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Title: Social network analysis to support decision-making

Abstract

The growing importance of decision-making within web context requires defining and implementing efficient mechanisms to support its activities. The social networks, seen as opportunities for organizational collaboration, allow people to interact across continents and time zones, expressing opinions and sharing information. They also constitute an increasingly used means for decision support, when seeking information, which can produce a massive amount. Therefore, it is necessary to analyze such information in order to establish opinions and points of view on a variety of issues that can play an important role for decision-making.

As the web discourses (of opinion and information) often encompass knowledge construction, interaction and the consequent development of online social networks capturing and understanding all interactions can be extremely valuable for building indicators to support decision-making. Accordingly, the main objective of this work is to explore the interactions and discursive exchanges between social actors, in order to extract information towards decision support. We intend to investigate whether it is possible to structure collected data from online social networks, integrating human interaction and network structure, namely by using Social Network Analysis (SNA) to study the network from a duofold manner: the web discourse, which depends on the transmission of information; and the interaction among social actors, as information disseminators. Our work intends to determine whether social actors and their interactions are consistent with the creation of indicators fit for decision support.

Keywords: Social Network Analysis, Social Networks, Decision Support, Web Discourse.

1. Introduction

Businesses can use tools to monitor social networks, to filter social conversations (web discourse) based on certain keywords, such as company name, services, etc. The information collected can be integrated into internal systems to improve their view of customer interaction with data visualization. Automated systems (agents) can capture these interactions based on customer needs and historical activity.

The extraction of predictive information from interactions between online social networking actors is something to explore. However, discursive exchanges do not merely comprise the structure of messages but a sense built amongst stakeholders. Understanding relationships between messages and interpreting the meaning of what is exchanged usually refers to speech analysis, which is, by itself, a multidisciplinary area. Furthermore, web discourse leads us to the computer mediated communication where, according to Herring (2001, 2010), communication is characterized by a fusion between written language and spoken discourse. This usually leads to disordered, incomplete and sometimes garbled data. Nevertheless, according to Osei-Bryson and Rayward-Smith (2009), if used correctly and if well exploited, these data can be a valuable resource for the organizations' management.

As web discourse often encompasses knowledge construction, interaction and the consequent development of online social networks, capturing and understanding all interactions can be extremely valuable in building indicators for decision support. We intend to investigate whether it is possible to structure collected data from online social networks, integrating human interaction and network structure, namely by using SNA. Our work intends to determine whether social actors and their

interactions are consistent with the creation of indicators fit for decision support. The way we acquire, consult, treat and use information to decide on any problem, when properly combined with technologies, generates insight to support decision-making.

This paper discusses how Social Network Analysis can help to get useful information from network structures and relationships to support decision, and pretende responder a duas questões. Em primeiro lugar, como pode a análise de redes sociais (SNA) ser aplicada de forma a identificar palavras-chave que resumam o conteúdo do discurso web produzido nas redes sociais. Em segundo lugar, como é que os dados recolhidos podem ser usados no apoio a decisão em contexto de crise. A análise efetuada aos dados recolhidos da página da TAP também evidencia a capacidade que técnicas de cluster (comunidades) têm para revelar e identificar os principais temas e preocupações debatidos pelos clientes durante a greve, bem como a dinâmica da própria rede social.

2. Using Social network analysis to support decision-making

According to Marmo (2011), the combination of SNA methodology and web mining, gives a useful degree of innovative detail to social networks analysis, particularly in terms of decision-making. Therefore, it is important to look at the content produced by social actors, in particular for the web discourse because, as stated by Antunes, Freire, and Costa (2014), the structuring of a group discourse allows a better understanding of the expressed views, as well as a logical sequence of the discussion itself.

Dealing with data from social networks is largely the domain of information and computing systems. However, according to Power and Phillips-Wren (2012) Web 2.0 may be the managers' greatest technological innovation on decision support. Since the information flowing in social networks involves virtual collaboration, including the execution of virtual organizational tasks, understanding the effects of online collaboration and sharing of information (compared to the face collaboration or face-to-face) is a very relevant matter to sustain and support decision-making in the current context. In contemporary organizations, the decision maker needs to gather relevant information to increase knowledge about the alternatives pertaining to a particular choice. Therefore, the decision-maker engages a quest for information, spending time and effort while limited by its cognitive ability to process the collected data, which makes it unimportant to capture and analyze everything a social actor publishes (text, image, etc.), but rather to identify and select what can meet the needs of the moment, and do a faster judgment on the results achieved using simple tools.

