Analysing discussions in social networks using group decision making methods and sentiment analysis

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Abstract

Social networks are one of the most preferred environments for people to carry out debates. Due to the fact that a high amount of people can participate in the process, there is a need of tools that can analyse these discussions and extract useful information from them. In this paper, a novel way of determining how the debate is going on, if there is consensus among the participants and which alternatives are preferred is presented. Sentiment analysis is used in order to measure the level of preference that social media users have about a certain set of alternatives. In order to test the presented scheme, a real application example that makes use of Twitter information is presented.

Keywords: Group decision making, Social networks, consensus measures, sentiment analysis

1. Introduction

Discussions are the main tool used by humans to make decisions. If the decision involves a set of people or several points of view need to be considered, it is usually a process that is made in groups. Group decision making

[7, 21] is a process that is clearly present in our everyday life. Before Internet occupied an important part of our lives, it was necessary to gather together in a specific place, discuss the issue and reach a solution. Nevertheless, thanks to Internet and Web 2.0 [1, 12], experts can now connect and debate independently of where they are located. They can perform this activity on different Internet platforms, but, there is no doubt that social networks are the most preferred one for experts to debate an communicate among themselves. This paradigm change presents several challenges that novel group decision making methods could overcome. In this paper, the following both challenges are covered:

- **The quantity of information and the number of experts are increased**: In social networks [14], there is room for every participant and every opinion. Therefore, there is a need for group decision making methods to process high amount of opinions that large groups of experts could provide. Before Web 2.0, only few experts participated in each group decision making process but now, situation has completely changed. In the developed method, an information retrieval process made over the social network stored information is carried out in order to take into account all users opinion about a certain alternative in a certain moment. The exponential increase in group decision making participants also makes difficult to apply traditional consensus measuring. Nevertheless, the consensus information is extremely useful in this cases since it allows us to know which are the preferred alternatives and the percentage of participants that support them. Therefore, there is a need of tools that are capable of determining the level of agreement among the experts. In order to overcome this issue, a novel way of calculating the consensus value in this kind of environments is presented.

- **Experts express their opinions in free text**: In traditional group decision making methods, experts are clearly asked to provide a specific opinion value to the system [4, 6, 24]. Nevertheless, in social networks, experts participate by providing a medium size text where they specify their opinions. This can become a problem since this kind of texts are hardly recognized by a computer. Therefore, there is a need of tools that allow the computer system to transform the provided text into a preference value that can be used for the required computations. One way of solving this issue, is to use sentiment analysis techniques [8, 27].

In such a way, it is possible to obtain a measure of the user feeling. Then, we can determine the preference value that a certain alternative has for him/her.

In this article, we present a novel method that allows us to extract useful information about the debates that are carried out in a social network. By combining sentiment analysis techniques with group decision making and consensus models, it is possible to analyse in an organized and reliable manner the outcome of the debate and the consensus that has emerged in it. In a normal social network debate, it is possible to identify a set of people that argue about a certain number of alternatives and try to sort them from best to worst. Therefore, it is possible to follow a group decision making scheme in order to manage the discussion framework that is carried out in a social network. Instead of directly provide their preferences, we assume that users make use of a short free text where they specify their opinions about a certain topic or alternative in a social network. This is even more frequent in social networks such as Twitter, where users have a limited character size to express their opinion. Thanks to sentiment analysis, it is possible to determine the level of acceptance that an expert has about a certain alternative and obtain a preference value that can be used for group decision making purposes.

The article is structured as follows. In section 2, basis needed to comprehend the presented method are exposed. In section 3, the novel developed process structure is defined. In section 4, an application example using Twitter is presented. In section 5, advantages, drawbacks and applications of the method are presented. Finally, in section 6, some conclusions are pointed out.

2. Preliminaries

To make this paper as self-contained as possible, this section is introducing concepts and methods to be referred to thorough this paper. In subsection 2.1, basis of Group Decision Making methods are exposed. Finally, in subsection 2.2, sentiment analysis procedure is introduced.

2.1. Group Decision Making

Group Decision Making is a field that has been present in the literature since the late 80's [2] until nowadays [13, 15, 19, 25, 29]. Generally, a typical group decision making problem can be formally defined as follows. Let

$E = \{e_1, \dots, e_n\}$ be a set of experts and $X = \{x_1, \dots, x_m\}$ a set of alternatives. A group decision making problem tries to sort X using the preferences values P^k, $\forall k \in [1, n]$, provided by the experts.

