A sentiment analysis solution for the re-design of product-service systems

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***Abstract*—In an extremely competitive economy, companies need to get ahead of competition as fast as possible, both in delivering quality of products and services, but also in extending their lifecycle to match the expectations and needs of customers. Analysing where product and service systems are lacking in terms of customer requirements is crucial. Currently it might take some time for information to travel from customer to producer, since the connection may include stores and local representatives before reaching the products' and services' designers. Although this information is readily available in social networks, the issue resides in efficiently merging and showing it in a simple and meaningful way to the designer of new products and systems. By identifying important parameters in posts and opinions, data becomes easier to qualify and, as a result, easier to identify by a designer. In this document, we describe a solution for this problem.**

Keywords—sentiment; opinion; product-service system; stakeholders' feedback; social networks; design

I. INTRODUCTION

Rising levels of consumption by the rich and the doubling of the world's population over the next forty years demand a change in technology as far as sustainability is concerned. As modern enterprises, acting in the global market, seek a way to remain competitive, a new trend is arising, in the form of PSS (product-service systems), supporting networks and infrastructure that is designed to be competitive, satisfy customer needs and have a lower environmental impact than traditional business models [1].

To design a PSS, the exchange of knowledge among its various stakeholders, including designers and manufacturers, as well as customers and suppliers, is of extreme importance to identify the points in manufacturing, integration and operation stages that need to be improved.

This paper presents the results of the research and development performed in the scope of the DIVERSITY project [2]. DIVERSITY aims at providing a cloud-based engineering environment and a set of methods/tools to support the collaborative design of PSS based on the knowledge captured and shared across the value-chain actors and the PSS life cycle. It relies on a combination of four main areas of research: lean PSS design; key performance index (KPI) assessment; context sensitivity; and sentiment analysis. This paper focuses on the latter.

Among other things, we studied the potential impact of feedback from users from social networks in the design or re-design of product service systems.

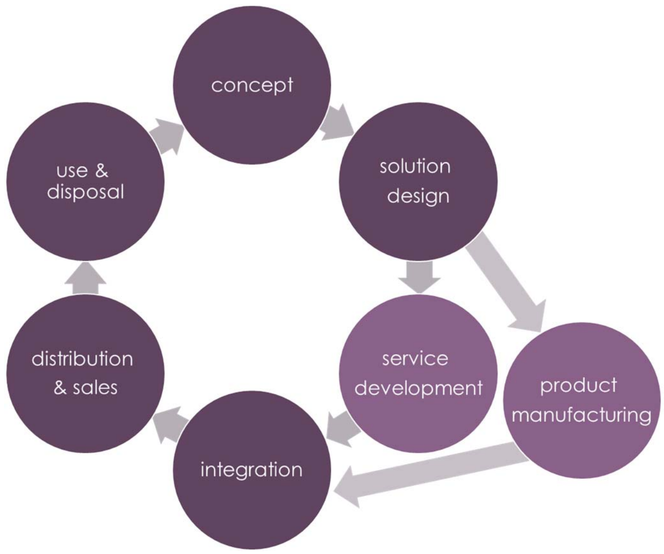

Figure 1 - PSS Life Cycle

The phases of a PSS lifecycle are depicted in Figure 1, from the initial concept to the final disposal [3]. The concept phase comprises the set of objectives to be attained and the added value to the target customer. The solution design has its own, more detailed, lifecycle, since it is the focal point of action in this project. It is composed not only by an iterative process, but also a counter-current loop providing feedback knowledge to the previous phases. The product manufacturing and associated services implementation take place in parallel. The integration phase ensures the compatibility of the PSS products and services. Thereafter, the PSS is taken to the market and specific customer relationships are established and maintained in the distribution and sales phase. In close connection with the previous phase, the use of the PSS (until and including its disposal) is the longest of the lifecycle and the most crucial on

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knowledge provision for re-conceptualisation and re-design of the PSS.

When designing a PSS, it is important to understand whether or not the PSS creates final products, i.e. products intended to be used by a consumer. A PSS may have one or more final products, or none. This last design choice normally occurs when the PSS is not designed to be sold to the end-user, but instead to be (part of) a structure that manufactures this final product.

