Social Networks of Teachers in Twitter

Hernán Gil Ramírez
College of Education
Carrera 27 #10-02
Barrio Alamos
Pereira, Risaralda (Colombia)
ZIP code 660003
hegil@utp.edu.co

Rosa María Guilleumas García
College of Humanities and Fine Arts
Carrera 27 #10-02
Barrio Alamos
Pereira, Risaralda (Colombia)
ZIP code 660003
roguiga@utp.edu.co

Abstract

This research aimed at identifying the trends in the topics of interest of the tweets published by 43 expert professors in the field of ICT and education and the network of their followers and followed in Tweeter, as well as their relationship with the characteristics of that network. With this purpose, NodeXL was employed to import, directly and automatically, 185.517 tweets which gave origin to a network of connections of 49.229 nodes. Data analysis involved social network analysis, text extraction and text mining using NodeXL, Excel and T-Lab. The research hypothesis was that there is a direct correlation between the trends identified in the topics of interest and the characteristics of the network of connections that emerge from the imported tweets.Among the conclusions of the study we can highlight that most of the trends identified from the analyzed tweets were related to education and educational technologies that could enhance teaching and learning processes; the association between education and technologies found through the text mining procedure applied to the tweets; and finally that the analysis of lemmas seems to be more promising than that of hashtags for detecting trends in the tweets.

1 Introduction

Currently, social networks in digital spaces are an important part of the life of a good number of people and institutions. Nevertheless, their study poses important challenges for researchers, since the huge volume of data circulating through them implies -for collection, processing, and analysis-, the use of specialized software, powerful equipment, complex analysis methods, and qualified people, items that are not always available in the small and middle-size educational institutions.

Though many users exchange through Twitter what Ferriter (2010) calls "digital noise," this researcher claims that professionals in education have found ways to use Twitter to share resources and provide a quick support to colleagues with similar interests, turning this service into a valuable source of ideas to explore.

Twitter may be used for communication purposes, but also to share information and build, collectively, academic communities. This social network enables interaction with other people, access to their interests and identification of trends from the published messages.

2 Research background

This work takes as referents some previous research on Twitter and the generation, exchange and propagation of information; it also considers works about the influence of users on this digital space. Shneiderman (2011) explores the reasons for the success of social media like Facebook, Twitter, YouTube, Blogs, and the traditional discussion groups and he concludes that it is due to the fact that they allow people to participate actively in local and global communities; the role of Twitter as a communication resource and information exchange tool during a crisis is tackled in Herverin and Lisl (2010) research, and also in Chew and Eysenback's (2010) work.

Weng, Lim, Jiang and He (2010) focus on the issue of the identification of the influential users of Twitter; Bakshy, Hofman, Mason and Watts (2011) study the features and relative influence of Twitter's users. Regarding the propagation of information, our referents are Lerman and Ghosh (2010), as well as the research carried out by Gómez, Leskovec, and Krause (2010), where they state that the diffusion of information, and viral propagation are fundamental processes in the networks; we finally highlight the work done by Wu, Hofman, Mason and Watts (2011), where they stress the importance of understanding the channels through which information flows, in order to comprehend how it is transmitted.

3 Theoretical considerations

Castells (2011) thinks that the Internet is revolutionizing communication thanks to its horizontality, feature which permits users to create their own communication network and to express whatever they want, from citizen to citizen, generating a capacity of massive communication, not mediated by the traditional mass communication media. This communication networks are the basis of the "network society," a concept which was popularized by this author, who describes it as the social structure that characterizes the society of the early 21st century, a social structure constructed around (but not determined by) digital communication networks. (Castells, 2009, p.24). It is in the space and the time of the network society where the studied group of teachers constructs communication networks using Twitter, making out of it more than just a simple technology, a tool for communication, encounter, and assistance.

