SENTIMENT AND CONTENT ANALYSIS TO CLUSTER NEUTRAL MESSAGES ONLINE

ABSTRACT

The purpose of this research is to apply both *sentiment and content* analysis methods to neutral messages posted online. Past studies have revealed that the classical method adopted to conduct sentiment analysis has important limitations. First, neutral messages are often considered "good-for-nothing" material or literally something that tools are not yet able to classify. However, some new studies have shown the importance of considering neutral messages as a proper category with its own aspects because of its potential for improving the accuracy of positive and negative classifications. This paper aims to articulate a more reliable method for understanding neutral posts, based on a combination of sentiment and content analysis; then provide new "labels" for the creation of ad-hoc clusters of neutral messages. By doing so, we contribute to the discussion in online content analysis depth and analysis methods and represents one piece of a larger research project examining the quality of e-relationships as expressed through online content.

KEYWORDS

social media, sentiment analysis, content analysis, text mining, neutral messages

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INTRODUCTION AND OBJECTIVES

The aim of this paper is to propose an improved method of analysis to evaluate neutral messages posted online. To show the value of this method, an explorative research had to be taken analyzing size and quality of conversations between brands and consumers online.

Many reasons motivated this study, within the e-relationship marketing paradigm and the need of an updated communication monitoring system.

It is known that the relationship marketing paradigm gives high importance to relations and interactions, and that marketing mix is considered the operational element that support relationships (*Gummesson, 1994*). In particular, e-relationships (*Gummesson, 1999*), as IT based interactions, live and prosper in a different environments where personal and business relations dynamically interact creating deep changes in socio-cultural and socio-economical contexts (*Li, 2011; Song, 2010*). In these environments, all members can interact to share content and to create value and sense of belonging (*Ransbotham et al., 2012; Vorvoreanu, 2009; Fouser, 2010*). Social media marketing should be planned not only with the goal of connecting companies with customers and viceversa, but to enhance the quality of interactionswithin the E-relationships (*Bressan and Signori, 2014*).

However, corporate communication planning in social media still show a lack of ability in monitoring online brand performance (*Vernuccio, 2014*). A set of rules for successful corporate communications in order to generate trust, promote value and share experiences on social network sites is needed (*Wirtz et al.2013; Gensler at al. 2013*). New tools are requested, to update the auditing system and to identify whether e-contexts have an impact on corporate communication processes and strategies (*Signori and Confente, 2011*).

Quality of e-relationships may be affected by quality of interactions, so that many research studies have focused on communication in the Internet, in particular insocial media contexts. Some past research has already investigated tools and models for the measurement of consumer engagement through social networks (*Vargo and Lush, 2004*), suggesting potential action for brands through social media (*Vargo, 2008*), defining objectives that a brand should pursue through dialogue in social networks (*Owyang and Lovett, 2010*), defining new brand-users conversation metrics (*Mandelli and Accoto, 2012*), or proposing an analysis method from relational sociology (*Signori and Grosso, 2014*). As commonly discussed the need to complete the analysis of online conversations, due to the fact that popular metrics which usually focus on size of interaction and engagement, can't explain the real quality of a relationship.

To monitor the overall attitude of social media conversations, the importance of studying the valence with sentiment analysis methods is growing. Basically, analysts should be driven by main principles of the *Appraisal Theory* (*Sherer et al., 2001*), which suggests that an emotional state, as evidenced by words used in context, suggests overall attitudes and future intent.

However, actually sentiment analysis methods, even if they are rigorously taken, are offering only positive, negative or neutral classifications without deeply exploring respective contents. These techniques hide a number of limitations if neutral messages are considered "good-for-nothing" material or literally something that tools are not yet able to classify.

Moreover, recent studies showed that a large percentage of online messages around a brand on social media platforms is classified as "neutral"(*Signori and Confente, 2014)*, with some describing different varieties of neutrals (*Koppel et Schler 2006*), or showing the importance of considering neutral messages as a proper category, with its own aspects because of its potential for improving the accuracy of positive and negative classifications (*Wilson et al. 2009, Tang Y.T. et al. 2014*).