Making choices usually involves uncertainty, either because the decision-maker refers to actions taking part in the future, or because he is not based on knowledge or absolute principles, but on assumptions, perceptions and/or opinions supported by personal values or beliefs. Therefore, when a choice has to be made, argumentation gets into the "game". Reasoning and decision-making describe processes by which decision-makers seek the best possible alternatives within a context of uncertainty and ambiguity. This means that most of the decisions made by managers take place in this context. To Antunes and Costa (2011), the main purpose of decision-making support processes is to help incorporate rationality, offsetting decision makers' intuition, thereby contributing to improve the quality of taken decisions.

SNA in particular includes various metrics associated with the study of social networks. However, as stated by Hanneman and Riddle (2005), from the range of mathematical techniques available in the methodology, there are neither forms nor right or wrong indicators in the approach to social networks. Brandes and Erlebach (2005) point out that, depending on the network in question, several concepts can be used. For each case, a set of techniques can be selected, according to the study objectives and topological characteristics as well as the network dynamics to be analyzed.

A social network connects a number of entities through social relationships (Shum, Cannavacciuolo, De Liddo, Iandoli, & Quinto, 2011), facilitating the exchange of information (Jamali & Abolhassani, 2006; Marmo, 2011). In view of this statement, it is possible to measure these relationships to describe the group structure and analyze the impact of this structure on group

behaviour and/or the influence of this structure on the individuals in the group (Wasserman & Faust, 1994). The application on the web discourse of SNA metrics and display methods can allow a deeper understanding of it, thus helping to get useful information about the network structure and relationship patterns, such as who talks to whom and what content was transmitted.

A ideia de identificar, extrair e fazer sobressair ideias implícitas em textos, para apoio a decisão, com o apoio de ferramentas gráficas não é nova. A literatura têm mostrado uma quantidade crescente de trabalhos sobre a utilização da análise de redes para o efeito. Este facto provocou o aparecimento de novos conceitos e métodos, que vão desde a mineração de textos, análise de rede semântica, análise de conteúdo, que são atualmente utilizados com foco em análise orientadas para a criação de ontologias uteis a web semantica.

3. The Web discourse

The Web, especially the social web (online social networks), comprises interaction processes where the emerging networks are built through an established dialogue (discourse). As a means of communication, it has encouraged research to find explanations and to define theoretical models to understand its operations. The complexity associated to these processes and the interpersonal and social relations require the use of concepts studied and validated in different areas of knowledge, in order to explain the discursive phenomena of communication.

Regarding web discourse, studies essentially address the computer mediated communication point of view (Herring, 2001, 2004, 2010, 2013), natural language processing (NLP), web content analysis (Herring, 2010) or discourse analysis (Moser, Groenewegen, & Huysman, 2013), commonly focused on text analysis, using other areas knowledge. Most studies are focused not only on the discursive aspects, but also on rhetorical, argumentative, semantic and pragmatic issues, to analyze the text produced in the web discourse.

Briefly, the discourse produced on facebook has at least **three entities** (users, posts and concepts) that can be analyzed individually or aggregated. Normally the studies are focused on the analysis of interactions between users. However, as show in Figure 1, one can put these three entities on the same level to analyze:

- The interactions between users;
- Users and posts;
- Posts and concepts to identify the most used in each post.

Each entity (users, posts and concepts) results in a **square matrix**. These **three matrices** were used to construct a **multilevel matrix** from which the main network was created show in Figure 2, 3, 4, 5 and 6. For the purposes of this study the following matrices were built:

- Users -> Users;
- Users -> Posts;
- Posts -> Concepts (semantic network).

We assumed that the other matrices “Posts -> Posts” and “Concepts -> Concepts” had null values. Para perceber e analisar as interações entre users e post, bem como posts e concepts construíram-se redes Two mode Network. No total para representar o discurso web dos 10 dias de greve e para os 5 conjuntos de dados, foram utilizadas 30 matrizes.

