expressed opinions in their tweets. The layout of the network produced by the power-law layout algorithm clearly highlights that author nodes aggregate in several groups and subgroups based on their connections with brand nodes. The aggregation of author nodes can be analysed from different perspectives, discussed in Sections 4.3.1 – 4.3.5, respectively.

4.3.1 Multi-Clusters

The groups of author nodes cluster together all those authors that are connected to the same hubs (i.e. brands). This provides a visual clustering for those authors who have tweeted about the same brand. For example, Figure 3 highlights clusters that group all the authors who tweeted about 7 distinct brands, in which 'ROME' and 'NAPLES' are seem to be mostly tweeted by authors i.e. they possess 'high specificity'. Hence, we can visually interpret the cluster strength, i.e. 'Brand Fidelity'.

4.3.2 Multi-Layered Peripheral Spread

The network layout shows that clusters are placed at a different distance from the visualization centre based on the number of hubs to which they are connected. In other words, the most peripheral clusters are those in which nodes are connected to only one hub, while the central cluster is the one in which nodes are connected to the highest number of hub nodes. Within a single cluster, multiple layers seem to be formed. By implementing the *l*-shell decomposition methodology, the outside layer consists of author nodes who posted a tweet only once, as we move inward towards the brand node (hub), the frequency of tweeting increases. Hence, the closest nodes to a hub represent the authors who tweeted most about that brand.

The power-law layout algorithm has provided a network layout that is very effective in highlighting a specific property of authors which was not a measured

Table 2: Descriptive statistics on the dimensions of the N_1 and N_2 networks.

Authors	$N_r(a)$	N_1				N_2			
		$N_t(a)$	Expressed Sentiments			$N_t(a)$	Expressed Sentiments		
			Negative	Positive	Neutral		Negative	Positive	Neutral
398	92	856	58	203	595	1,913	68	328	1,517
1,662	364	2,905	158	581	2,166	5,959	197	885	4,877
10,710	2,907	12,559	326	1,282	10,951	18,498	387	1,669	16,442
18,711	5,329	21,140	483	1,846	18,811	29,842	566	2,307	26,969
30,310	8,690	33,684	688	2,683	30,313	46,120	805	3,318	41,997
37,626	10,529	41,620	804	3,263	37,553	56,960	937	3,991	52,032
47,295	12,833	52,208	1,027	4,033	47,148	71,667	1,191	4,867	65,609

Key to symbols: $N_r(a)$: Total No. of authors' retweets; $N_t(a)$: Total No. of authors' tweets (Frequency).

variable in our dataset, i.e. their specificity (or generality) with respect to a topic (i.e. a brand in Figure 3). Authors belonging to different clusters (i.e. peripheral) are in fact those who are more generalist in their content sharing, since they tweet about multiple different brands. On the contrary, authors belonging to the innermost clusters are those who are very specific in sharing content related to just one brand.

Since the *specificity* (generality) and *frequency* and expressed sentiments of authors was not an explicit measured variable in our dataset, it is possible to posit that the proposed network layout algorithm can be considered as a powerful visual data analysis tool, since it is effective in providing visual representations of networks that help unveiling specific (implicit) properties of the represented networks. Moreover, Figures 6(cfr. Appendix) provide further visualization of networks N_1 and N_2 of our dataset.

4.3.3 Brand Fidelity

Network N_1 is related to the relationship between authors and brands, i.e., touristic destinations. In this case, the clustering of nodes provides a distinct clustering of those authors who have tweeted about the same destination. The layering of nodes around brands is instead related to the intensity of tweeting about a given destination; i.e., authors closer to a brand node tweet a higher number of times about that destination with respect to farther authors. The emerging semantic of the network visualization is in this case related to the *brand fidelity* of authors. The visualized network layout supports the visual analysis of those authors who have a higher fidelity to a given brand, or those authors who never tweet about that brand. Moreover, it is possible to point out which authors are tweeting about a brand as well as a competing brands to support the definition of specific marketing campaigns.