Within this background, our paper aims to articulate a more reliable and effective method for understanding neutral posts, based on a combination of *sentiment and content analysis*; then provide new labels for the creation of ad-hoc clusters of neutral messages.

The objective of the research presented in this article is only a part of a broader research project. A focused study on the quality of engagement will lead to a refined online attitude monitoring approach, improving online communication audits, so that firms will be able to evaluate the quality of e-relationships more completely.

LITERATURE BACKGROUND ON SENTIMENT AND CONTENT ANALYSIS

Social media monitoring and analysis have been extensively investigated under different points of view and disciplines, generating a great proliferation of terms (*Zabin and Jefferies, 2008*).Undoubtedly, social media platforms together with other Web technologies have recently played a fundamental role in the marketing and communication field (*Stephen and Andriole, 2010; Stephen and Galak, 2012*). In fact, the content of these platforms have modified the Web into a vast repository of comments on many topics by generating a potential source of information for social science research (*Thelwall et al., 2008*). As consumers become even more familiar with the usage of social media platforms, firms try to spend their energy and investments on storing and analyzing this information and formulating new communication strategies, especially in word-of-mouth marketing (*Sonnier et al., 2011*).

The new E-context is dynamic and complex: websites, mobile apps, tools and platforms are continuously changing in number, potentiality and usability. Within these evolving contexts, companies could track the "*social/web ratio*" *(Signori and Confente, 2014*)to evaluate the impact of social noise on total web communication around a specific brand. When the noise around a brand on social media platforms is significant, then a deeper analysis is suggested. Usually, the most frequently used method is referred to as "*sentiment analysis*": generally defined as an automatic analysis of evaluative texts, which aims to label a message as positive, negative or neutral. When software based, it is considered "an automatic analysis of evaluative text and tracking of the predictive judgments" (*Das and Chen, 2007*). Sentiment analysis has many constraints in dealing with a large variety of texts and it seems that content analysis, which considers more than a simple binary classification, is more suitable to get richer results, especially on from those of a neutral nature.

Sentiment Analysis

Sentiment analysis is a sub-category of automated and semi-automated text mining techniques, which represents the evolution of manual content analysis. Sentiment analysis is considered therefore the modern and technological evolution of manual EAA, Evaluative Assertion Analysis (*Osgood, 1956*), which is just one of six different methods to conduct manual and classical content analysis. Since 2001 sentiment analysis and opinion mining have becomewidely used, as the rise of machine learning methods in natural language processing, the availability of dataset for machine learning algorithms to be trained on, and the realization of commercial applications have increased (*PangandLee, 2004*). Although the two terms 'sentiment analysis' and 'opinion mining' are largely used today as synonymous, their difference is still not clear. The term 'sentiment', with regard to the automatic analysis of evaluative text and tracking of predictive judgments, were applied initiallyto analyze market sentiment(*Tong, 2001; Das and Chen, 2007*). In the meantime, other authors stated that "the ideal opinion mining tool would process a set of search results for a given term, generating a list of product attributes and aggregating opinions about each of them" (*Dave et al., 2003*). Moreover, sentiment analysis is recognized nowadays as focused on NLP, Neuro-Linguistic Programming(*Lovett et al., 2013*): a considerable number of articles mentioned 'sentiment analysis' on the specific application of classifying reviews or natural language documents as to their polarity or valence (either positive or negative). However, nowadays, many use the term sentiment analysis more broadly to mean the computational treatment of opinion, sentiment and subjectivity in text (*Nga et al., 2013*).

The discriminate element, which represents also the limitations in text/semantic analysis, is the binary classification on which it is constructed. While in a more general fact-based analysis the researcher classifies documents by possibly unlimited categories, depending on what he is searching for in the text, in the evaluative text analysis the researcher should use just a binary taxonomy, positive or negative, and what is neither positive neither negative is considered neutral (*Dave et al., 2003*).