Usually, in order to solve the formulated problem, the next steps are followed [9]:

- **Providing preferences step:** Experts are asked to provide their preferences about a certain set of alternatives.
- **Aggregation step:** All experts preferences are aggregated into a single collective preference piece of information. These pieces of information represent the overall opinion for all the experts.
- **Selection step:** Using the collective preference piece of information, alternatives are ranked according to the level of preference provided by the experts.
- **Consensus calculation [3, 23]:** Calculating consensus measures can help us to know if the experts have reached an agreement or, on the contrary, they need more debate in order to reach a reasonable level of consensus. It is important, in order to improve the reliability of the decision making results, to allow experts to carry out a thorough debate before reaching a final decision. Therefore, if the consensus is lower than expected, it is possible to ask the experts to carry out more debate and modify their preferences. Usually, a maximum number of rounds is also established in case the experts do not reach a consensus in a reasonable period of time.

In Figure 1, a graphical representation of this process is shown.

2.2. Sentiment analysis

User-computer communication is complicated problem to handle. The way that computers deal with the information is completely different from how humans do it. Computers are used to deal with objective data that can be represented numerically since they need that representation in order to operate. On the contrary, humans are more used to express themselves using concepts and imprecise information. Therefore, there is a communication gap that must be reduced. In order to carry out this process there are

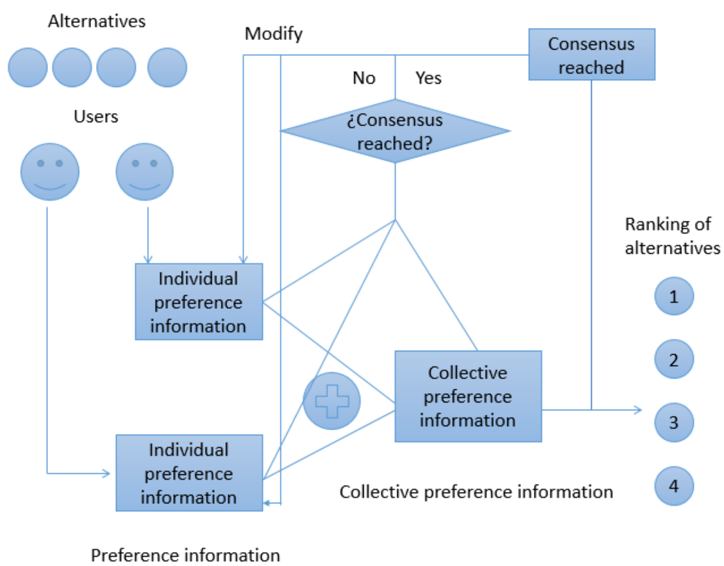

Figure 1: Group Decision Making general scheme.

several tools in the literature. For instance, when using linguistic modelling [18, 30, 31, 32], experts can express their preferences to the system in a linguistic manner. Nevertheless, this implementation has the drawback of only allowing a fixed number of terms.

In real world and, specifically, in the Internet and the social networks, users are use to express themselves using free natural text. It is, indeed, a matter of fact, that there are tons of information in the Internet that use this representation. Therefore, there is a need of tools that are capable to allow computers to analyse and extract useful information from the data. In the case of our developed method, it is interesting to know how experts feel about a certain alternative and transform the free text that they use into a measure that the computer can deal with. In order to carry out this process, sentiment analysis [5, 22] can be used.

Sentiment analysis tries to provide a measure to how a specific person feel about an specific topic by analysing the words that he/she uses to describe and discuss about the topic. For instance, if a user is using words such as *happy*, *good* and *interesting* when discussing a certain topic, it is clear that the user feels positive about it. On the contrary, if he/she is using words such as *bad*, *horrible* and *disgusting*, then it can be assured that the user has a negative opinion about the topic. According to the kind of sentiment that want to be tested, several specific lists of words are used.

Generally, in order to carry out a sentiment analysis over an specific text, the following steps can be followed:

- **Selecting the kind of sentiment that want to be measured:** Sentiment analysis provides a measure for an specific sentiment. Example of sentiments can be happiness, rage, sadness, ... Therefore, the first step is to select the set of sentiments that need to be identified from the texts.

- **Creating a list of words**: For each sentiment that need to be analysed, a list of words that are typically used when expressing it must be created.

- **Carrying out the text analysis**: All the words from the text are compared with the word lists created in the previous step. The more words from the list appearing in the text, the most probable is that the user was experiencing the feeling that is being tested when he/she wrote the text.