4.3.4 Influencers and Influence Spread

The breadth of the audience was considered the first and foremost indicator of influence for traditional media, such as television or radio. However, traditional media are based on broadcasting rather than communication, while social media are truly interactive. It is very common that influencers say something totally uninteresting and, as a consequence, they obtain little or no attention. On the contrary, if social media users are interested in something, they typically show it by participating in the conversation with a variety of mechanisms and, most commonly, by sharing the content that they have liked. Influencers are prominent social media users, but we cannot expect that the content that they share is bound to have high influence (Benevenuto et al., 2010).

The proposed visualization approach gives us a way to visually explore social networks and to identify the most influential authors, who tweet most about different categories and brands. The author's specificity N_S, frequency N_W and N_R (i.e. no. of retweets) can be considered as essential parameters to visually identify the influencers in social network. Similarly, our proposed approach produces multi-layered peripheral and clustered layout, in which we can observe the spread of influence through the multi-layered periphery across authors' nodes. The outlier authors along the periphery can be potential influence *spreaders*, if they connect with other clusters through retweeting.

4.3.5 Sentiment Analysis

Sentiment analysis refers to the task of extracting public sentiment from textual data (Dehkharghani et al., 2014). Exploiting semantic information, as the polarity of the opinions expressed in users' comments, can further improve the understanding of the dynamics of influence. The literature on sentiment analysis is rich. More specifically, opinion classification has always

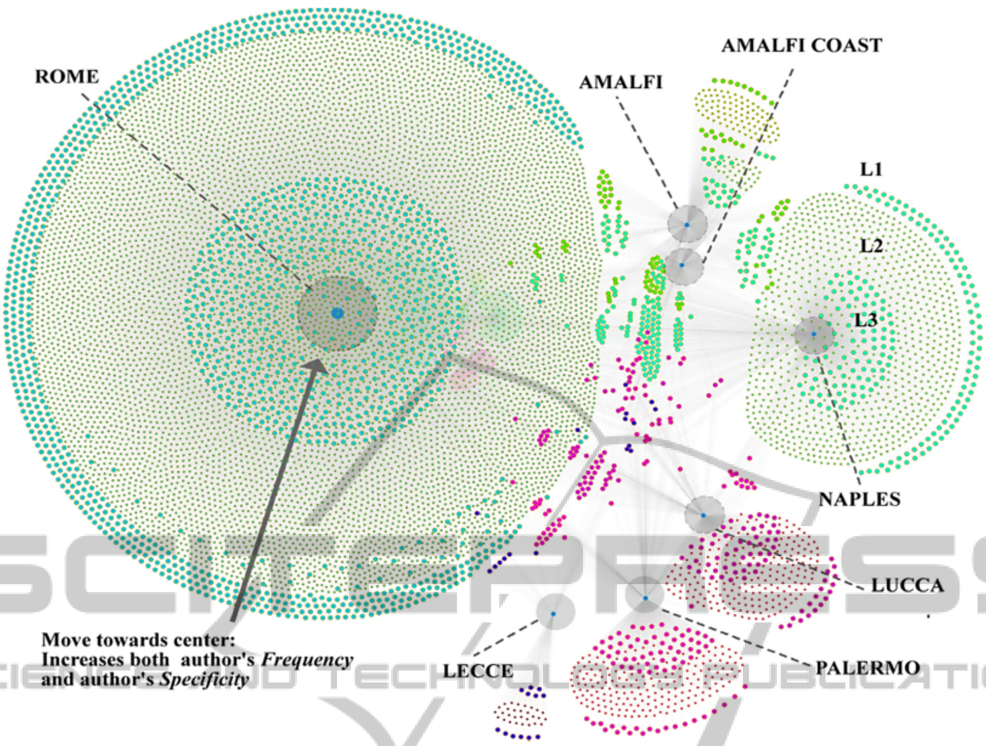


Figure 3: N_1: Author → Brand (Enlarged View).

been one of the main topics in the academic field of sentiment analysis (Bigonha et al., 2012; Blitzer et al., 2007; Godbole et al., 2007; Barbagallo et al., 2012; Hao et al., 2011).

The visualizations provides us a way to visually explore the social networks and we are also able to analyse the sentiments expressed by authors over specific brand or category. Sentiment can either be *positive*, *negative* or *neutral*. On our graph canvas, the edge connecting the author node with the brand or category node, represents the expressed sentiment of our author, whose label can be either positive, negative, or neutral, as per the author's opinion expressed in specific tweet. In this way, we can also perform sentiment analysis over a specific brand or category, to measure an author's response(s). Sentiment has been assessed with *WISPO*, a sentiment analysis tool, presented in (Barbagallo, 2010; Barbagallo et al., 2012; Bruni, 2010).