Sentiment analysis works following three different phases:*Tagging, Computing, Classification*.*Tagging*, is normally divided into two steps, *product feature extraction* and *sentiment words definition*; *Computing* enables counting of the distance between each sentiment word and every product feature by summing up the covered weighted distances;C*lassification*assigns each sentiment word to each product feature until no sentiment words remain (*Pang and Lee, 2004*).After having sorted each sentiment word by its distance to product features, it is necessary to assign each sentiment word to product features until the sentiment word with the largest of the smallest distance from each sentiment is assigned. For each product feature it is essential to compute the sentiment score by adding up assigned entries from positive/negative sentiment lexicons. The category with the highest score wins; a tie results finally in the neutral label.

The label neutral can be interpreted in many ways, as lack of opinion, or in a sentiment that lies beyond the positive and the negative (*Pang and Lee, 2008*). Most sentence level and even paragraph level classification methods are based on word or phrase sentiment classification. Automatic and semiautomatic methods for the purpose have been explored by several researches. There are basically two approaches: the *corpus-based* approach and the *dictionary-based* approach. The first one finds co-occurrence patterns of words originally from the text analyzed to determine the overall valence of the text, while the second one-uses synonyms, antonyms and hierarchies in ad-hoc dictionaries to determine word sentiments.

Some researchers have adopted this tool to analyze data under a managerial perspective, considering comments or opinions just on brands, products or services (*Shin et al., 2010*; *Onishi andManchanda, 2010; Sonnier et al., 2011*). Other studies have presented a text-mining method to support the analysis and visualization of market structure by automatically eliciting product attributes and brands' relative positions from the voice of the consumer as expressed in online reviews*(Lee and Bradlow, 2011*). Recently other scholars argued that we still have a limited understanding of the individual's decision to contribute these opinions (*Moe and Schweidel, 2012*).

Content Analysis

According to many authors (*Holsti, 1969; Kassarjian, 1977; Krippendorf, 2004*) content analysis is a complex group of procedures applied by some researchers who want to investigate a certain kind of text. Adopting *Krippendorf*'s (2004) scientific systematization it is possible to detect three different main classes of content analysis procedures, which stem from three different theoretical backgrounds.

For the semantic approach, based on*Berelson* theory (1952*)*, content analysis is a "research technique useful to describe in an objective, systematic and quantitative way the manifest content of the communication". Following this definition the researcher should be able to define encoded meanings in the content, which are the same as those comprehended by readers and any relevant audience. This theoretical background is the foundation for the most common used quantitative method known as *quantitative semantics* where different parts of the text such as words, themes or characters are studied as independent variables to make inference on the communication structure. From its naissance to its last evolution due to the introduction of semiautomatic and automated tools, this research method has met several changes. However this approach seems to us quite reductive because it relies on a basic assumption: there is a kind of linearity of the meanings created by the sender and messages conveyed and that which is received by the receiver/audience. Furthermore, as *Krippendorf* (2004) stated, it seems quite difficult to measure the objectivity and the orderliness of the content analysis when, in dealing with a written text, especially in the reading phase, we are always doing a qualitative analysis.

For the instrumental approach, the content analysis is seen as an instrument, often associated with some aspects or features, which belongs to the sender/producer of the message. This second approach is derived from the *Lasswell 5W framework* (1949). *Lasswell* theorized a new approach to investigate mediated communication by focusing the communication process of the "What", as in the content of the messages, by considering also the other Ws: “Who says that”, “to What extent”, “to Whom”, and “with what effect”? Later, *Holsti* (1969)modified the model of the 5 Ws and improved it by considering the processes of encoding and decoding, which originate among the communication’s actors. Thus,content analysis is askedto also understand the communication process with regard to communicative intentions (the sender’s reasons).