- **Presenting results:** Sentiment analysis results are presented. Depending on the length of the texts that are being used, it is possible to establish a threshold. This way, if the number of words that appeared in the list surpasses it, then, the sentiment was present in the users when they wrote the text. On the contrary, if the number of words are below, it is considered that the user was not feeling the specified sentiment.

In Figure 2, a graphical scheme of the process is shown.

Sentiment analysis is a field that is present in the recent literature. For instance, in [20] and [26], sentiment analysis is used in order to evaluate short texts coming from Twitter and other resources. On [28], several multimodal sentiment analysis methods are reviewed. Finally, in [16], sentiment analysis is applied in movie reviews.

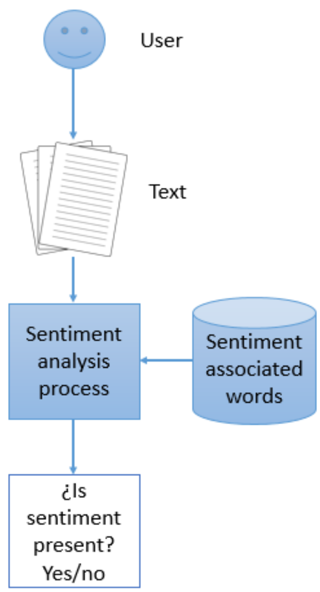

Figure 2: Sentiment analysis general scheme.

3. A Group Decision Making method to analyze social network discussions

In this section, the novel developed method is described in detail. Thanks to sentiment analysis, our method is able to determine how each expert feels about a certain alternative. Afterwards, a preference value is assigned according to it and, finally, the group decision making process and consensus measures calculations can be carried out. Broadly, the novel developed method follows the next steps in order to carry out the discussion analysis:

- **Decision making process definition**: The first step consists in defining the group decision making process required parameters. This include the alternatives description and, as optional, a list of experts. Other optional parameters such as a consensus threshold value can be defined and included.

- **Extracting natural text from social networks**: Once that the alternatives have been defined, it is necessary to extract experts entries from the social network. Only texts referring to the group decision making defined alternatives are needed.

- **Extracting Individual preferences**: Experts entries associated to each alternative are analysed in order to determine the feelings of each expert about the alternative. A specific preference value is assigned to it.

- **Calculating collective preferences aggregation**: Preference values are aggregated in order to calculate an specific collective preference value for each alternative.

- **Ranking alternatives**: Using the collective preference values for each alternative, they are sorted. This way, it is possible to determine the most preferred alternatives for the social network community or for a subset of community members.

- **Calculating consensus values**: Collective values can help us to determine the level of consensus of the discussion. This is very helpful since it allows us to determine if people of the network community have a common opinion or if there are several irreconcilable positions.

All of these steps are commented in more detail in the following subsections.

3.1. Group Decision Making process definition

First of all, it is necessary to define the type of analysis that it should be carried out. For this purpose, it is important to focus on the following aspects:

- **Alternatives definition**: The purpose of the analysis proposed in this paper, as it has been stated in subsection 2.1, is to know how a set of experts participating in a social network feel about a certain set of alternatives. First of all, it is necessary to define the set of alternatives that will be part of the ranking that the method will obtain for us. Each of the alternatives, $X = \{x_1, \ldots, x_n\}$ need an associated keyword, $K = \{k_1, \ldots, k_n\}$ formed by words that unequivocally allow us to find texts that contain opinions about the alternative. For instance, if several singers want to be ranked based on the opinions of social networks users, the keyword association shown on Table 1 could be used.

- **Experts definition**: Depending on our needs, experts set can be defined using one of the following two options:

Alternative	Keywords
Calvin Harris	Calvin Harris
Ed Sheeran	Sheeran
Justin Bieber	Bieber
Imagine Dragons	Imagine Dragons

Table 1: Keyword association example.

  - **Fixed set of experts:** This option restricts the number of experts that participate in the discussion analysis. In order to do this, a finite set of experts, $E = \{e_1, \ldots, e_m\}$ is defined. Only texts belonging to the experts from the set will be used for the text extraction step. It is a good option to choose when the discussion that we are trying to analyse is focused on an specific set of experts or when only a predefined set of experts opinions matter.
  - **Open set of experts:** There are cases where there is no need to create any restriction on the set of experts that participates in the discussion. In this case, any opinion on the dealt topic made by any social network user is acceptable. In this case, a global search in performed over the social network and every text is retrieved without establishing any restriction on the person who wrote it.