Sentiment analysis aims to analyse people's sentiments, opinions, attitudes, emotions, etc., towards elements such as topics, products, individuals, organizations, and services [4]. In DIVERSITY, it is responsible for acquiring feedback from end-users and stakeholders across the lifecycle of the PSS. Sentiment analysis is composed of 4 modules: opinion modelling, where users define which PSS they want to monitor for sentiments and where to look for those sentiments; opinion monitoring, which cyclically looks for newly acquired posts and processes them; opinion extraction, where users can view the results of existing opinion models; and opinion prediction, where users can infer the evolution of sentiment towards a specific PSS according to similar systems and their sentiment data history.

This paper is organized as follows: Section II describes how the feedback is acquired from the stakeholders and its structure and processing steps, Section III presents the impact of stakeholders' feedback on the (re-)design of PSS. Finally, Section IV shows the implemented results and Section V discusses and concludes this paper.

II. ACQUISITION OF STAKEHOLDERS' FEEDBACK

DIVERSITY's feedback can be obtained from two types of stakeholders: external stakeholders i.e. users on social media; and internal actors i.e. users from the company itself, business partners and business customers. The two types of feedback, although similar in opinion content, need to be analysed independently, since they focus on different stages of the lifecycle and characteristics of the PSS. Furthermore, internal feedback does not have the same exposure and reach as something posted on a social network.

Post performance needs to consider patterns related to our human responses [5]. Creating the post at specific times grants the best returns in terms of accountable appreciation. For example, for Instagram, the time you post influences how many people see it: posting between specific hours guarantees the most efficient propagation of the content [6].

Currently the two big social networks - Facebook and Twitter - each have specific API [7], [8] to allow for post KPI overview. Facebook uses a mix of 3 types of Reach (Fan, Organic, Viral) [9], 'Fan' reach is calculated using all action that page followers have on the page, 'Organic' uses all actions done by followers even if outside the page, 'Viral' means every action that is done to a post by anyone. Facebook also uses two other indicators, Engagement and Story-tellers. 'Engagement' is related to every interaction with the post (clicks, likes, opening photos, etc.). 'Story-tellers' provides an inference of the post's reach, indicating key authors that shared the post and had themselves great reach, i.e. authors with big influence on the community. Currently, Facebook doesn't calculate post polarity, but nevertheless has a negative feedback information regarding actions as "unfollow", "hide this page" and "report as spam". Twitter uses mostly the same information, but using retweets and other media source specific options.

Opinions from internal stakeholders are typically obtained from internal social networks and collaboration applications (either in-house deployment or, more recently, cloud-based solutions), since they focus on design and production-related content, which is confidential by nature and thus companies are not open to its exposure on public networks [10], [11].

Internal users and key stakeholders from partners involved in the production activities engage in conversations regarding claims, issues, improvements, clarifications and other aspects, which include in some cases their opinions and sentiment regarding the PSS. These become especially relevant when the resulting PSS is not a final product and the connection between feedback from consumers and the results of the design process becomes less evident.

In order to acquire and analyse sentiment, the designer will be using a tool to process opinions from acquired posts, composed of multiple independent modules, such as opinion extraction, opinion modelling, opinion monitoring and opinion prediction (as seen in Figure 2).

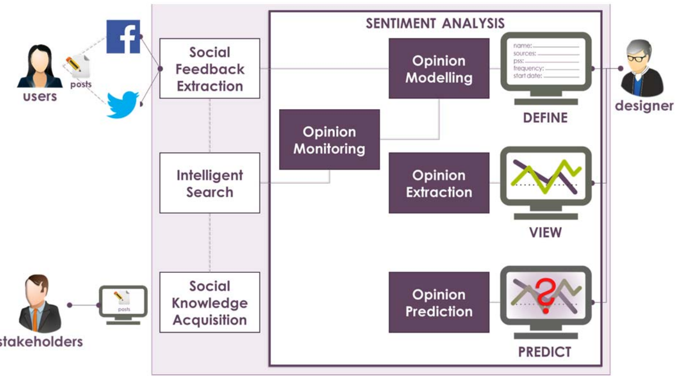

Figure 2 - Sentiment Analysis Architecture

Opinion monitoring is the central module of this architecture. This module is responsible for figuring out relationships between posts that arrive through other modules, like parent post and replies, and calculating their reach and influence. Reach is calculated based on the amount of people that replied to those posts, as well as the number of likes and views. These values are normalised according to the average reach of other existing posts in the same universe. Influence measures an author's audience, by comparing the reach of the author's posts history against the average influence of all other authors in the same universe. Opinion modelling and opinion monitoring are complementary: modelling interacts with the user, for the definition of the parameters to be monitored (which PSS to consider, which accounts to monitor, when to monitor them), and opinion monitoring is the module in charge of keeping information updated according to what the user defined in the modelling stage.