Castells defines a network as a set of interconnected nodes. The nodes may have more or less relevance for the network as a whole, so those of higher importance are called "centers" in some versions of the network theory. At any rate, any component of a network (including the "centers") is a node, and its function and meaning depend on the network programs and on its interaction with other nodes in it. (2009, p.45) This author explains that the importance of the nodes in a network is higher or lower depending on how much important information they absorb and process efficiently, that is, it is determined by their capacity to contribute to the effectiveness of the network in the achievement of its programmed objectives (values and interests).

In this sense, we approach the study of the communication networks created by teachers from connections they establish in Twitter. In this case, each user, and each web domain, hashtag, lemma, constitutes a node which establishes connections in the network under study, where it is evidenced that there are nodes with higher relevance than others. This is precisely what contributes to the understanding of the dynamics of these networks: what nodes are more important in the network, which are their contributions, and in what way they make up the structures of these relationships.

Social networks, as posed by Lévy (2004), provide tools for human groups to join mental efforts so as to constitute intellects or collective imaginaries. This allows for connecting informatics to be part of a technical infrastructure of the collective brain of lively communities, which profit from social and cognitive individual potentialities for their mutual development. Lévy (2004) describes collective intelligence as "una inteligencia repartida en todas partes, valorizada constantemente, coordinada en tiempo real, que conduce a una movilización efectiva de las competencias…" y agrega que "…el fundamento y el objetivo de la inteligencia colectiva es el reconocimiento y el enriquecimiento mutuo de las personas (…)".

Concerning this point, we can sustain that networks like Twitter create the suitable space to integrate the intelligence of many people, located in different places around the world; an intelligence that is permanently updating, allowing people linked to the network to widen their horizons and possibilities to access information. Our intent in this research is, following Lévy`s pathway, to appraise the potential of Twitter as a space for interaction in the network of the teachers under study, and also to value the information they exchange and which can be accessed through this means, as a manifestation of collective intelligence.

4 Methodology

This research followed a quantitative approach with a trans-sectional, correlational, non-experimental design, which allowed for the establishment of the relation between the trends in the topics of interest detected and the structure of the network of connections that emerged from the tweets published by the selected group.

In order to select the group to be studied, we adapted the snowball sampling method. An initial group of seven (7) professors was intentionally identified and selected on the basis of their academic background related to the use of the ICTs in education, and their academic contributions via the Internet, in particular through Twitter. In a second phase, there was a follow-up of these seven professors' Twitter accounts, in order to identify other teachers who followed them or that they followed, and who, on the basis of their contributions in Twitter, their publications and academic output about the use of ICT in education, could be part of the studied group. This procedure was repeated once again until finally it was formed, in a not probabilistic way, a group of 43 teachers.

Of the selected group, 65% were University professors, 23% primary and secondary teachers and 12% belonged to other type of institutions (non-formal, virtual tutors and advisors). Concerning their nationalities, 84% were from Spain, 7% from Argentina, 5% from Colombia, 2% from Mexico and 2% from Venezuela.

Using NodeXL we imported from Twitter, 185.517 tweets published by the network of connections of the 43 selected teachers between February the 4th and June the 6th, 2014.

As data collection instruments, we used NodeXL templates (which include not only the tweets but also the information of the edges, as well as that of the nodes). From the imported data rose a network of connections made up 49229 nodes and 98.494 edges.

These nodes were located in 128 countries. 88.3% of them were concentrated in 10 countries, among them, Spain, Argentina, The United States, Colombia, and Mexico. About one third of the nodes registered in their profile professions related with education.

In order to identify the trends in the topics of interest in the published tweets and their relationship with the features of the network from which they emerged, we made a graphic representation of the network and calculated its metrics, using NodeXL. Likewise, we identified the trends in the topics of interest by analyzing the imported tweets to quantify the frequencies of appearance of the hashtags and by applying text mining to the content of the tweets. We also identified the trends in the web domains and established the correlation among the frequencies of the topics of interest detected as trends and the metrics of the network, using multivariate analysis, and Pearson's correlation coefficient. For data analysis we used the programs NodeXL, Excel, T-Lab and Statgraphics.