  From now on, due to its generality, we will choose by default the second option.

- **Consensus threshold definition**: One important part of the discussion analysis that is being performed is the consensus measuring. An specific consensus threshold can be establish in a way that, if the reached consensus is higher, then it can be considered that social networks users have a similar opinion. On the contrary, if the consensus is lower, then it can be stated that there is a certain polemic associated to the alternative ranking results.

Once that the analysis parameters have been defined, the required information can be obtained from the social networks.

3.2. Extracting natural text from social networks

Once that X, K and E have been defined, data must be extracted from the selected information source. Although, according to the structure that we are defining, the most common source of information should be a social network, the method is able to work with any text coming from any source. In case that the set of experts had been predefined before carrying out the retrieval, only texts coming from the specified users should be used. On the contrary, if the set of experts remains empty at this point, any text from the social network can be used.

It is common for social networks users to use posts in order to express some preference or provide their feelings about an specific topic. Therefore, this is a reliable source for extracting the required information. Among all the available social networks, Twitter stands out due to the following reasons:

- **Short texts:** Twitter only allows the user to introduce 140 characters in each post. Therefore, users that use this social network need to be very specific and precise in their posts when providing opinions. Thanks to this, it is easier for the sentiment analysis methods to carry out the required word analysis.

- **Typically used for providing opinions:** Twitter is one of the most preferred social networks when carrying out discussions and debates. It also promotes public profiles making it not the best option when using it for friends communication. Therefore, it is more used to provide opinions about matters that affect worldwide population than for private peer to peer communication. This fact makes it a good option for the method that is being designed.

- **Widely used:** Twitter is worldwide known and one of the most used and active networks. Therefore, it generates tons of information every second. This makes Twitter a good source of information about any topic that we need to deal with.

Because all of this, Twitter is the social network that we have selected to carry out the illustrative example in section 4. Twitter provides an API that allow us to carry out searches among all social network users posts. This is the mean that has been selected for extracting information in the illustrative example section. Nevertheless, as it has been stated, any text coming from any source can be used for extracting the data. In order to carry out the searches, K set is used.

Once that the data, $T = \{t_{11}, \ldots, t_{nm}\}$, has been extracted, each text is associated with an specific alternative and expert. For instance, t_{ij} is the associated text from expert i that refers to alternative j. Each piece of information t_{ij} is a text written in free natural language. Therefore, there is a need to transform each t_{ij} into a value that the system can use for carrying out operations. For this purpose, sentiment analysis is applied in the extracting individual preferences step. It is important to notice that the number of experts involved in the discussion is not known until the social network search is made. This, of course, does not occur if a fixed set of experts is used before carrying out the text extraction.

3.3. Extracting individual preferences

As it has been stated, computers and algorithms are used to work using precise information. Nevertheless, humans are more used to express themselves using natural text and imprecise and conceptual information. At this point, social networks users preferences are a collection of free texts that cannot be processed by any computational system. In order to solve this problem, it is necessary to transform the information in a way that the system can understand and consume.

In order to transform natural text into a adequate representation for the system, a sentiment analysis procedure is applied. Since the text analysis that is required need to determine whether the experts have positive or negative feelings about a certain alternative, two word lists [11] are used:

- **Positive words list**: This list stores words that are typically related with positive feelings. The use of words belonging to it implies that social network users agree and support the alternative that they are commenting.

- **Negative words list**: This list stores words that people usually use when they dislike or are against some issue. Finding words in this list related to the alternative that is being discussed means that the user does not support it.

It is important to notice that the word lists can be modified in order to search for more specific feelings or apply the method with another perspective. For instance, it is possible to define several positive word lists where each of them represent an specific positive feeling. The same can be done with different types of negative feelings. Afterwards, a weighted aggregation operator can be applied in order to calculate an unique value that represents the level of positiveness or negativeness of the social network user. This way, it is possible to provide more importance to an specific sentiment. For instance, it would be possible to emphasize hatred to sadness in the negative value calculation.

When providing the same importance to each of the feelings, having two word list that represents positive and negative feelings respectively is enough.