A typical operation cycle begins in opinion modelling, where the user defines what PSS and what parameters should be included in that model. After this, opinion monitoring includes this model on its cyclic verifications. When new posts are found, they are sent to opinion monitoring which then creates a new structure of data, which consists of the initial post, replies and all aggregated indicators from those posts (likes, views, etc.). The reach of posts and influence of authors are also calculated in this module. In DIVERSITY, polarity of opinions ranges from 0 to 100 and is considered negative when below 50. The calculation of this value is possible either by interfacing with existing commercial tools or by way of an internal, dictionary-based solution, which processes the contents of posts and matches them to a list of expressions whose scores are then combined to calculate the post's overall polarity.

Once polarity is calculated, it is then averaged using the influence weights of the user that created said post, so that the opinion of users with more influence has a stronger effect on the global polarity of the conversation (i.e. the original post plus replies or comments). This ends the cycle of feedback acquisition. Reach is then used to provide a weighted measure of the overall sentiment towards the PSS [12]. For the purpose of monitoring opinions, external or internal stakeholders are not differentiated. This distinction is available to the user when consulting the results.

In the future, existing information about the sentiment towards PSS will be used to help the designer in predicting how similar new PSS may perform.

III. Impact of feedback on the Design of PSS

To design a PSS, one can adopt different methodologies [13], [14]. However, the initial phase of the design process is common to most of those methodologies: identification of a problem/need to satisfy. After the need is identified, the PSS is developed, and while the need may be temporarily satisfied, the process does not stop there: user feedback must be considered so that the overall quality of the PSS can be improved or a need for new PSS is identified.

A. Sentiment as a trigger for updating PSS

User feedback can be measured by analysing social network posts related to a PSS and assigning a value to each of those posts, representing how satisfied the poster is about a specific PSS. By combining these values for posts within a pre-established universe of users in a timeframe, we obtain the overall sentiment indicating how users feel about the PSS in that period of time. Additionally, we can also measure the evolution of the sentiment value over time. This allows us to determine how the PSS is performing and whether or not action is necessary, i.e. if we need to update the PSS or not.

B. Non-standard feedback tools

As previously mentioned, sentiment analysis focuses heavily on the study of data based on user opinions and feelings, which can be subjective and difficult to quantify. As such, to increase the quality of the visualisations provided in the opinion extraction module we propose the usage of two different feedback tools: a top five posts table and a tag cloud. The top five posts table allows the direct analysis of the posts with the highest influence and their respective comments, which let us extract the general tone and feel of the post by reading it in full context. On the other hand, the tag cloud gives us a set of words extracted from the analysed posts, which allows for a quick, 'at a glance' analysis of the most frequent expressions used when discussing the PSS or final product.

From a scientific perspective, while the tag cloud has some drawbacks, it is a simple and effective tool for PSS designers to identify the general trend from a large set of data [15]. From a business perspective, it is a way of determining what words are most associated to a PSS: a tag cloud related to a well performing PSS will feature words like "great", "amazing" or "fantastic", while a poorly performing PSS will be among the lines of "poor", "bad" or "terrible". Additional information can also be obtained from the frequency of words, such as a specific feature or characteristic of a product being the focus of appraisal (negative of positive), which may lead to identifying specific improvements or pinpointing exact parts of the production line that are responsible for it. This information, accompanied by the visualisation of temporal trends and by the possibility to analyse specific points in time, provides a very important insight into the PSS for identifying new needs.

The sentiment analysis solution described in this paper is aimed at PSS and their (sometimes indirect) interaction with end-users. This is a differentiating aspect when compared to other opinion mining tools in the market, which are more focused on marketing and brands, instead of the feedback for design purposes. It also has unique characteristics in its use of reach and influence from elements of electronic word-of-mouth to weigh the relative importance of each opinion to the overall sentiment index and for its focus on the specificities of PSS [12].

IV. Results

For the DIVERSITY project, we developed a set of functionalities that work together to provide an accurate visual representation of the sentiment analysis data, according to the description provided in the previous sections.