For the interpretative approach (*Krippendorf, 2004*), it is suggestedthat content analysis be made in an objective and systematic way, on the condition that the content is studied with regard to the context in which it is created and transmitted. It means recognizing that texts exist because they are products of social interactions, and for this reason they should be analyzed in the environment in which they are created and transmitted. The role of the analyst/researcher is also different: texts do not show particular objective aspects, because the informative patrimony from which the texts are created, does not exist alone, but rather depends on the analyst who is another kind of reader. It means that meanings are not predetermined and present in a text. Doing content analysis means doing interpretation. So here, the analyst gives meaning to different parts of the texts and then makes hypotheses on these attributions in order to verify their final validity.

Neutral Message analysis: from residual to crucial

In the computational linguistics and computer science, neutral messages are messages with a lack of opinion or they are messages where we can find an exact balance between positive and negative product aspects(*Pang and Lee, 2008*). For years the neutral category has been created as a residual one, without a specific or clear "sentiment", and including messages that tools were not able to classify.

A recent study (*Tang et al., 2014*) has highlighted important implications of neutral UGC (User-Generated Content) on sales by differentiating *mixed-neutral* and *indifferent-neutral*: mixed-neutral contains an equal amount of positive and negative claims; indifferent-neutral includes neither positive nor negative claims. Primary findings of that study indicate that ignoring mixed- or indifferent-neutral UGC leads to substantial under- or overestimation of the effects of positive and negative UGC. The effects of neutral UGC on sales thus are not truly neutral, and the direction of the bias depends on both the type of UGC and the distribution of positive and negative UGC. This consideration should lead further research to refine analysis techniques and consider neutral messages as an important source of information for marketing decisions.

In addition, if the volume of neutral messages online is significant (*Signori and Confente, 2014*), it may imply that classical sentiment analysis alone is not suitable because it gives only a positive, negative or neutral classification and does not provide other information in that category. Other researchers have confirmed that it is possible and fundamental to cluster neutral categories (*Koppel and Schler, 2006; Wilson et al., 2009; Tang et al., 2014*).

In particular, atwo-stage, multi-research method approach has beenused already to bypass classical sentiment analysis limits(*Wilson et al., 2009*). In the first stagethe text is classified as neutral or sentiment-bearing: if it is classified as "opinionated content", it enters the second step and its polarity (positive vs. negative) is determined. This process enables the automatic identification of contextual polarity, achieving results that are significantly better than baseline. With this approach, neutrals are definitely considered as a unique category with proper characteristics that need to be studied. Additionally, the polarity is called "contextual", which means there is a specific and more restricted area of analysis on the messages, which considers properly the context in which they are emitted or exchanged.

METHODOLOGY

The research presented in this article is only a part of a broader research project. The main research design tries to connect quality of e-relationship with quality of engagement and highlights the importance of methods for online interaction analysis.

To reach this main objective, previous research steps already defined an analysis model, called *Prism Analysis Table* (*Signori and Confente, 2011; 2014*). It is an external communication impact analysis model, which tries to evaluate the valence of online noise and connect it to the relative effect. This model allows a content analysis of conversations online, in order to understand if these interactions modified or distorted the planned company message. *PAT (Prism Analysis Table)* connects "valence" and "content", from both supply and demand sides. Exploring the "valence" variable, it is possible to understand how the demand side receives and rebounds these messages: enhanced, neutral, distorted. On the other side, through a "what analysis", *PAT* classifies the kind of messages coming from external sources, known as the supply side such as online communities and social networks. *PAT* also offers some managerial implications as a response to different external communication stimuli. However, in testing this framework it became clear how "neutral" conversations were hiding important pieces of information and that this category is rising in its important from residual to crucial.

Detailed research goals for this research step were then to: 1) show the richness in information of the "neutral" category; 2) set a more reliable analysis technique to study and classify contents in online conversations.

Research method

In order to contribute to the theoretical development of online neutral message analysis, this study is based on a multi-phase research process. To develop the research, the methods of textual discourse observation and analysis were applied.