The process followed by our method in order to extract the individual preference value, p_{ij} for each t_{ij} is described below:

1. **Searching for positive words**: Every word of t_{ij} is searched in the positive words list. The number of matches, $pwcount_{ij}$ is stored. It represents the number of positive words that the social network user i has used for describing alternative j.
2. **Searching for negative words**: The same step is performed for negative words. The number of matches with this list, $nwcount_{ij}$ represents the number of negative words that the social network user i has used for describing alternative j.
3. **Calculating the individual preference value**: The following expression is used for calculating the individual preference value for the user:
$$p_{ij} = \frac{pwcount_{ij} - nwcount_{ij}}{pwcount_{ij} + nwcount_{ij}} \tag{1}$$
It is important to notice that we divide by the total number of words in order to make the obtained value independent of the number of words used for carrying out the description. This way, it is possible to compare the level of agreement of two users by simply comparing their p_{ij} values. The comparison does not take into account the longitude of their texts.

The individual preference value is able to represent in one numerical value the preference level that one expert has for one specific alternative. Nevertheless, it is also useful to maintain the amount of positive and negative words since it gives us an idea whether the user finds something positive about the alternative or he/she totally dislike the alternative that he/she is describing.

The calculated values are in the $[-1, 1]$ range where -1 indicates that he/she totally hates the alternative, 1 indicates that he/she totally likes the alternative and 0 means that the expert neither likes or dislike it.

3.4. Calculating collective preferences aggregation

Once that all the p_{ij} values have been calculated, they are aggregated in order to know, for each alternative, the overall opinion of all the social networks users involved in the discussion. For this purpose, the collective preference values, $C = \{c_1, \ldots, c_n\}$, are calculated. Each c_i indicates the aggregated preference value for the alternative i. In order to calculate each c_i, the following expression can be used:

$$c_i = \phi(p_{i1}, \ldots, p_{im}) \tag{2}$$

where ϕ refers to the mean operator. Since p_ij values are located in $[-1, 1]$, the resulting collective preference values are also located in that interval. It is important to notice that c_i values allow us to compare alternatives and determine which alternatives are the most valuable and which ones are the less desired. Once that the aggregated preference values for each alternative is calculated, it is possible generate the alternatives ranking.

3.5. Ranking alternatives

Once that the c_i values are calculated, the system can determine the alternatives ranking. Alternatives from $X = \{x_1, \ldots, x_n\}$ are sort according to their associated c_i value. Since preferences are provided over the alternatives, there is no need to apply further transformations. This makes our method more computationally efficient which is a good characteristic when dealing with high amount of information.

Since ranking information is shown to the discussion analysers as a result, it is possible to apply a linguistic transformation in order to present the result using a label instead of a number. This makes the information easier to understand and consume. For this purpose, 2-tuple linguistic modelling [10, 17] can be used in order to transform a numerical value located in the the interval [-1,1] into a linguistic label that the reader can better understand.

A linguistic 2-tuple is a tuple (s, α) where:

- s is a linguistic label.
- α is called the symbolic translation and is located in the interval $[-0.5, 0.5]$.

Each linguistic 2-tuple value can be expressed numerically as a numerical value β by aggregating the label index of the used linguistic label with the α value. On the other way around, it is possible to calculate the symbolic translation using the following expression:

$$\alpha = \beta - round(\beta) \tag{3}$$

Taking into account this definition, it is possible to notice that α provides a measure of the distance from the numerical aggregated value to the closest label in the linguistic label set. In order to carry out conversions among the numerical value, β to the 2-tuple form, (s, α), the following operator can be used:

$$\begin{aligned} &\Delta : [0, g] \rightarrow S \times [-0.5, 0.5) \\ &\Delta(\beta) = (s_i, \alpha) \ with \begin{cases} s_i & i = round(\beta) \\ \alpha = \beta - i & \alpha \in [-0.5, 0.5) \end{cases} \end{aligned} \tag{4}$$

On the contrary, (s, α) can be expressed numerically as follows:

$$\begin{aligned} &\Delta^{-1} : S \times [-0.5, 0.5) \rightarrow [0, g] \\ &\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta \end{aligned} \tag{5}$$

These transformation operations make it possible to transform any numerical result obtained in the developed method process into a linguistic label that the discussion analysers can easily understand. Since our method works with values located in the interval $[-1, 1]$, in order to express results in a linguistic way, it is necessary to define linguistic label sets that have the following structure:

$$S = \{s_{-l}, \ldots, s_0, \ldots, s_l\} \tag{6}$$

where l indicates the number of labels that are used for expressing positive or negative results.

Example. In Table 3, an application example is shown. Several alternatives have been ranked according to the c_i values. In order for the discussion

Label index	Word
s_{-3}	Totally disliked
s_{-2}	Disliked much
s_{-1}	Disliked a little
s_0	Neither like or dislike
s_1	Liked a little
s_2	Liked much
s_3	Totally liked

Table 2: S_7 linguistic label set.