4.4 Empirical Testing and Evaluation

This section dedicated to empirical testing and evaluation of our experiment and proposed hypotheses. Here, we discuss the research model and proposed hypotheses with statistical test results.

4.4.1 Definitions

Each graph G (A, T) has a node set A representing authors and an edge set T representing tweets. We define as $N_t(a)$ the total number of tweets posted by author a. We define as $N_r(a)$ total number of times author a has been retweeted. Tweets can refer to a brand b or to a category c. We define as $N_b(a)$ the total number of brands mentioned by each author a in all his/her tweets, i.e. *brand specificity*. Similarly, $N_c(a)$ represents the total number of categories mentioned by each author a in all his/her tweets, i.e. *category specificity*.

4.4.2 Research Model and Hypotheses

A post is influential if it raises attention from other users (Anger and Kittl, 2011). A fundamental goal of any social media user is to post content that is shared frequently, by many other users and over extended periods of time before fading (Asur et al., 2011). However, the literature does not provide systematic and visual evidence on how behavioral decisions regarding *content specificity*, *frequency of sharing* and *frequency of retweets* exert an impact on influence. Our claim is that in social media, content plays a key role in determining the influence of information.

AMOS 20 (Arbuckle, 2011) has been used in this paper to analyse the research model by means of structural equation modelling (SEM). SEM techniques are second-generation data analysis techniques (Bagozzi and Fornell, 1982; Chung, 2007) that are commonly used to test the extent to which IS research meets recognized standards for high-quality statistical analysis.

Figure 4 shows our research model. SEM allows the relationships among variables to be expressed through hierarchical or non-hierarchical structural equations (Bullock et al., 1994)). According to SEM's graphic format, rectangular boxes represent observed variables, oval boxes represent latent variables, arrows represent relations between variables, and circles represent the Gaussian errors associated with each dependent variable. For the sake of clarity, Figure 4 reports for each variable relationship only its standardized regression coefficient's sign (note that signs are consistent between the two data sets N_1 and N_2), where $N_t(a)$ represents a dependent variable as it is measured with multiple independent variables,i.e. $N_r(a)$, $N_b(a)$, and $N_c(a)$.

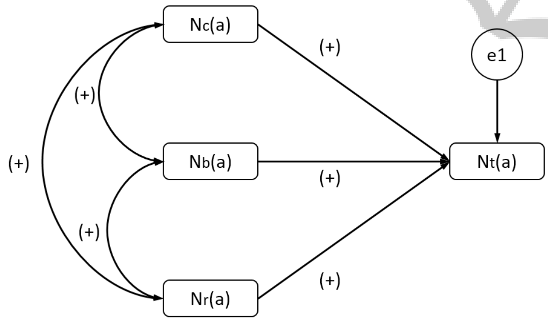


Figure 4: Research Model.

In this section, we put forward few hypotheses that tie *content specificity*, *frequency of sharing* and *frequency of retweets*. Hypotheses are tested on two samples of roughly one million tweets. Later in Section 4.4.3, we will statistically verify these propositions, which can also be visually verified via proposed visualization approach.

As noted before, social media users wish to be influential (Anger and Kittl, 2011). In particular, it has been found that fundamental goal of any social media user is to post content that is shared frequently, by many other users and over extended periods of time before fading (Asur et al., 2011). Following are the hypothesis that tie *content specificity*, *frequency of sharing*, and *frequency of retweets*.

- Hypothesis H1: *Content specificity is positively associated with frequency of tweets.* As noted before, social media users wish to be influential (Anger and Kittl, 2011). In particular, it has been found that fundamental goal of any social media user is to post content that is shared frequently, by many other users and over extended periods of time before fading (Asur et al., 2011). We call here $N_b(a)$, and $N_c(a)$, to check association with $N_t(a)$.
- Hypothesis H2: *Frequency of retweets is positively associated with frequency of tweets.* The literature has studied the role of social media, especially Twitter, as a source of news (Boyd et al., 2010; Kwak et al., 2010). In particular, the literature has discussed the ability of social networks to quickly spread information and the relative volatility of information created and "consumed" by users. (Kwak et al., 2010) show that most trending topics have an active period of one week, while half of retweets of a given tweet occurs within one hour and 75% within one day. Building on previous results, we call here $N_r(a)$ to check association with $N_t(a)$.