In the first research phase,a basic sentiment analysis was conducted to understand the extent of the "neutral" phenomenon. The conversion of textual material to quantitative data is not new in the marketing literature (*Mohr and Nevin, 1990; Noble et al., 2002*).A data collection method and a text mining approach through software have been used (*Miller, 2005*). For this reason, we needed a Web crawler technology to capture and classify this sort of communication. The adoption of automated sentiment analysis was required to classify the valence of social media posts: a free online software was used for sentiment analysis and valence information. This tool was useful to convert messages into quantitative data in order to get information, at first glance, on their amount and valence and then have the right information for the sample selection.

In the second research phase, a manual content analysis was conducted on the most frequently used social media source (i.e., Facebook) for the selected industry sample, both to validate the first research phase and to gain a deeper understanding of the nature and content of neutral messages about a selected panel of brand.

Sample Selection and data collection

The complete analysis was conducted on social media conversations around seven brandsin the mobile technology industry. These brands were: Apple, Blackberry, Canon, Microsoft, Nokia, Samsung, and Sony.

The sample wasextracted, per industry, from the best 50 global brands included both in the Top 100 Global Brands (Brand Value ranking 2011, by Interbrand) and in the SMR list (Social Media Reputation Index 2011, by Yomego).

The "technology" industry (14 brands in the group of 50), showed in 2012 the following demand profile on social media platforms: high level of brand strength (31.1%), brand reach (35.4%) and brand passion (49.5%). Brand strength is defined as the likelihood that a brand is being discussed in social media, and calculated tracking phrase mentions within the last 24 hours divided by total possible mentions; brand reach is a measure of the range of influence, as the number of unique authors referencing a brand divided by the total number of mentions;and brand passion is a measure of the likelihood that individuals talking about a brand will do so repeatedly. These metricswere collected in the first research phase with automatic software online in 2012 (*SocialMention*), and gave initial information about the selected industry and their communication in social media platforms.Then, another selection included those brand more related to the "mobile technology" in order to focus the analysis on a specific sector of activity to gather homogenous information (similar communication strategies and styles). Seven brands were finally selected for the next research analysis, with means of 32% of brand strength, 33.1% of brand reach and 54.1% of brand passion. Then, classical sentiment analysis, conducted with the same software, showed the importance of positive, negative and neutral messages of the selected 7 brands (as shown in Tab. 1 - note that the classifications A-G are randomly assigned to the seven different firms/Brands).

Table 1: Sentiment analysis on seven brands of the mobile technology industry (on 3438 messages in social media, August 2012)

	% positive	% negative	% neutral
A	17.6	2.7	79.7
B	16.4	2.3	81.3
C	24.9	1.7	73.4
D	25.2	2.3	72.5
E	17.8	1.4	80.9
F	22.3	5.1	72.6
G	20.5	1.8	77.6

As the first research phase indicated the importance of the volume of neutrals, the second research phase investigated deeply the nature of those online conversations about those seven brands. As shown in Tab. 1, a large number of messageswere classified as neutral by the automatic sentiment analysis (76.9% industry average). Many research questions then arose:

Why are there so many neutral messages? What do users write in these messages? Are general sentiment analysis tools suitable for social online conversation analysis?

In particular, from the previous study emerged that the majority of the messages were exchanged within Facebook. For that reason the second research was based on that media (with a data collection in 2012). Moreover, selecting messages in one media only helps becauseit is possible to find similar structures in message writing and conversation features. In addition, Facebook enables focused conversations around a brand, its products and its general activitieson a single dedicated page. It is therefore possible to get clear information on therelationship among brands and users.

With the support of another softwareprogram (Blogmeter) we captured 1158 messages, exchanged in Facebook (FB) in 2012 around the selected seven brands.

Data analysis

In order to understand the nature of neutral messages in social media platforms (in particular in Facebook), it is relevant to study the context of the platform, how it structured, the nature of messages, how they are transmitted, making also some inferences on the reasons why people exchange information. Also for this reason we chose to interpret the entire text in the seven different Facebookbrand profiles. Different kinds of senders (company or individuals) were included in the analysis. First because the conversations online have multiple senders and receivers, both active and with interchangeable roles, then because we needed to understand senders intentions to interpret correctly the message.