Rank	Alternative	c_i	$l(c_i)$
2	Calvin Harris	0.6	Liked much
3	Ed Sheeran	-0.1	Neither like or dislike
4	Justin Bieber	-0.7	Disliked much
1	Imagine Dragons	0.9	Totally liked

Table 3: Linguistic representation of results transformation example.

analysers to better understand the results, linguistic values $l(c_i)$ have been calculated. The linguistic label set S_7 exposed in Table 2 is used for representing results in a linguistic manner. In order to calculate the $l(c_i)$ column, the transformation function (4) has been applied as follows:

$$l(c_i) = s_i \ where \ i = round(c_i * l) \tag{7}$$

where, in the case of S_7, $l = 3$. The α value of the 2-tuple is not necessary since it introduces complexity in the value representation making the information more difficult to understand for the discussion analysers. It is important to notice that omitting the α value introduces imprecision in the calculated result. Nevertheless, in this case, the introduced imprecision is affordable since it is only being used for exposing results and the ranking is made using the numerical precise representation.

For instance, for calculating the $l(c_i)$ of the first row of Table 3, the following calculation has been performed:

$$l(0.6) = round(0.6 * 3) = round(1.8) = 2 \rightarrow s_2 \tag{8}$$

As it can be observed, $l(c_i)$ values are easier to read that the c_i values that the system uses to carry out the necessary computations.

3.6. Calculating consensus values

Once that the ranking has been performed, it is possible to complete the obtained ranking results with a consensus analysis. Thanks to this, it is possible to have an idea of whether there exist consensus among the social network users or, on the contrary, there exists strong disagreements or insecurities about the dealt topic. Ranking results that are accompanied by a high consensus value indicate that the discussion has reach an agreement and, therefore, the social network users have similar opinions. On the contrary, ranking results that have a low consensus value attached indicates that the results are not reliable since the community is not sure about what they should feel about the dealt topic. According to the level of specification, there are three different consensus values that can be calculated:

- **Alternative level**: This measure refers to the agreement level that is present in an specific alternative. Since experts preferences are calculated over the alternative, it is possible to calculate the alternative level consensus using the following expression:

$$CA_i = abs(c_i) \tag{9}$$

  where abs is the absolute operator. As it can be seen, c_i values close to -1 and 1 indicate that a high amount of experts agree in their positive or negative comments. Values close to 0, on the contrary, show that it is not sure whether the alternative is liked or not and, therefore, more debate will be needed in order to reach an agreement.

- **Global discussion level**: An unique global consensus value can be assigned to the discussion if the CA_i values are aggregated into a single one. This way, if experts agree in all of the alternatives, the discussion consensus value will be high. On the contrary, if they do not agree, then the consensus value will be low. The global level of consensus can be calculated as follows:

$$C = \phi(CA_i) \tag{10}$$

  where ϕ is the mean operator.

- **Expert level**: The previous commented values are very interesting in order to have an overall idea of how the discussion is going on. Nevertheless, there are cases where it can be interesting to know if an specific expert agrees with the main flow of opinion. This is a good point to

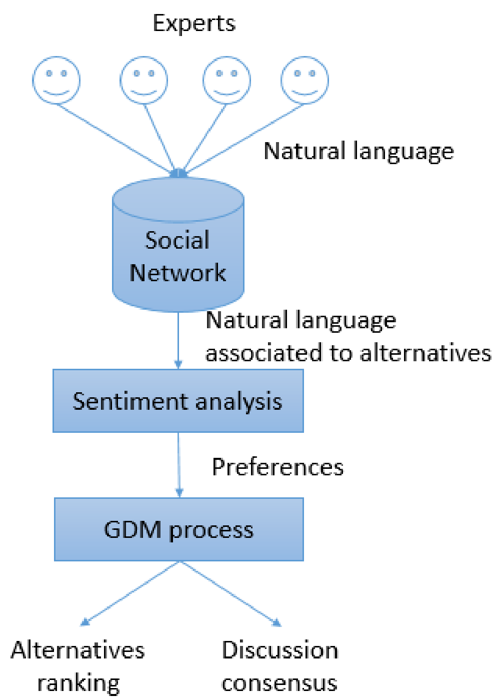

Figure 3: Developed method scheme.

take into account specially in closed discussions where the experts involved in the discussion are previously known. In open social network discussions, where thousands of experts participate, the consensus level of an specific expert does not provide critical information about the discussion. The consensus level that an expert j has for the alternative i can be calculated as follows:

$$CE_{ij} = 1 - abs(p_{ij} - c_i)/2 \quad (11)$$

As it can be seen, the closer an expert is to the global opinion, the more his/her opinion is similar to the global flow of opinion.