4.4.3 Statistical Analysis and Results

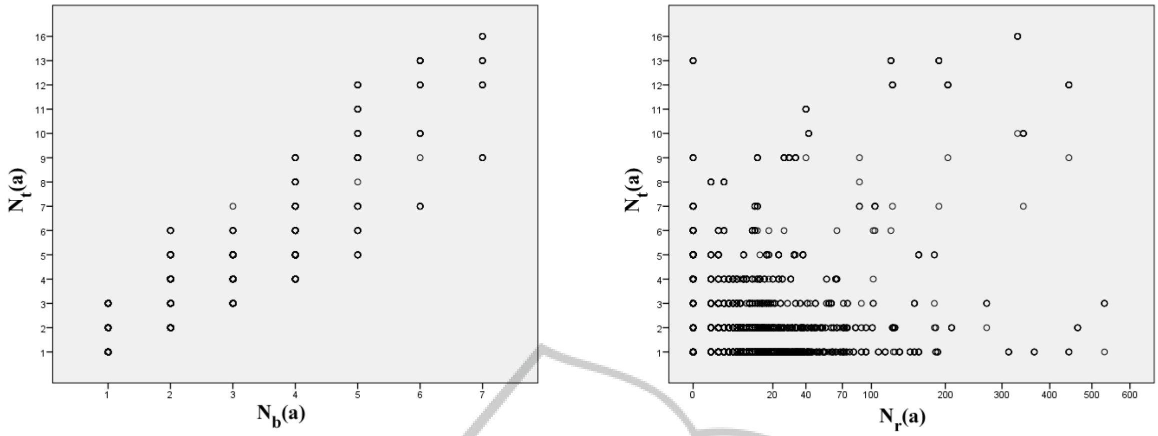
All statistical analyses have been performed with SPSS 20 (Pallant, 2010). Correlation and Regression analyses have been performed on our data set to verify the assumption that the metrics associated with the persistence of the retweeting process represent coherent properties of the same phenomenon. Table 3 reports the correlation matrix of our data variables and Table 4 reports the estimates of regression weights of our research model (Figure 4) variables (i.e., $N_t(a)$: author's *frequency*, $N_r(a)$: author's *retweets*, $N_b(a)$: author's *brand specificity*, and $N_c(a)$: author's *category specificity*).

Table 3: Correlation matrix of persistence variables (Pearson Index).

	$N_t(a)$	$N_r(a)$	$N_b(a)$	$N_c(a)$
$N_t(a)$	1	.286	.779	.528
$N_r(a)$	.286	1	.227	.219
$N_b(a)$	.779	.227	1	.397
$N_c(a)$	.528	.219	.397	1

From Table 3 follows that correlation is significant at 0.01 level (2-tailed). All persistence variables are positively correlated with each other, and thus have a significant impact upon each other. This yields to the notion that *specificity*, *frequency*, and *retweets* are significant parameters to measure author influence.

The regression estimation results of the research model as shown in Figure 4 are shown in Table 4. All relationships between persistence metrics (i.e. $N_r(a)$, $N_b(a)$ and $N_c(a)$) and the persistence latent variable



(a) (b)

Figure 5: Scatter Plots between a) Brand Specificity and Frequency b) Retweets and Frequency.

(i.e. $N_t(a)$) are significant, with $p < 0.001$. Moreover, Figure 5 shows the example scatter plots of dependent and independent variables in our research model.

Table 4: Estimates of regression weights for the research model.