For each unit of analysis we noted and recorded the presence or absence of coding variables based on five classification criteria applying the instrumental approach. In this case "Where" was classified for all texts as the FB brand page and the permalink. For the other categories, the stakeholders involved in the conversation (Who?), the predominant theme of the content (What?), the predominant author post motivation (Why?), the predominant post type used in writing the text (How?) and the reaction of other members to the post (With which effect?). The Table 2 summarizes the key points applied to study neutral messages.

Table 2: Data analysis approach and coding variables

W	***Classification criterion***	***Coding variable***
Who?	The author of the message	Customer/user Staff members/firm
What?	The predominant theme of the content	Service/Product Leisure/Fun
Why?	The motivation to take part in the conversation	Rational Playful/Emotional
How?	The means by which the message is conveyed	Status (simple text message) Photo Link Video Question (the predetermined questionnaire realized by FB for FB Business Page)
With which effect? (TOTAL Engagement)	How the other community member react	No.of Likes No.of Shares No. of comments Most brand replies Most user replies

Later, thequalitative variables listed above were in turn used to see if it was possible to individualize different neutral categories among the messages analyzed.

Finally, the interpretative approach was applied manually by two independent researchers who compared and matched their results and interpretative methods.

RESULTS

The main result of this two phases research is related to the size of neutrals that emerged from the analysis: the first sentiment analysis made with the automated software (SocialMention) classified neutrals the 76.9% of all the conversations; while a deeper content analysis manually made obtained a 91.2% of neutrals. Comparing sentiment results of the first research phase (Table 1) and the sentiment results of the FB conversations only, a lower defined sentiment attitude is shown in FB, where the neutrals seem to be predominant. Manual coding conducted with a more precise approach (see Table 2), was able to bypass classical automated software limitations.

With both analysis methods, our results highly confirm the predominant of neutral category size.

This research showed in particular that senders (*Who*) of these neutral conversations are equally distributed between firm staff (45%) and consumers (46.2%).

Exploring their content (*What*) it is evident that only a small percentage is highly negative or positive: all the other messages are classifiable as “leisure” or “service”. In particular, neutral messages categories found in this research (on 7 different brands of mobile tech) were:

- Interaction stimuli (27.043%);
- Ask for assistance (17.979%);
- Asking information (9.807%);
- New product presentation (8.172%);
- Intrusion (5.498%);
- New product usage (5.349%);
- Fun communication from brands (4.903%);
- Details (4.755%);
- Fun communication from users (3.418%);
- Makin proposal (1.486%);
- Sales promotion (1.486%);
- Competitor comparison (1.337%).

Thanks to the interpretative manual coding, it is possible to understand a single brand online personality within the communication context, connecting it with users conversation behavior.

As said results showed that the two first major categories are equally divided between two main senders: the users and the company. This is a partial confirmation of the conversation structure of the social media platform where in turn there are different actors who write a message in order to communicate something with different purposes. It can also occur, as for the Brand G, that the firm does not let users to write messages as replies or simply user generated contents. The result is that the total amount of messages belongs to the company only. In other cases, as for the brand E, the situation is opposite where there are a lot of messages from users and few firm generated ones.

Results are clearly demonstrating the informative importance of neutral category, often been considered as residual.

FINDINGS

Thanks to acombined instrumental and interpretative analysis it was possible to initially define fourdifferent major neutral clusters, from two different kinds of senders, brand or user:

- Fun-brand content (28%);
- Service-brandcontent (17%);
- Service-usercontent (30%);
- Other user contents (16.2%).

Each cluster showed particular characteristics.