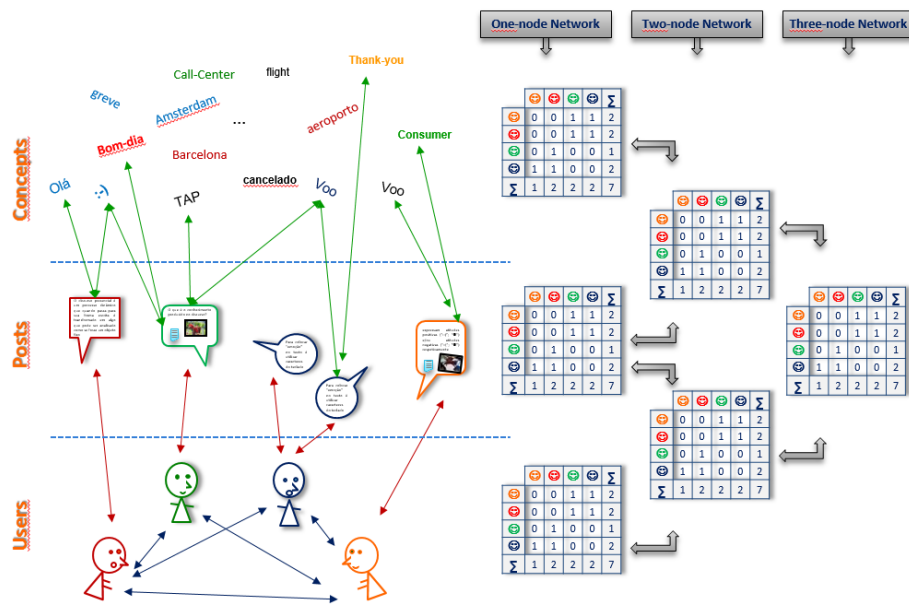


Figure 1: Levels of web discourse

4. The Study

Traditional channels like call centers, e-mail, Skype and service counters, continue to be the preferred interaction channels for a TAP customer. However, channels such as social networks are being increasingly used when there is no response through traditional channels. The 10-day strike was chaotic for TAP and many customers used Facebook in order to make a complaint, know about the cancellation (or not) of a flight, cancel a reservation, etc.

The specific objectives of this study are to analyze the data generated by customers' interaction, within the 10 days strike of TAP, in order to understand if it is possible to structure data, from web communication within its Facebook social network. To check service/responsiveness of TAP to customers in the days of strike through Facebook communication channel. To develop indicators to review and/or fortify strategies in customer service on a strike situation, using SNA methodology. This is only possible with the aid of SNA software as Nodexl (Hansen, Shneiderman, & Smith, 2011) and Gephi (Bastianand, Heymann, & Jacomy, 2009).

5. Facebook data extraction

Data extraction was made by using NodeXL. However, the data gathering had some limitations. Data were collected periodically (every two days), due to software limitations and data processing capacity. Thus, there are 5 data sets. Only one type of network ("User->Users") is allowed when collecting data. So for each dataset, we created two more networks. One to identify the most relevant posts and another to identify the concepts that are used the most. These two networks were semi-automatically built, using Microsoft Excel. At the end we had 5 data sets to construct 5 networks. Each networks was composed by three sub-networks:

- Users -> Users;
- Users -> Posts;
- Posts -> Concepts (semantic network).

Data collected and processed were treated in Gephi because it responds to the needs of graphic studies using graphical user interface (GUI) and is open source. Gephi allows visualization and simple manipulation of networks, processing most of the significant social network analysis metrics. Afterwards, we applied SNA techniques over the collected data in order to study the network. With SNA metrics you can identify the most relevant social actors, classify them according to their relevance within a community, show and describe results of sub-communities.

According to text mining literature (Feldman and Sanger, 2007; Markov and Larose, 2007; Russell, 2013), there are concepts pertaining to the natural language that can be discarded when treating and recovering information because they have no great significance. The reason why they should be removed relates to the fact that the simplification of the text just turns it easier to analyze. The most common concepts to withdraw are, among others, the ones that do not add meaning to the text: prepositions (because they express relations between two parts of a sentence), conjunctions (because they establish the connection between two or more elements and do not play syntactic functions in the sentence to which they belong), definite articles (because aim to individualize or highlight something) and indefinite articles (because they have the objective of determining vaguely something). These concepts are called “noise words” and consequently were eliminated from the posts, because they are not considered keywords in text mining.

After cleaning those “noise words” from the 769 posts, 20.438 concepts have been identified that formed the basis for construction of the matrix that connects and identifies which concepts exist in each post. For the purpose of analysis we considered as concepts the ellipsis (“...”), smiles (“:”) and question mark (“?”) identified in the discursive exchanges. In comparison with each data set, as shown in Table 1, day 1 and 2 had the highest number of users (394), day 5 and 6 had the highest number of posts and concepts (201 posts and concepts).

Table 1: Type and number of nodes in each data set

Data Sets	Users	Post	Concepts
01 and 02 May-15	394	189	4 818
03 and 04 May-15	216	143	4 236
05 and 06 May-15	315	201	5 458
07 and 08 May-15	168	144	3 500
09 and 10 May-15	159	92	2 426
Total	1.252	769	20.438

For each data set, we selected the posts containing text and created: The network “Users -> Posts” and a “semantic network”. The resulting data set, consisting of 769 posts, was treated semi-automatically with Excel, in order to obtain data that were imported into Gephi. Taking into account that keywords can be considered as a summary of the posts text, the **semantic network** was created with all identified concepts and respective post.