5 Analysis and data interpretation

For data analysis and interpretation, we examined the features of the network of connections of the 43 teachers selected. Besides, based on the tweets published by the mentioned network, we identified the trends in the topics of interest and studied their correlation with the values obtained in the two previous steps.

5.1 Features of the communication network

We used NodeXL to make the graph of the network of connections as well as to calculate its metrics.

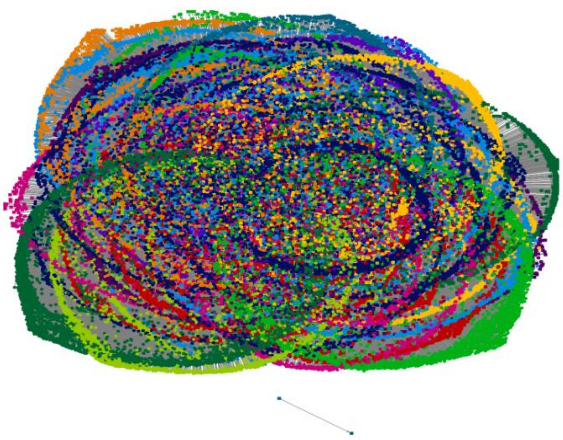

Figure 1. Communication network emerging from the imported tweets.

Taking a look at figure 1 with its 49.229 nodes and 98.494 edges, it is evident that, given their location, not all the nodes have the same importance in the network. A representative group of nodes, located in the center, are the most connected; a significant amount, the least connected, are displaced outwards, and a couple of them, though connected to each other, are disconnected from the network.

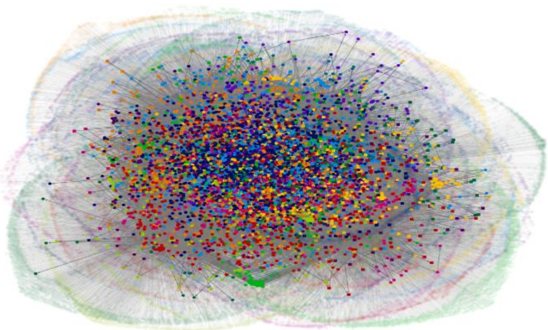

Figure 2. Communication network emerging from the imported tweets, filtered.

Figure 2 corresponds to the same network after the application of a filter based on the Betweenness Centrality index of the nodes and it shows only those with a value higher than 1 for that index. This produced a reduction of the network to 8.725 nodes (a 17.7% of the total). This process allowed us to note, more clearly, the set of nodes that occupied the center, while in the periphery, in opaque tones, there can be seen the remaining nodes, those out of the established filter.

Thus, we can see the configuration of a network, that as Castells sustains (2009:45), is made up of interconnected nodes; some, the so-called centers, of greater importance for the network, and others, less important, depending on their capacity to access information and process it efficiently; that is, on account of their capacity to contribute to the achievement of the objectives of the network itself.

The process of analysis implied, likewise, the calculation of the graph's metrics, as a basis for the quantitative measurement of the indices associated to the nodes and their edges. The graph is directed. The relation of reciprocity of the edges is of 0.27. The In-Degree ranges between 0 and 3.439, the Out-Degree between 0 and 1.789 and the Betweenness Centrality index between 0.0 and 354805308.32.

Of the 49.229 nodes analyzed, the 10 nodes with a higher In-Degree, Out-Degree, and Betweenness Centrality, belonged to the initial group of 43 teachers selected. This shows that, in addition to a relative high level of edges between the nodes of the network, the initial group of 43 teachers selected, from which the network of connections emerged, had a significant weight within the network, both for the amount of nodes connected to them as for the amount of nodes to which they were connected and therefore for their intermediation potential in the network. This is particularly important in a scenario where just a few nodes had high degrees of intermediation.