V_D	V_I	R_W	S.E	p-value
$N_c(a)$	$N_t(a)$	0.248	.001	< 0.001
$N_b(a)$	$N_t(a)$	0.662	.003	< 0.001
$N_r(a)$	$N_t(a)$	0.082	.000	< 0.001
Covariances				
$N_b(a)$	$N_c(a)$	0.103	.001	< 0.001
$N_r(a)$	$N_b(a)$	0.533	.006	< 0.001
$N_r(a)$	$N_c(a)$	2.217	.026	< 0.001

V_D = Dependent Variables

V_I = Independent Variable

Hypothesis H1: (*Content specificity is positively associated with frequency of tweets.*) As $N_t(a)$ is positively correlated with both $N_b(a)$ and $N_c(a)$, which yields to the notion that authors with *high frequency* seems to have *high specificity* and vice versa, i.e. authors belonging to different clusters are in fact those who are more *generalist* in their content sharing, since they tweet about multiple different topics (brands or categories) with *high specificity*. On the contrary, authors belonging to the innermost clusters with *low frequency* value are those who are very *specific* in sharing content related to one selected brand i.e. *low specificity* value.

Hypothesis H2: (*Frequency of retweets is positively associated with frequency of tweets*). As $N_t(a)$ and $N_r(a)$ are also positively correlated, which yields to the notion that, authors with *high frequency* seems to have *high retweets* and vice versa. Although the correlation coefficient is not high, the p-value in Table 4 showing significance and seems to support a positive (though weak) correlation between $N_t(a)$ and $N_r(a)$. Thus, *generalist* authors in peripheral nodes or belonging to different clusters have a greater probability of being retweeted. On the contrary, authors belonging to the innermost clusters have lower probability of being retweeted.

From Table 2, it's also evident that as the graph size grows, $N_r(a)$ increases with increase of $N_t(a)$, thus increase in probability of potential influencers by intensity of retweeting. Moreover, if $N_t(a)$ increases,authors seems to tweet about more topic, which increases their specificity, either $N_b(a)$ or $N_c(a)$.

Similarly, as the graph sizes increases, more peripheral layers seems to be formed surrounding around hub node, which increases the influence spread across newly formed peripheral layers in multi-layered form, and thus outlier authors along periphery can be potential influence spreaders. We can visually identify the increase in influence spread, as shown in Figure 6(a), which is larger graph of N_1 type network, as compare to Figure 3, where the addition of more multi-layered peripheral nodes around hub-node (i.e. brand) increase the influence spread across those peripheral layers. Thus, the influence seems to spread across multi-layered periphery of authors' nodes. The outlier authors along the periphery can be potential influence spreaders, if they connect with other clusters through retweeting and, thus, play a critical role in determining influence of content.

5 CONCLUSION AND FUTURE WORK

This paper proposes a novel visual aspect for the analysis and exploration of social networks in order to identify and visually highlight influencers (i.e., hub nodes), and influence (i.e., spread of multi-layer peripheral nodes), represented by the opinions expressed by social media users on a given set of topics. Results show that our approach produces aesthetically pleasant graph layouts, by highlighting multi-layered clusters of nodes surrounding hub nodes (the main topics). These multi-layered peripheral node clusters represent a visual aid to understand influence.

Our approach exploits the underlying concept of power-law degree distribution with the metaphor of k-shell decomposition, thus we able to visualize social networks in multi-layered, clustered peripheries around hub-nodes, which not only preserves the graph drawing aesthetic criteria, but also effectively represent multi-layered peripheral clusters around hub nodes. We analysed multi-clusters, spread of multi-layered peripheries, brand fidelity, content specificity, and sentiment analysis through our proposed visual framework.

Empirical testing and evaluation results show that specificity, frequency, and retweets are mutually correlated, and have a significant impact on an author's influence and encourage us to further explore social network's intrinsic characteristics. Although our experiment can be repeated with data from entities different from tourism, additional empirical work is needed to extend testing to multiple datasets and domains.

Future work will consider measures of influence with additional parameters besides frequency of sharing, content specificity and frequency of retweets. In our current work, we are studying an achievable measure of influence through proposed visualization approach, that can be used to rank influential nodes in social networks (Metra, 2014).