The posts were written in 7 different languages (**Language: DE:** German; **ES:** Spanish; **FR:** French; **IT:** Italian; **NL:** Dutch; **PT:** Portuguese; **UK:** English). Portuguese and English were the languages more commonly used, as shown in Table 2.

Os dados das redes sociais por norma não estão num formato adequado para extração de informação, assim foi necessário a aplicação de métodos para extração e integração, transformação, limpeza, seleção e redução do volume dos dados, antes da etapa de mineração. A extração e integração envolveu a recolha dos posts, formando 5 conjuntos de dados. A transformação permitiu ajustar os dados para serem utilizados na de extração de palavras-chave. Como os dados podem apresentar incoerencias, tais como erros de escrita, etc., foram necessarias técnicas de limpeza, no sentido de garantir a qualidade dos mesmos. Esse processo foi também utilizado para remover valores inválidos de determinados atributos ou uniformizar alguns tipos de dados (por exemplo datas, horas, número dos voos, designação dos aeroportos).

A standardization of the concepts (designation of airports, dates, times, etc.) had to be made. A “words bag” with the “noise words” for each language was created.

Table 2: % of languages found in the collected posts for each data set

Data Sets	DE	ES	FR	IT	NL	PT	UK	Total Concepts
01 and 02 May-15		2%	3%			76%	19%	4818
03 and 04 May-15		3%	11%			52%	34%	4236
05 and 06 May-15	1%	4%	7%	0%		51%	38%	5458

07 and 08 May-15	0%	2%	4%	0%	1%	55%	38%	3500
09 and 10 May-15	3%	1%	11%	2%		54%	29%	2426
Total	1%	2%	7%	0%	0%	58%	32%	20.438

6. Results

After the construction of the **five networks** (one for each data set) we used SNA to analyze the structure of the networks and the interactions between the three entities. For this purpose, as mentioned above, we used Gephi.

A SNA é um método poderoso para representação gráfica das relações existentes entre os diferentes conceitos (palavras) ou outros símbolos textuais existentes no discurso web. As redes são amplamente utilizadas na análise de conteúdo ou de mineração de texto para estruturar e compreender um texto. Estudos recentes utilizam abordagens baseadas em rede para construção de redes semânticas, criação de resumos semânticos de documentos, analisar o feedback do cliente, ou ainda a analisar respostas de texto livre (Aggarwal, 2011; Elo, 2015; Freire, Antunes, & Costa, 2015; Moser et al., 2013).

Para análise e visualização dos dados recolhidos foi utilizado o Gephi. Combinamos dois algoritmos de agrupamento e layout para criar as representações das diferentes redes, e as poder comparar entre si, como mostra a Seção 5. O layout utilizado para a criação dos gráficos foi baseado no algoritmo Força Atlas2 (Jacomy, Venturini, Heymann, & Bastian, 2014) e Fruchterman and Reingold (Fruchterman & Reingold, 1991). O primeiro empurrar os nós mais ligados entre si para longe uns dos outros (para destacar visualmente as diferentes comunidades) e os nós ligados entre si ficam aglomerados em torno do nó principal (Hub). A combinação destes dois algoritmos ajudar na interpretação dos dados.

A maior parte das informações utilizadas pelas empresas para a tomada de decisão vem de reuniões e relatórios internos. Analisar as redes sociais através da SNA, para “Ouvir” diretamente os clientes, permite responder de forma rápida e tomar decisões críticas em situações de crise.

6.1. Three mode Network: Users -> Posts -> Concepts

The Table 3 and the Figure 2, 3, 4, 5 and 6 show the results obtained for all 5 analysed networks. We use Modularity Class algorithm to identify communities in the network. With the centrality metrics we tried to perceive who or were the most important social actors and how they positioned themselves in the network. The graphs show that:

- All the 5 networks have a different structure;
- The first network (Figure 2) evidences two clusters that are isolated from other members of the network;
- Network 2, 3 and 4 (Figure 3, 4, 5, respectively), are the most dense;
- In networks 5 (Figure 6) we can view multiple cluster of smaller dimensions.

This indicates that we have some social actors more active in the network than others, and identifies who they are and how important they are.