The 49.229 nodes of the network were organized in 24 groups of diverse sizes, according to the number of nodes in them. There was a high amount of edges inside each group, as well as among the different groups. For instance, group 1 had 8.220 nodes (16.7% of the total) and 174.397 edges. At the other end in size and edges were group 23 (with 525 nodes, 1.1% of the total and 586 connections) and group 24 (disconnected from the network, with just 2 nodes and a single edge between them).

Regarding the making up of the groups, we want to state that within a network of connections it is difficult to establish groups as well as their precise borders since the nodes can be involved in different relations and belong to more than one group.

In this research, the clusters were conformed with NodeXL, using the Clauset-Newman-Moore algorithm for clusters, that automatically identifies the groups from the network structure, placing the densely connected nodes in separated groups; that is, conforming each group with a set of nodes that are more connected to one another than what they are to other nodes.

On average, each of the 24 groups had 2.051 nodes, 2.939 inner edges and was connected to 21 of the 24 existing groups through 1.164 edges, what shows a highly connected network. In this respect, it is worth noting the existence of groups that were rather highly connected to other groups, as for example, group 1 with 5.678 edges, and group 2 with 3.076.

We believe that the communication that exists among the nodes, inside the conformed groups and among them, facilitates the access to information and its distribution inside the studied network, thanks to what Castells (2001) calls the process of horizontality, which allows all the nodes connected to the network to communicate massively, to share whatever they wish and thus build their communication networks, in this case through the use of Twitter.

As a summary, we can affirm that the network studied was decentralized, though not in the classic sense of the term since some nodes were connected to one or more central nodes, which in turn were often connected to several nodes, central or not, making the structure of this network more complex and robust, in such a way that if one of the central nodes were to disappear, this would not cause the disconnection of a great amount of nodes or the disappearance of the network.

The study of the tweets exchanged in the studied network showed that, within it, the identified trends (hashtags, lemmas and web domains) were the origin of other networks.

5.2 Identification of tendencies of the topics of interest to be published

The web domains referenced in the tweets, as well as the hashtags and slogans more used, led to the identification of the trends in the topics of interest to be published in the studied network.

Tendencies identified from the hashtags referenced in the tweets.

Of the 185.517 imported tweets, 31, 5% (58.349) included hashtags. The total of referenced hashtags was 88.798, out of which 29.590 were unique hashtags. We identified the hasthtags referenced in the tweets and calculated their frequency of appearance. The 10 hashtags with a higher referencing frequency (0.03% of the total) were used 6% of the times, while the remaining 29.590 (99.97%) appeared the 94% of the times.

The first place was for the hashtag *#educación,* followed by #ABPmooc_intef and #elearning, #tic, *#edtech, #educacion, #eduPLEmooc*, among others.

The ten hashtags with a higher frequency of use in the tweets could be grouped around three main topics: education (8 hashtags), politics (1 hashtag), and technology (1 hashtag). The predominance of the hashtags related to the topic of education could seem obvious in a network initially composed by teachers; however, we should remember that the 43 initially selected teachers were the seed of a network that was enlarged to include 49.299 nodes; this suggests that the 43 teachers followed and were followed either mainly by teachers, or by people interested in and concerned about education.

This piece of data may show some degree of homophily in the studied network of connections, since despite the fact that Twitter users are not forced to correspond to their followers (directed network) and most of the links are not corresponded, the users tend, however, to connect to others exhibiting interests and activities similar to their own (Kwan, Lee, Park, and Moon, 2010). This situation also matches Wu, Hofman, Mason and Watts's findings (2011), who highlight the significant homophily found in their research.

Network of tendencies identified from the 10 most referenced hashtags

The tendencies identified from the 10 most referenced hashtags enabled the conformation of a network of connections between the nodes referencing the hashtags (source node) and the hashtags which were being referenced (target node).