An overall scheme of the novel presented method can be observed in Figure 3.

4. Illustrative Example

In order to ease the comprehension of the method, a method application is performed in this section. Imagine that the discussion analysers want to determine which US politician is the most appreciated in the social networks. In order to determine it, a discussion analysis is performed taking into account the following aspects:

- **Alternatives set**: A fixed set o politicians must be determined in order to carry out the analysis. In this example, four candidates are tested: Hillary Clinton, Donald Trump, Bernie Sanders and Barack Obama. It should be noticed that there is no restriction on the number of alternatives that can be included in the alternatives set.

- **Experts set**: Since the main goal of this analysis is to determine the global opinion of all the social networks users in the Web, no restriction is applied on the experts. Therefore, any expert post is included as long as it refers to one of the alternatives.

- **Information source**: Twitter is the social network selected to carry out this example. It is an interesting choice due to the composition of the users posts that it allows and because it is one of the networks that people use to communicate with anyone in the world and carry out debates.

- **Consensus measures**: The purpose of this analysis is to determine what social networks think about a certain topic in an specific moment. For this purpose, several tweets are retrieved in an specific moment and the analysis is carried out using that information. In this process, consensus measures help us to know whether there is consensus in the process, that is, experts agree in a certain stance or, on the contrary, there is disagreement and people think in very different ways.

Once that the analysis parameters have been determined, it is necessary to define the keywords that will be used in the information retrieval step. Chosen keywords are exposed in Table 4.

Twitter API is used in order to retrieve social network users texts. After carrying out the necessary commands, a high number of texts are retrieved. The specific number for reach alternative can be seen in Table 4. It should be noticed that not all the experts have provided information about all the alternatives. Nevertheless, since there is a high amount of information for all the alternatives, it is possible to calculate the collective preference values

Alternative	**Keywords**	**Number of tweets**
Donald Trump	Trump	1214
Hillary Clinton	Hillary Clinton	509
Barack Obama	Obama	1002
Bernie Sanders	Sanders	2699

Table 4: Keywords used for retrieving alternatives text.

Experts	**Alternative**	$pwcount_{ij}$	$nwcount_{ij}$	p_{ij}
e_1	Trump	2	1	$2-1/2+1=0.33$
e_2	Hillary	2	0	1
e_3	Obama	1	1	0
e_4	Sanders	0	1	-1
...	...	...	...	...

Table 5: Individual preferences calculation example.

for all of them. Since the retrieved information is expressed in free text, it is necessary to apply a sentiment analysis procedure in order to calculate the individual preference values. In Table 5, several examples about these are shown. In order to calculate p_{ij}, expression (1) is used. It is important to notice that each individual preference shown refers to each one of the alternatives.

Once that all the preferences have been calculated, c_i values are computed by aggregating the individual preference values for each alternative. Results are shown on Table 6. According to the results, the ranking of alternatives, based on the preferences provided by the experts, is as follows: $R = \{Hillary, Trump, Obama, Sanders\}$. c_i can be represented in a linguistic way, $l(c_i)$, using expression (7) and linguistic label set S_7 defined in Table

Alternative	c_i	$l(c_i)$
Donald Trump	-0.1967	Disliked a little
Hillary Clinton	-0.0478	Neither like or dislike
Barack Obama	-0.2604	Disliked a little
Bernie Sanders	-0.2911	Disliked a little

Table 6: Collective preference values.

2. Calculations are shown below:

$$l(-0.1967) = -0.1967 * 3 = -0.5901 = (s_{-1}, -0.4090) = s_{-1}$$
$$s_{-1} = Disliked\ a\ little$$
$$l(-0.0478) = -0.0478 * 3 = -0.1434 = (s_0, -0.1434) = s_0$$
$$s_0 = Neither\ like\ or\ dislike$$
$$l(-0.2604) = -0.2604 * 3 = -0.7812 = (s_{-1}, -0.2188) = s_{-1}$$
$$s_{-1} = Disliked\ a\ little$$
$$l(-0.2911) = -0.2911 * 3 = -0.8733 = (s_{-1}, -0.1267) = s_{-1}$$
$$s_{-1} = Disliked\ a\ little$$

Thanks to these transformation, obtained results are easier to interpret than if a numerical number is provided.