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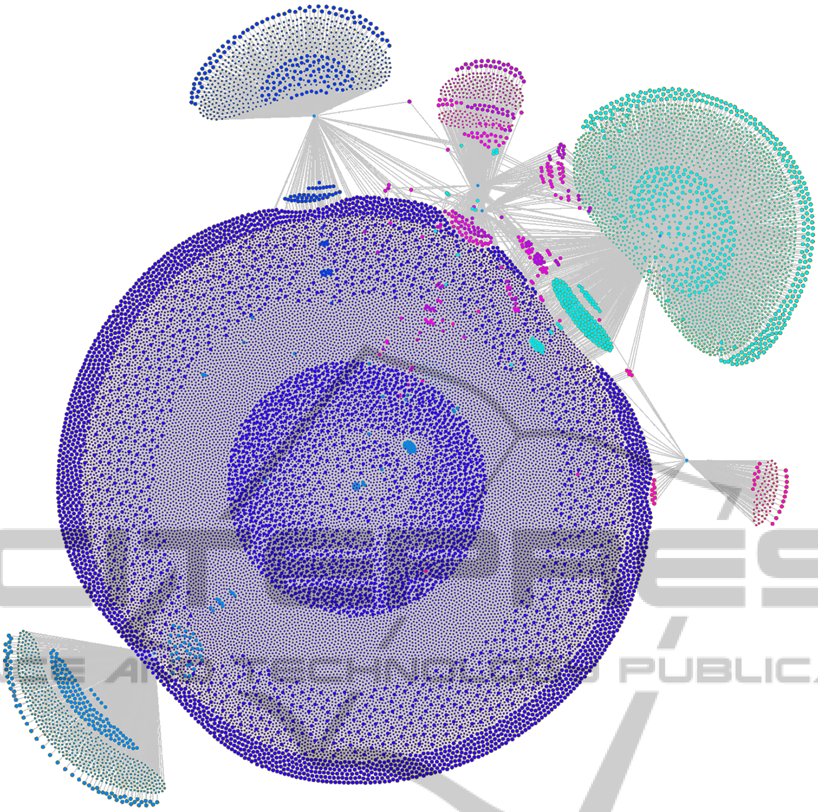
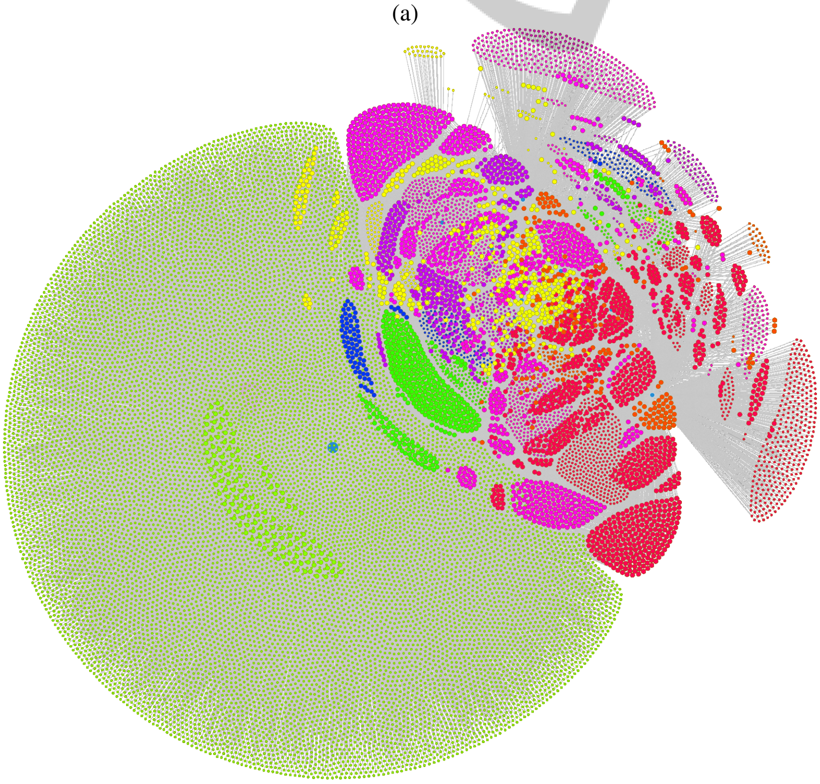
APPENDIX

Figure 6 provide further visualization of networks N_1 and N_2 of our dataset. An enlarged and zoomable version of the network layouts can be accessed online at the following URL: http://goo.gl/4uj66k.



(a)



(b)

Figure 6: Network visualizations of networks a) N_1 (Author → Brand) b)N_2 (Author → Category).