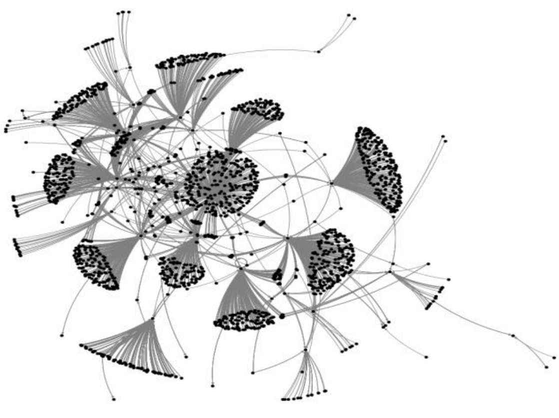

Figure 3. Network of connections of the 10 most referenced hashtags

Figure 3 illustrates how most of the connections were grouped around a specific hashtags. There are very few cases in which a node used more than one hashtag. However, as an example of this case, we can mention *#eduPLEmooc y #ABPmooc_intef,* which set up some connections with the same users.

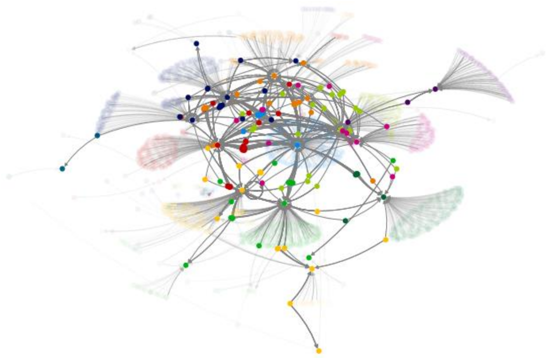

Figure 4. Network of connections of the 10 most referenced hashtags, filtered.

Figure 4 was the result of the application of a filter based on the Betweenness Centrality index of the nodes. It shows the 154 nodes (8.2% of the total) with a higher than the average value of this index. This process allowed the visualization of those nodes with greater force of intermediation in the network, located in the central part of the graphic. It also let us observe that most of them, about 91.8% have a low or no force of intermediation at all. These nodes, represented with opaque tones, were located in the periphery of the graphic according to the decreasing value of the index, a value that reached 0 for 1.533 nodes, that is, for the 81.3%.

As we can observe from these metrics, there was an important number of nodes which could be considered as "lurkers" since they do not contribute much to the network; they are mainly silent participants.

The In-Degree index in this network ranged between 0 and 335, the Out-Degree between 0 and a 6; and the Betweenness Centrality between 0 and 1.453.757,65. Although a hashtag can receive many entries (as in the case of #educación, with an In-Degree of 335, or #ElReyAbdica, with 237), these are generated by many nodes. We can then assert that the tendencies detected are actually a product of the individual contributions of an important number of network nodes, what evidences the materialization of Lévy's collective intelligence.

Within the network of connections of the 10 hashtags with a higher frequency of use in the tweets, 21 groups were conformed. On average, each group connected only to 2 other groups, and there were even some groups that were not connected to any. It is remarkable that the groups with a larger number of nodes connected to a greater amount of groups. One example of this is Group 1, which having 271 nodes, was connected to 5 groups. In contrast, the groups with a lower number of nodes showed the tendency of not setting up connections to any group. This was the case of group 21, which having 2 nodes, did not connect to any group.

Trends identified in the lemmas of the tweets

In order to advance in the identification of the topics of interest in the tweets published by the network of connections of the group of selected teachers, we resorted to text mining. The analysis of the content of the tweets was done with T-Lab, using the automatic lemmatization (word grouping) and the selection of key words.

Starting from the 185.517 imported tweets, the corpus of analyzed data was made up of 175.122 elementary contexts (EC), 179.374 words, 162.072 themes, and 2.574.255 occurrences. The program automatically selected the 500 words with the higher level of occurrence in the corpus, out of which the non-meaningful terms were manually deleted later (articles, preposition, etc.) giving a remainder of 310 items. For text segmentation (elementary contexts), we used the paragraph, which in this case was equivalent to a tweet. For the selection of key words we employed the method of occurrences.