Discussion results of the debate carried out by the social network users at the specific moment when the post were retrieved are clear. Nevertheless, did they all agreed or results were just an aggregation of very different opinions? In order to answer this question, consensus measures, as exposed in subsection 3.6, can be applied. In Table 7, consensus values are presented. In the second column, individual consensus values for the experts from Table 5 are calculated. Due to the high quantity of experts involved in the decision, only four examples are provided. In the third column, consensus for each alternative is provided.

As it can be observed in the Table, e_1 and e_2 opinions are quite similar to the main flow of opinions while e_4 is also similar since the value is higher than 0.5. e_2, on the contrary, has an opinion that differs from the one generated when aggregating all the experts individual preferences. Therefore, his/her opinion differs from the majority. When observing the obtained CA values,

Alternative	CE	CA
Donald Trump	0.7366	0.1967
Hillary Clinton	0.4761	0.0478
Barack Obama	0.8698	0.2604
Bernie Sanders	0.6455	0.2911

Table 7: Consensus values for the discussion analysis.

it can be seen that all of them are below 0.5. Therefore, it can be stated that there is a high amount of contrary opinions about all the alternatives. There is no single alternative in this discussion where the experts have similar opinions.

If all the CA_i values are aggregated, a global consensus value for the discussion is obtained. In this case, the global consensus value is 0.199. As it can be seen, the obtained result is quite low and is a clear sign of the disagreement generated by the analysed discussion.

5. Discussion and Applications

In this paper, a novel method that allow us to analyse social network discussions using a Group Decision Making method scheme and sentiment analysis procedures is introduced. Consensus measures are also applied in order to determine the level of agreement of the people involved in the debate.

Although, in the provided example, posts of a social network are used for the information retrieval step, our method is capable of working with any kind of text independently of their origin. Therefore, any information source can be used in order to extract the preferences information. One of the main advantages of the novel presented methodology is that it allows the discussion participants to express themselves using any kind of free text. Thanks to sentiment analysis, it is possible to analyse any text and obtain a preference value that the system can easily use for carrying out the necessary computations.

Although the method has been presented as a tool to extract information about an already carried out discussion, it is also possible to use our method to model a Group Decision Making process from the beginning. This way, it is possible to create an scenario where experts use a social network to discuss a certain matter using free text. In the case of Twitter and other social networks, it is possible to make experts use hashtags in order to identify the posts that are associated with an specific group decision making process. Hashtags for associating text to alternatives can also be used. This way, the proposed method does not have any problem in identifying which text refers to which alternative and discussion. Thanks to this, it is possible to carry out several group decision making processes at the same time using the same social network.

As it has been stated in the illustrative example proposed, results are always delimited to the period of time when the experts provided their preferences and wrote their opinion texts. However, this can be a good opportunity to use our method to analyse how experts opinions change during a certain period of time. Also, it is possible to use our method to observe how an specific event affects the overall opinions of the social network users. This way, it is possible to carry out the same analysis in several periods of time and compare the results.

Another good advantage of our developed method is that it is completely suitable for cases in which experts have not provided preference information for all of the alternatives. Since, specially in open discussions, there is a high amount of information, the fact that a single expert has not provided information for an specific alternative has little effect on the final result. Thanks to this, experts are not forced to provide opinions about the alternatives that they do not know much about. This fact increases the reliability of the final generated results and the information provided by the experts to the system.

6. Conclusions

The appearance of Web 2.0 and the social networks have generated novel means that people use to discuss all kind of matters. They are becoming quite popular due to their ability to generate discussion frameworks where every person located in any place of the world can participate. In this paper, a novel developed method that tries to model and analyse this kind of discussions is presented. Our method applies group decision making methods scheme in order to determine what has been decided and how the discussion is going on in an organized and fair way. Sentiment analysis procedures are also used in order for converting the natural texts that the experts use for providing opinion into numerical values that the system can interpret. In order to measure the reliability of the generated results, consensus measures for different aspects of the decision are presented.

Thanks to the presented method, it is possible to model group decision making procedures using the most preferred environment for carrying out discussions: the social network. Also, our method is able to generate, in a fair and organized way, ranking results of the discussed alternatives. Specially in cases where a high number of experts have participated in the group decision making process on the net, our method is an useful computational tool that assists the analysers in handling the high amount of information that must be processed.

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