A. Opinion Modelling

The first of those features is the creation of what we call an opinion model, which is a tool that allows us to define the type and source of the data we want to monitor. This is done by selecting a specific PSS, as well as a group of social network profiles, from which posts will be gathered and analysed. An important feature is the ability to select whether we wish to include final products in our opinion model or not. Additionally, we also included an option to define how often the model should be updated, i.e. how frequently should the sentiment analysis tool gather posts and perform analysis on those posts. The update frequency feature can be modified at any time after the model creation, and new social network accounts can be added to the monitor list. It is also possible to select when to start monitoring the sources (i.e. to define a specific date in the past or future to start acquiring posts).

B. Opinion Monitoring

Another feature is the opinion monitoring module, which is responsible for gathering the data related to each opinion model. More specifically, this module consists of a cycle that runs in the background and checks which opinion models need to be updated with new data, by adding the update frequency to the current date whenever new data arrives. The data used to update the models is gathered from the sources defined when creating the opinion model: the posts used to generate the sentiment analysis data come from the accounts and social networks specified in the opinion modelling section.

C. Opinion Extraction

To visualize the data, we developed an opinion extraction tool, which combines all the data relative to a specific opinion model in a single page. Since we defined that each opinion model is associated to a single PSS, this page gives us an overview of how that PSS is performing among its users. Notwithstanding, more than one model may be created for the same PSS for segmentation purposes.

Figure 3 – Filtering options

The opinion extraction tool provides a filtering section (see Figure 3), where the user decides whether to apply filtering and segmentation to the data. Filtering can be done by gender, location, age and final product (if final products were included when creating the opinion model).

This allows us to analyse the feedback of a specific user group relative to the PSS. If our PSS is targeted, for example, at female European elders, we can specify those segments in the dropdown boxes and the data will show the results for that specific user group. If we wish to compare the results of e. g. male and female users, we can apply the gender segmentation and the data will be split into those two groups.

After filtering, we offer three distinct types of data visualization tools: charts, a tag cloud and a post table. The chart visualization is split into six parts, each serving a different purpose:

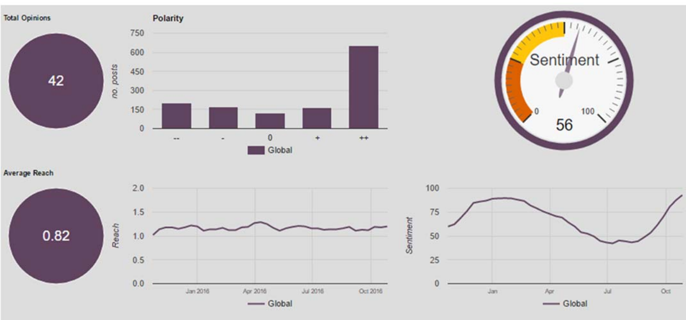

Figure 4 - Extraction Page

Figure 4 represents the chart section of an opinion model. Starting from the top left, we have the total number of opinions used to generate the displayed data. In the top middle, we have a column chart for the polarity value, to which we assigned a domain of '--' (very negative), '-' (negative), '0' (neutral), '+' (positive) and '++' (very positive). For each of these values, the number of posts (both original posts and comments) associated is displayed in a column. In this specific example, we can see that the PSS has a generally positive polarity, which means that most of the monitored posters made positive comments about the PSS. The top right chart is a gauge that displays the present sentiment value associated to the PSS.

On the bottom row, starting from the left, we have the average reach value of the current opinion model. The bottom middle chart is a representation of how the reach value evolved over time. Finally, on the bottom right corner, we have a line chart that displays the sentiment value over time. This chart has the same granularity of the reach over time chart, which corresponds to the update frequency defined when creating the model. This means that the distance between each point in the chart is the update frequency of the opinion model.

Together, these charts provide an overview of the performance of the PSS and can be inspected individually to identify specific details about each indicator.

Our next visualization tool is a tag cloud. A tag cloud is a set of keywords where each keyword has an associated weight, represented through its features like size or colour. More specifically, the sentiment analysis tag cloud displays the most mentioned words across the top user posts (that is, a certain number of posts with the highest reach value), where the size of each word is directly related to the number of occurrences of that word, i.e. the larger words in the tag cloud are the ones that appear more often in the users' posts and comments.