Nº	Lemmas	EC
1	Educación	4.024
2	Nuevo	2.543
3	Educativo	2.415
4	Social	2.404
5	Aprender	2303
6	Curso	2.238
7	Seguir	2.201
8	Blog	2.143
9	Stories	2.117
10	Vida	2.063

Table 1. Lemmas and Elementary Contexts (EC)

Lemmas associated with education, such as *educación, educativo, aprendizaje* or *curso* stood out in frequency of citation in the tweets as shown in Table 1. The lemma *educación* had already been identified as one of the 10 most referenced hashtags.

Analysis of co-occurrences/word associations

The co-occurrence is the number of times (frequency) that a lexical unity (LU) appears in the corpus or within the elementary contexts (EC), in this case in the tweets. The function *word association* was used to detect which words, in the elementary contexts, were the co-occurrences with the lemma *educación*.

The lemma *Education*, found in 4.024 of the 175.122 elementary contexts (EC) analyzed, was associated to a group of lemmas, considered as relatively close, among them *tic, technology*. Their relation with the lemma *educación* is confirmed by the higher values of the index of association presented in Table 2. *Tic, 0.166:* technology, 0.166. The closer the association between two lemmas, the higher the coefficient.

Table 2 presents data of the relationships between occurrences and co-occurrences of the lemma *educacion* in the elementary contexts.

LEMMA (B)	COEFF	E.C. (B)	E.C. (AB)
tic	0,166	1577	419
tecnología	0,166	1285	377
congreso	0,109	744	189
básico	0,107	396	135
innovación	0,1	634	160
ciencia	0,082	641	131
infantil	0,076	653	124
futuro	0,065	804	117
Blog	0,065	2143	191

Table 2. Lemma Educación (Theme A)[1]. Partial List

In addition, the lemma *tic* appeared in 1.577 elementary contexts, and the lemmas *educación* and *tic* were referenced together in 419 elementary contexts. As we can observe in Tables 1 and 2, there was evidence of the prevalence of lemmas associated with education, as well as of the close association between them, in the elementary contexts analyzed.

[1] Conventions: LEMMA A= Educación; LEMMA B = Lemmas associated with LEMMA (A); COEFF = Value of the index of association selected; E.C. (AB) = Total of EC in which the lemmas “A” and “B” are associated (co-occurrences).

Tendencies of the web domains identified in the tweets

Out of the 185.517 imported tweets, 59,4% included references to web domains. Using Excel, 113.361 domains were identified, out of which 18.448 were unique web domains. In order to detect the tendencies in the domains, we calculated their frequency of reference and located the 10 with the highest levels of reference. It is worth noting the great amount of references accumulated by these 10 domains, since making up just for a 0.05% of the amount of unique domains found in the tweets, they were referenced in the 25,4% of the occasions.

Among the 10 most cited web domains were blog sites (blogspot, 1st position), sites for video publishing (Youtube, 2nd position); social networks (Facebook, 3rd position; Instagram, 6th position; LinkedIn, 7th position; Foursquare, 9th position); online newspapers and journals (Paper.li, 5th position; eldiario.es, 10th position); content curation sites (Scoop.it, 4th position).

It should be highlighted that most of the referenced domains (4 out of 10) were social network applications. Likewise, we must point out the importance of the blogs for the studied network, since besides the tweets that included mentions to blogs of blogspot, there was also a considerable amount of domains making reference to other blogs, like in the case of blogs.elpais, blog.educalab, blog.tiching, blog.fernandotrujullo and blogthinkbig.

This listing of web domains in general and blogs in particular, permits the visualization of tendencies in the use of the web, and may help teachers approach the best possibilities to explore them and integrate them in their teaching practices.

Network of the tendencies of the web domains identified in the tweets.

The 10 domains more cited in the tweets allowed shaping a network of connections between these 10 web domains (target nodes) and the users referencing them (source node). This new network was made up of 10.900 nodes and 28.745 connections (7.319 unique connections and 21.426 duplicated connections).