Fun-brandcontent

These messages are edited by staff members and are mostly focused on corporate/product brands. They are written to have playful interaction with community members and to create positive bonds between the brand and the customer. Depending on the brand they also receive significant engagement in number of likes and shares. The majority of these texts weresupported by images, videos or links.Fun-brand message cluster examples:

"Here below, isthe picture of June. This is a picture made by the fan Marco with the xxx [product name]. But how many cats are there??"

"How many hours did you spend with it? –Picture of an old version of xxx [product name]"

These messages were posted online clearly to stimulate an interaction with actual or potential consumers online. Evidently, this type of message is considered neutral by a standard sentiment analysis. A standard content analysis, based on a quantitative semantic approach, may classify this type of post as a "question" detecting a certain number of "?", but these posts have a completely different nature andmight be very important if they are stimulating a fun interaction and serve as a viral rebound of company messages.

Service-brand content

These messages were posted bystaff members of the company and were created in order to advertise products, introduce new product features, make competitor comparisons or to communicate sales promotions. Depending on the brand they normally scored low on engagement. Those thatwere mostly emotional centered scored more likes and shares. These messages were always conveyed through animage, useful to show the product and a text message with a brief description. Service-brand message cluster examples:

"The new xxx [product name] is arriving. It seems that someone can't stop talking about it. And you? What do you think about it? See the link www.xxxx.ttt".

"Are you going to buy the new xxx[product name]? Have you just ordered it? Be sure of purchasing a xxx in Italian and by means of registration to this link www.nnn.xxx you will be able to win 2 special presents: a 100 euro coupon, valid to buy xxx [corporate name] Accessories from xxx [corporate name] mobile store, and a free subscription to a theft assurance lasting a year."

The level of engagement of this case should also be measured including the click-through rate, coupon returns and number of subscriptions. Thistype of message in fact was stimulating action on other media or channels, and as such, an engagement index also should integrate other kind of effects. A limited sentiment analysis, extracting conversationsfrom a single media form,without considering the integration of the communication on- and offline is very reductive and is not useful for marketing decisions.

Service-user content

These postswere written by users/customers who use the platforms to ask questions about products. Most of the time communicators also wrote descriptions of their problem with the product and requested assistance. These messages were mostlyrationally-based and were conveyed through status messages on the FB page. They scored a high level of engagement in terms of firm and other user replies, depending on the brand. This means that some firms tried to give an answer to assist customers, while others did not seem to care about them. In this case, the replies were composed only of user's messages. In addition there is a percentage of users who wrote messages just to make a suggestion on different product usage or on how the staff should care aboutclients and so on. Service-user cluster examples:

> *"Hello, I have a problem with my new xxx [product name]. The on/off button does not work properly, the home button too. In addition I have some problems with the Wi-Fi connection and I am sure they do not depend on the net or the router. How can I ask for assistance? Should I go to the shop where I bought it or is there a direct link on the xxx's [corporate name] web site? Thank you very much."*
>
> *"Hi everyone. Does someone know how to install xxx [software name]? I need some help please!"*

The nature of these conversations was all about customer service. In this case, social media is considered a tool to more quickly and easily access certain kinds of information or solve a practical problem quickly. Our results showed that some brands really do not consider it important to reply to or assist those customers online.

Other user contents

In this category we can find some other messages coming from users who wanted to have fun. There are also the so-called "intrusion" messages. They come from users who were not interested in taking part to brand conversations and wrote messages just to annoy other people or the company staff."Other" messages were also those labeled as "pictures", which were exclusively messages coming from users who wanted to display to the community their own creations. In this category we could generally find a miscellaneous set of messages, which shows high scoring just on one brand or low scoring for different brands.

DISCUSSION

The nature of these texts reveals to be mixed. We can find some evaluative texts, but they are not the majority (just 7% of the entire sample). This means that a sentiment analysis is not a suitable means to discover better FB Social media message natureand structure. A content analysis could give richer and more accurate results.

In addition, by making a more detailed analysis on each of the four categories, it is possible to individualize other minor clusters, which denote the different kinds of communication dynamics. For the firm, it is possible to understand how social media platforms are exploited and derive a trend in communication strategies differentiated bybrand. For marketing analysis it may be important to understand which are brands and users behaviors and intentions online in specific contexts.