Figure 5 – Tag cloud

The Figure 5 tag cloud was generated by going through the top posts related to a PSS with a single product, the fictional sneakers 'Morris Ground 1'. At a glance, we can infer that the overall opinion is that the PSS is *phenomenal* and *world-class*, which allows us to assume that the users enjoy the product. However, a general tag cloud may not be adequate in some cases: suppose we have a poorly performing PSS at launch and that its sentiment value gradually increases over time, until it becomes a very successful PSS. This will result in a mix of very positive and very negative posts, leaving us with a confusing tag cloud with positive and negative words. To avoid this issue, we linked the tag cloud to the sentiment and reach charts mentioned above. This means that if the user selects a particular point in time, the tag cloud will only display posts with that specific date, allowing us to inspect the general opinion on different periods.

Our last visualization tool is called the Top 5 Table. This table is a set of the five posts with the highest reach related to the current model and contains data about these posts, like the author, date, polarity and reach, and information about the author, like location, gender and age.

Original Author	Post	Comments	Date	Polarity	Reach	Influence	Gender	Age
Sandra Goodrich	Tell me what you think of the new Morris Ground 1! I say phenomen No?	15	2015-11-04	86.4	1.33	0.66	Female	15
Eunice Waymoon	Check the new Morris Ground 1! What a phenomenal sneakers!	15	2015-12-06	87.81	1.33	0.66	Female	45
Jimmy Plant	Have you tested the Morris Ground 1? These sneakers are astonishin	15	2015-11-	86.06	1.33	0.71	Male	75
David Jones	They launched the new Morris Ground 1! ...sweet sneakers!	15	2015-12-03	86.31	1.33	0.66	Male	35
Christa Paffgen	Check the new Morris Ground 1! What a cool sneakers!	15	2015-10-28	63.02	1.33	0.65	Female	65

Figure 6 - Posts Overview

Figure 6 also displays the comments of each post, and can be filtered by selecting a point on the sentiment or reach charts, displaying only posts relative to the clicked date. This table is also linked to the tag cloud: by selecting a word in the tag cloud, the table will display posts that include the selected word.

These visualizations are an effective way of conveying the overall performance of a PSS among its target audience. Together they form a set of tools to assist not only in the maintenance of a PSS, but also in the design process of new PSS by providing information about the performance of the PSS in several time periods and for distinct user groups. Ultimately, this allows the PSS designers to determine how a PSS s performing globally and to identify specific periods and trends in its lifecycle.

V. CONCLUSION

This paper describes the importance of feedback when designing PSS, considering multiple feedback sources, in order to help designers to know how existing PSS are being seen by consumers, by using a wide variety of tools. These tools help to quickly identify problems in PSS, and a faster redesign to increase feedback polarity in the least amount of time possible. They also define a structured approach for acquiring data from sources, in a way that information can be handled and accessed in an integrated way, instead of being looked at one post at a time. Designers are thus able to identify weak or strong points, according to the feedback of users.

Future work is needed to enable designers to pre-emptively obtain this information. Implementation of well-defined hierarchical PSS connections will allow for accurate analysis of adequate combinations of Services and Products. This will be accomplished by calculating products and services similarity. The most similar ones will be used in a prediction module to calculate expected sentiment towards user-defined combinations. As mentioned in chapter III, having one tag cloud might not be very intuitive if very positive words (e.g. “amazing”) are shown together with very negative ones (e.g. awful). Having multiple tag clouds for each half of the polarity spectrum allows for a better visual identification of what should be kept and what should be changed. This feature will be available in a later version of the software. Another developing point regards the supported languages: in order to obtain sentiment of users in a global market, the support of the most commonly used languages is an important feature and should be considered to maximise the impact of this tool. But local characteristics are not limited to language. Outside elements like seasonal values (e.g. winter opinions vs. summer opinions, start of the week vs. weekend, urban vs rural) should be included in calculations as well.

“Beta” buyers also represent a future research topic: authors that always get new releases and comment on them tend to have more network ties and influence, but are also more influenced by perceived product reputation and features and by novelty than ‘regular’ users [16], [17], [18]. Sentiment calculation should consider evaluating these specificities in a differentiated manner along the lifecycle of the PSS.

By the end of the project, these topics will be considered and researched to understand the best methods for inclusion in the overall system.

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