To facilitate the analysis and interpretation of the graph, we applied a filter based on the Betweenness Centrality Index of the nodes, allowing the visualization of the nodes with a higher power of intermediation in the network, and therefore, with a greater significance in so far as the flow of information.

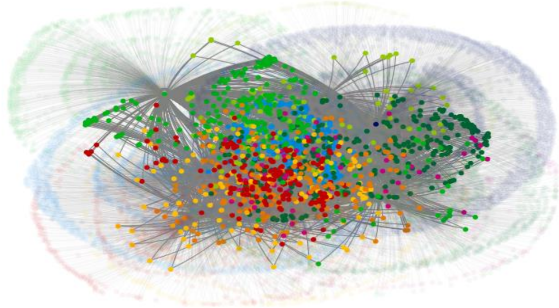

Figure 5. Network of connections of the 10 most referenced domains

Figure 5 shows the 1.397 nodes (about 12.8% of the total) with a higher than the average value. These were the small group of nodes located in the center of the graph. These nodes may be crucial in the flow of information, since they lied in the paths between other nodes in the network and therefore provided a link between them.

Toward the periphery, in opaque tones, we can see the remaining nodes, the ones left outside by the applied filter. The great majority of them had a low Betweenness Centrality index, that reached 0 for 9.295 nodes, that is, for the 85.3%. These values reflect a distribution of Pareto, in which a small number of nodes (about 13%) displayed the higher values of Betweenness Centrality, while a great number of nodes (87%) showed relatively low values in this index.

The In-Degree Index of this network had a minimum value of 0 and a maximum of 3.367; The Out-Degree presented a minimum of 0 and a maximum of 6; the Betweenness Centrality showed a minimum of 0 and a maximum of 56149284,89. These metrics evidenced a higher maximum value of In-Degree than of Out-Degree, what indicates that though a web domain may have been referenced many times (as the in the case of Youtube, with an In-Degree of 3.367), these references were done by many nodes. In other words, we can assert that the detected tendencies were actually a product of Lévy's collective intelligence, and not of reduced groups of nodes that fostered a particular interest.

Nine groups were configured inside the connection network of the 10 domains with the highest frequencies of appearance in the tweets. Group 1, despite being the most numerous, did not connect to any other groups, though other groups did connect to it. On average, each group established connections with five other groups; the average amount of nodes by group was 1.211 and that of the unique connections, 704.

We must highlight that the groups with a lower amount of nodes established connections with a greater amount of groups, to the point that groups 8 and 9 were connected to 8 of the 9 groups configured, while the groups with a greater amount of nodes –groups 1 and 2- were connected to less groups (0 and 1 group respectively). This could mean that a great number of the network nodes posted tweets referencing a particular web domain, while a minority of them, referenced in their tweets a greater variety of web domains.

Correlation between tendencies and metrics of the communication network.

In order to correlate the six (6) variables associated with the network of connections under study, we applied a multivariate analysis, relating pairs of variables of the metrics with the frequencies of the identified trends. The variables of the metrics were: In-Degree, Out-Degree, and Betweenness Centrality. The variables of the tendencies were: web domains (URL), hashtags, and lemmas.

	In-Degree	Out-Degree	Betweenness Centrality
URL	0,1627	**0,172**	0,146
Hashtag	0,0466	0,054	0,0454
Lemma	0,1961	**0,201**	**0,1833**

Table 3. Correlations

As shown in Table 3, in most of the relations between pairs of variables of the metrics and the tendencies of the topics of interest, we found a direct correlation, though weak.

The highest correlation was observed between lemmas and metrics, and the lowest between hashtags and metrics. In the first case, the highest correlation occurs between lemmas and out-degree, followed by lemmas and in-degree.

6 Conclusion

The methodological procedure used in this research allowed us to create a wide network of users interested in education starting from an initial group of 43 teachers.

Although the nodes of the initial group registered high values in the network metrics, their influence in the identified trends was low.