Table 3: Nodes and Edges of Three mode Network

Data Sets	Nodes	Edges
01 and 02 de May-15	2.626	9.223
03 and 04 de May-15	2.324	4.416
05 and 06 de May-15	2.944	7.107
07 and 08 de May-15	1.892	3.763
09 and 10 de May-15	1.566	3.010

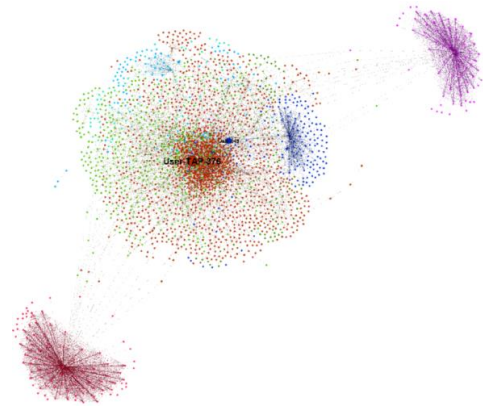


Figure 2: Day 1 and 2-May-2015

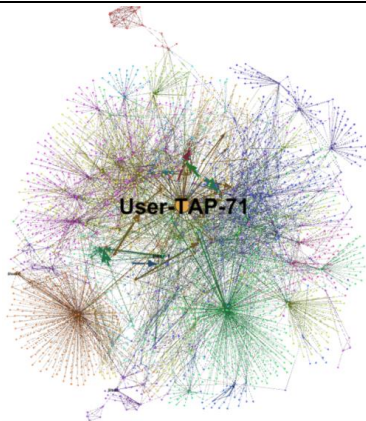


Figure 3: Day 3 and 4-May-2015

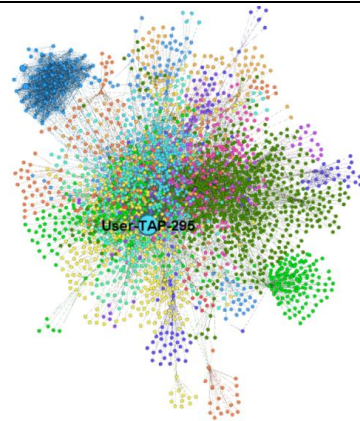


Figure 4: Day 5 and 6-May-2015

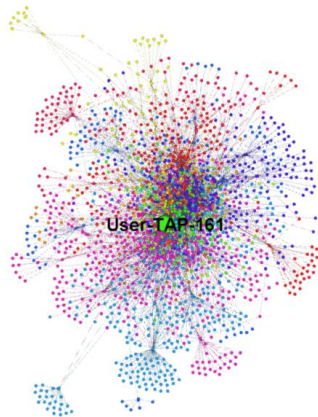


Figure 5: Day 7 and 8-May-2015

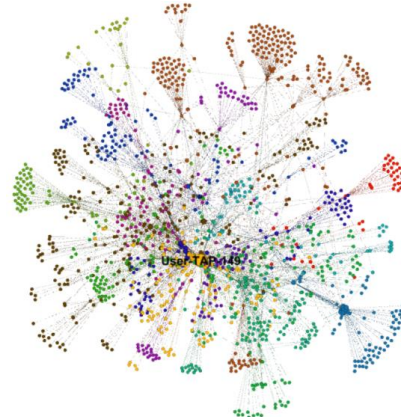


Figure 6: Day 9 and 10-May-2015

6.2. Two mode Network: Users -> Posts

With SNA we can “Zoom” on the most relevant social actors, in terms of its structural position in the network, and in terms their posts content. To check the responsiveness of the questions put by customers on TAP Facebook we used the following metrics:

- In-Degree - We considered that this metric is the number of contacts that User TAP received. This concept means how other actors send information or maintain ties with a particular actor, what clearly shows the importance of this actor’s posts. The fact that these posts are extensively commented or displayed might ascertain their significance;
- Out-Degree - We considered that this metric is the number of responses given by the User (responsiveness). This concept is usually a measure of how influential the actor can be inside the network, which substantiates the activity that the actor has to respond to others.

So, when we look at the interactions between users and posts it is possible to perceive the nodes that are isolated, they didn’t receive responses from TAP. For network 1 (Figure 7) and in a deeper

analysis we verified that the red post is not a complaint or a request for information. From the point of view of TAP, identifying these posts may be important (even if the only purpose could be to eliminate them). Nodes that have an established connection (link) with TAP are the posts that were answered by the operator. The Figure 7, 8, 9, 10 and 11 show that TAP, in the 10 day of the strike, answered many questions on Facebook.