On the other hand an interesting point is also to analyze consumer communication attitude. For example, the big cluster of service-user messages includes many different assistance/information requests and managers shouldindividualize the product features on which they are focused and measure also how the firm is able to give an answer to the user.

Doing a competitive analysis, practitioners should compare their performances online in terms of customer service and engagement rates.

This research began with an investigation of the naissance of sentiment analysis, as it was described in the literature, and carried on with an exploration and application of this discipline in the marketing and communication field, including a qualitative and quantitative analysis of social media messages. The data for this research project were comprised of 1158 Facebook posts about 7 Brands profiles in the mobile tech industry in 2012. Data were analyzed initially with a sentiment analysis (software based). An evident lack of information and trustworthiness of actual sentiment analysis tools required an additional step for exploring neutral messages: it drove researchers to deeply analyze messages with a detailed, manually conducted content analysis.

In particular, in this study we have focused our energy on the so-called neutral investigation. While many studies and commercial applications consider online messages scored as neutral as useless, we proved that, in reality, these messages are composed of interesting pieces of information. This research provided new cluster labels for the creation of ad-hoc clusters of neutral messages, useful for the classification stage in the sentiment and content analysis.

The use of an articulate and more reliable analysis method for understanding neutral posts, based on a combination of sentiment and content analysis, and applying both the instrumental and the interpretative approach, may drive further researched and the development of updated automated software.

THEORETICAL AND MANAGERIAL IMPLICATIONS

Sentiment analysis draws on natural language processing and computational linguistics to extract positive or negative reactions to experiences and attempt to predict future behavior. One of the key theoretical underpinnings was *Appraisal Theory*(*Sherer et al., 2001*), which suggests that an emotional state (as evidenced by words used in context) suggests overall attitudes and future intent. Absent these strong emotion-laden words, a message is classified as neutral. Yet the content still has meaning that is currently ignored. Additionally, within the nearly 50 years of customer satisfaction research, focus has built on the idea of a "zone of indifference" (*Woodruff et al., 1983*) where customers are neither satisfied nor dissatisfied and chosen to focus most of its attention on these two extremes, largely ignoring the middle. This middle zone of indifference is the equivalent of neutrals in this paper. Thus, our research contributes to filling this important research gap.

And these meanings can be classified further. Our research contributes to natural language analysis by extending appraisal theory and combining it with aspects of content analysis consistent with hermeneutics or the *Theory of Knowledge* (*Russell, 1926*), specifically to incorporate multiple methods using several theoretical lenses to increase the "truth value" of online text-based post interpretations. Without this approach, limited theoretical lenses leave a significant amount of meaningful data unexplored. Consequently there is the need for a change in perspective. We propose with this paper four new "labels" to classify and cluster neutral online messages.

We suggest a refined mixed method of sentiment and content analysis in order to improve and accelerate the 'classification process' and to make potential'communication diagnoses', which would enable companies to improve pre and post communication evaluations.

LIMITATIONS AND FURTHER RESEARCH

This project is limited to the analysis of Facebook posts on seven brands. It may be that additional classifications would emerge when analyzing different social media forms such as Twitter or Instagram (mostly image-based) or if this approach is applied to significantly different kinds of brands. It is also limited based on the current rather manual approach to content analysis. Future research should explore other social media forms, other brands and the effectiveness of more automated forms of content analysis, building on what is presented here. More important, future research could explore if there is a correlation between engagement quality and the environment/context where the conversation is taken. Are brand marketing efforts influencing frequency and mood of interaction? Or are users driving brand behavior online with a cause-effect model?

This research, in its first level of exploration,demonstrated the informative value of "neutral" conversation to open a new perspective of analysis for further research.

ACKNOWLEDGEMENT

We would like to acknowledge the generous support of Blogmeter and their interest in our work.

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