Most of the trends identified from the analyzed tweets were related to education and educational technologies that could enhance teaching and learning processes, as for instance, blogs, social networks as platforms for sharing documents and other resources, online journals and curation tools.

It stands out the association between education and technologies found through the text mining procedure applied to the tweets.

The importance of blogs as a trend was confirmed by its appearance among the web domains with the highest frequency of references in the tweets.

The direct correlation found particularly between the metrics of the network and the trends in the lemmas found in the analysis of the tweets, allows to conclude the importance of analyzing with particular attention the tweets published by users with a higher out-degree since they seemed to influence more the trends that arise from the studied network.

The analysis of lemmas seems to be more promising than that of hashtags for detecting trends in the tweets.

Since nearly 6 of each 10 tweets included a reference to a web domain, it would be interesting to be able to explore in a greater detail, what is what users are actually referencing through those web domains.

The results of this research and their usefulness for identifying trends in the topics of interest of educational professionals suggest we continue exploring the possibilities of social networks and the analysis of big data in the shaping academic communities.

References

Bakshy, E.; Hofman, J.M.; Mason, W.A.; Watts, D.J. (2011), Everyone's an Influencer: Quantifying Influence on Twitter, [en línea], disponible en: <http://research.yahoo.com/pub/3369>

Castells M. (2001), Internet y la sociedad red, [en línea], disponible en <http://tecnologiaedu.us.es/cuestionario/bibliovir/106.pdf>

Chew,C. and Eysenbach, G. (2010). Pandemics in the Age of Twitter: Content Analysis of Tweets during the 2009 H1N1 Outbreak., [en línea], disponible en <http://www.plosone.org/article/info:doi%2F10.1371%2Fjournal.pone.0014118>

Ferriter, W. M. (2010). Why teachers should try twitter. Educational Leadership, 67(5), 73. [en línea], disponible en

<http://ezproxy.utp.edu.co/docview/224840251?accountid=45809>

Gómez M., Leskovec J., Krause A., (2010), Inferring networks of diffusion and influence, [en línea], disponible en <http://dl.acm.org/citation.cfm?id=1835933>

Heverin, T. y Lisl, Z. (2010), Microblogging for Crisis Communication: Examination of Twitter Use in Response to a 2009 Violent Crisis in the Seattle-Tacoma, Washington Area, [en línea], disponible en <http://www.thomasheverin.com/uploads/4/6/5/8/4658640/heverin_iscram_2010.pdf>

Kwakn H., Lee C., Park H., and Moon S.,(2010), What is Twitter, a Social Network or a News Media?, [en línea], disponible en <http://an.kaist.ac.kr/~haewoon/papers/2010-www-twitter.pdf>

Lerman, K., and Ghosh, R.. (2010). Information contagion: an empirical study of the spread of news on digg and twitter social networks, *In Proceedings of 4th International Conference on Weblogs and Social Media (ICWSM)*. [en línea], disponible en <http://arxiv.org/PS_cache/arxiv/pdf/1003/1003.2664v1.pdf>

Lévy P (2004), Inteligencia colectiva. Por una antropología de ciberespacio (en línea), [en línea], disponible en <http://inteligenciacolectiva.bvsalud.org/public/documents/pdf/es/inteligenciaColectiva.pdf>

Shneiderman, B. (2011), Technology-Mediated Social Participation: The Next 25 Years of HCI Challenges, [en línea], disponible en <http://www.cs.umd.edu/localphp/hcil/tech-reports-search.php?number=2011-03>

Weng, J., Lim E., Jiang J., He Q., (2010), TwitterRank: finding topic-sensitive influential twitterers, [en línea], disponible en <http://dl.acm.org/citation.cfm?id=1718520>

Wu S., Hofman J.M, Mason J.,M., y Watts D. J, (2011), Who Says What to Whom on Twitter (¿Quién dice qué a quién en Twitter?), [en línea], disponible en http://research.yahoo.com/pub/3386