Table 4: Nodes and Edges of Two mode Network (“Users -> Posts”)

Data Sets	Nodes	Edges
01 and 02 de May-15	583	189
03 and 04 de May-15	359	143
05 and 06 de May-15	516	201
07 and 08 de May-15	312	144
09 and 10 de May-15	251	92

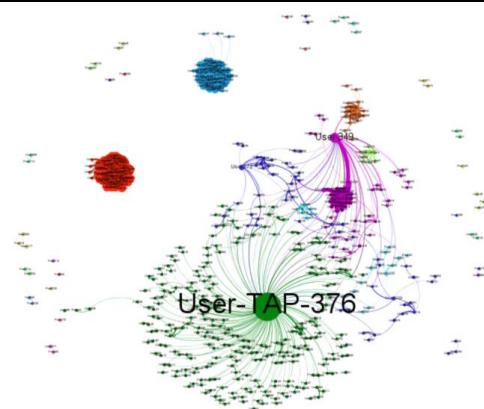


Figure 7: Day 1 and 2-May-2015

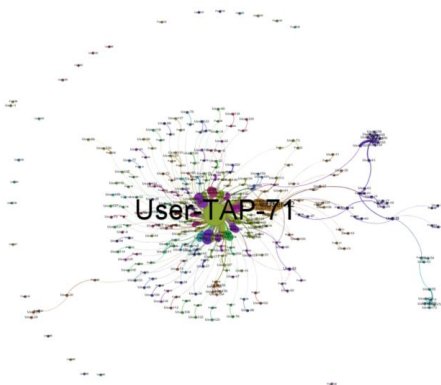


Figure 8: Day 3 and 4-May-2015

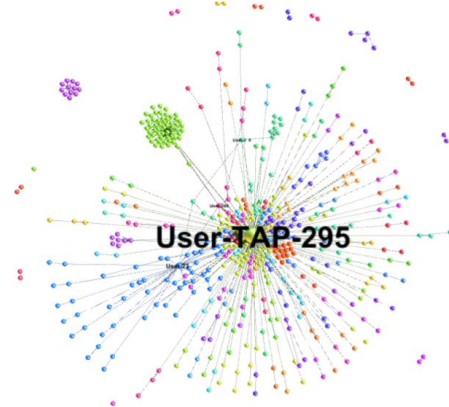


Figure 9: Day 5 and 6-May-2015

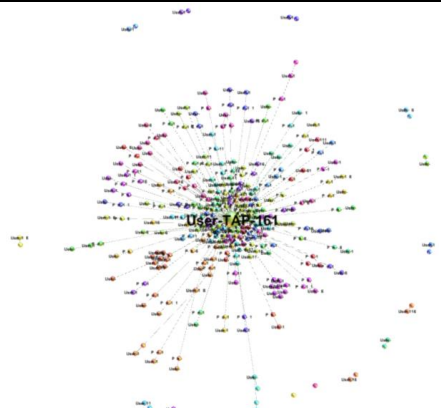


Figure 10: Day 7 and 8-May-2015

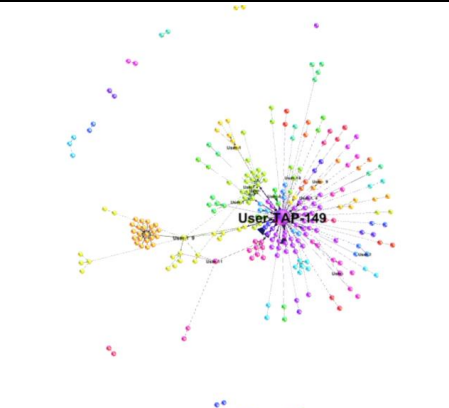


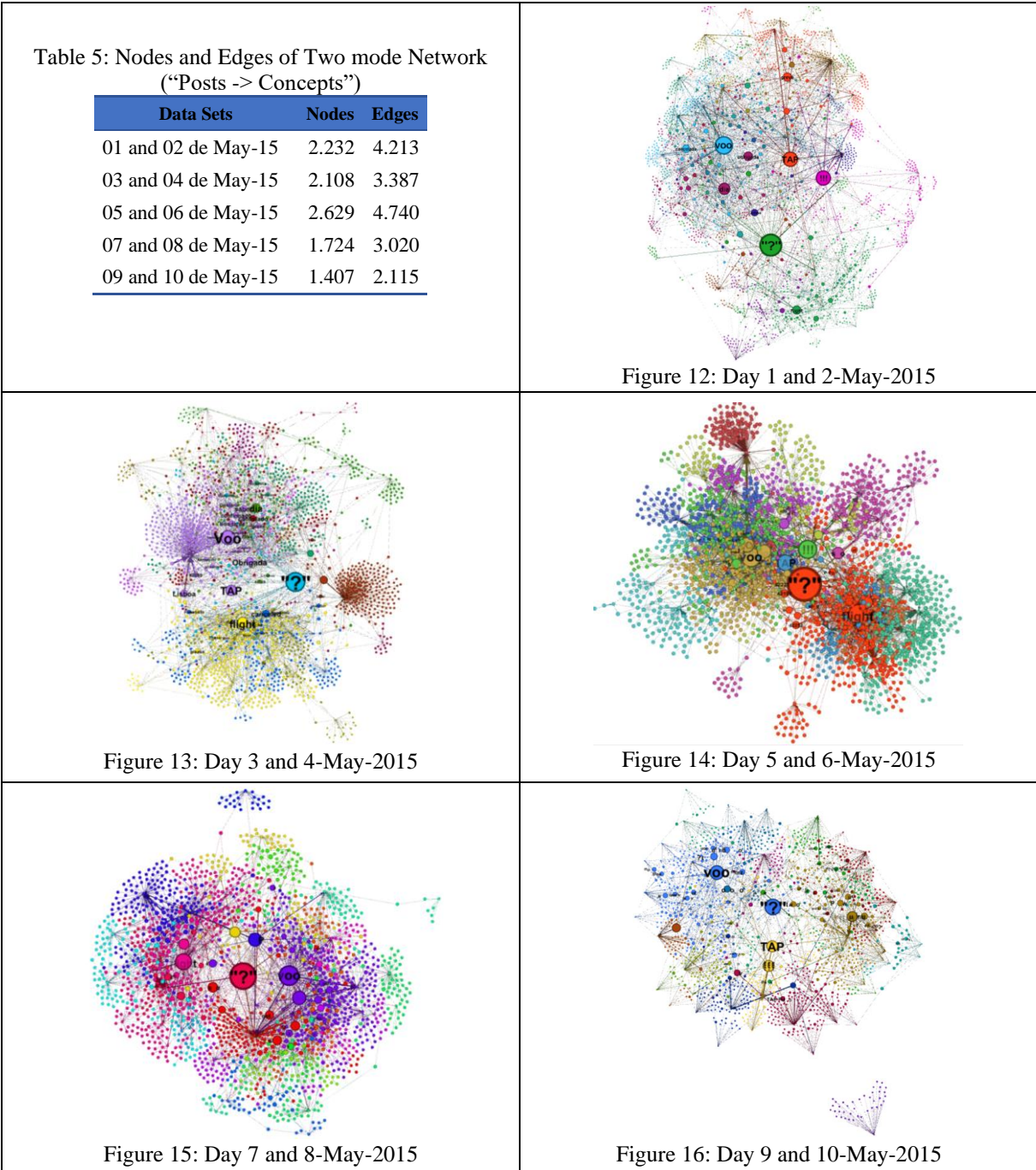
Figure 11: Day 9 and 10-May-2015

6.3. Two mode Network: Posts -> Concepts (out-degree)

Based on the constructed matrix, two tables (one for the posts and another for the concepts) to the five data sets were extracted, that served as Gephi input and semantic network implementation. The number of each nodes and links between them (Edges) for each network as show in Table 5. To Rubin and Babbie (2011), content analysis is a way to transform qualitative into quantitative data that can be applied to almost any type of communication being mainly composed by the coding of occurrences on the communicated content. The content analysis can be viewed as a process where

what is contained in the web discourse message is the base from which to draw conclusions and make inferences about it.

Taking into account that keywords can be considered as a summary of the posts text, the semantic network was created with all identified concepts and respective post. Keywords extraction is an important technique to identify the most relevant concepts used in posts. Thus, using the data collected, we selected posts containing text and built up a semantic network for each data set (network “Posts -> Concepts”). The resulting data set, consisting of 769 posts, was treated semi automatically with Excel in order to obtain data that were imported into Gephi. Gephi allows visualization and simple manipulation of networks, processing most of the significant social network analysis metrics. Afterwards, we applied SNA techniques over the collected data in order to study the network.



This 5 Networks show in Figure 12, 13, 14, 15 and 16 consists of all the concepts and identified posts (for each data set). With a semi automated textual analysis it's possible to extract a list of

commonly used keywords and rank them. Through Modularity Class algorithm all concepts belonging to the same post were added so as to be seen as a community.

Uma rede de palavras-chave incorpora informação relevante sobre a sua estrutura e as relações que estão subjacentes entre os posts e conceitos. Apesar de duas redes de palavras poderem parecer muito semelhante, através da SNA é possível evidenciar os desvios significativos das métricas. A SNA oferece métricas robustas que capturaram as diferenças escondidas, mas que são importantes.

In the Figure 17 there are the most commonly used concepts in each data set. To identify them we used the out-degree metric. It was found that the question mark, the exclamation mark and the ellipsis (although not concepts, Words) they were widely used. This is justified because, according to literature, social actors use abbreviations, symbols, images etc. to communicate quicker and express some emotions. The production direction of communication, comprising this language, is achieved through insertion and linkage of some (or all) of these resources within the web discourse.

01 and 02 May-15		03 and 04 May-15		05 and 06 May-15		07 and 08 May-15		09 and 10 May-15	
Top 20 concepts	Out-Degree	Top 20 - concepts	Out-Degree	Top 20 - concepts	Out-Degree	Top 20 - concepts	Out-Degree	Top 20 - concepts	Out-Degree
"?"	97	"?"	80	"?"	112	"?"	74	"?"	37
voo	77	voo	58	voo	61	voo	54	voo	32
TAP	63	TAP	41	flight	61	flight	43	TAP	25
!!!	63	flight	40	!!!	56	dia	35	!!!	25
dia	48	dia	33	TAP	48	TAP	34	flight	22
obrigada	36	obrigada	27	dia	43	cancelado	25	dia	18
greve	34	!!!	27	obrigada	40	!!!	25	obrigada	14
flight	34	Lisboa	24	Lisboa	31	Lisboa	23	aeroporto	13
cancelado	30	cancelado	23	cancelado	31	saber	21	cancelado	13
Lisboa	26	saber	21	greve	26	obrigada	21	greve	12
...	22	...	21	saber	24	Gostaria	19	Please	11
voucher	21	cancelado	19	...	21	Thank-you	17	cancelado	11
muito	20	confirmado	17	Thank-you	19	cancelado	16	Lisboa	10
Empresa	19	Boa-tarde	16	cancelado	19	09/05/2015	16	back	10
Thank-you	18	greve	14	Bom-dia	19	e-mail	15	...	10
reserva	18	Gostaria	13	08/05/2015	18	Please	14	Bom-dia	10
piloto	17	04/05/2015	13	07/05/2015	17	viagem	14	saber	9
serviço	16	Please	12	09/05/2015	16	Boa-tarde	14	10/05/2015	9
saber	16	RESPOSTA	11	Please	15	Bom-dia	14	Thank-you	8
Please	16	Day	11	TAP-Portugal	14	possível	13	website	8
Posts = 189		Posts = 143		Posts = 201		Posts = 144		Posts = 92	

Figure 17: Indicators: Top 20 Concepts used for each data set

7. Final remarks

Information technologies continue to offer opportunities to change the way decisions are made, either individually or at the organizational level. Social networks and technologies based on the Web 2.0/3.0 can help in this paradigm shift, because when combined they create insight to support decision-making. Thus, it is important to look at the content produced by social actors, in particular for the web discourse because the speech structure allows a better understanding of the expressed views, as well as a logical sequence of the discussion itself. However, these contents are difficult to automatically “translate”, efficiently and effectively, because the discourse is a distinct way of speaking, or write, and understand the world.

Em termos gerais, este trabalho teve dois objetivos. Primeiro, partindo da premissa de que palavras-chave são uma importante fonte de conhecimento, podem fornecer informação sobre a estrutura de conteúdo do discurso. Em segundo lugar, a SNA oferece métodos adequado para que a análise de redes revele informações importantes sobre as relações existentes dentro das mesmas.

By analyzing the content of the posts we perceived that they could be categorized (Figure 17). Categorizing posts provide the means to better focus/create task groups to address cases of complaints, requests for help/support in changing a reservation, requests for information (about hotel, luggage collection, refund procedures, etc.). Visualization and identification of keywords could have been used to reinforce the need for delivering permanent information (for instance through online channels

or service counters) on: whether a flight needed to be canceled or not; the list of canceled or available flights; how to reschedule/change the date of a flight.

In the analyzed posts many customers complained that the call center did not answer calls, they had no response to e-mails sent, airports with service counters (personal assistance) were closed and TAP website didn't have any information about the strike. Visualization allows to identify relevant conversations and provides direct and immediate insights about the customers' feelings and also can allow faster reactions to whether or not client dissatisfaction sentiment is being developed or aggravated; The analysis and web speech visualization can help TAP to identify potential service problems in traditional channels (call centers, e-mail, etc.) and address them more quickly in order to prevent future service breakdowns due to strike situations.

The calculation of different SNA metrics and the analysis of multiple networks allowed a richer, more structured view of those involved in discourse, as well as the most used concepts. The analysis and visualization of concepts used in web discourse can be used as insights for follow-up decisions, as it allows efficient access to key information. The obtained results provides information on the key terms used during the discursive exchanges and can be used to analyze various alternatives of a problem and to support decision making.

Capturing and realizing everything that circulates within web discourse can be very important for organizations. The exchanges (of opinion and information) originated in social networks are performed using computer-mediated communication. This contemporary reality requires that individuals within organizations develop new skills, particularly in terms of decision-making within the social web, by incorporating enhanced mechanisms of interaction, because its use is much more than a simple trend. By combining social networking, visualization tools and SNA, businesses can monitor the most relevant online conversations in real time, identify problems and extract indicators for decision support to improve customer service.

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