Using the Internet as Sensor for Customer Perception

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Abstract. In a highly competitive market such as the automotive sector it is no longer sufficient to define quality solely on technical aspects. Rather, quality must be analyzed holistically from the perspective of the customer. The customer perception of a product decides the buying behavior. Therefore, Kano et al. have created a special survey form to distinguish between different quality categories for product features. It allows a cost-optimized product design, maximizing customer satisfaction. Practical usage has shown that applying a Kano survey is a very critical process. In this work an alternative data source is proposed that bypasses systematically the problems of a Kano survey: the Internet. Due to the increasing number of fora, weblogs and other social networks there is a large amount of unsolicitedly provided and mostly unbiased customer feedback available. This is used in a prototype architecture to obtain customer satisfaction for different product features and the corresponding influence on customer perception. Different abstraction levels provide information to improve this perception over time.

1 Introduction

In a world of mature markets and intense competition, there are mainly two different product strategies: Either the product implements unique selling points or the product fulfills a high quality standard as a source of competitive advantage [1]. But what does "quality" mean? Today, quality is more or less defined in terms of customer satisfaction [2]. It is often distinguished between objective and subjective quality [3]. While objective quality can be controlled by ensuring the products to be faultless (e.g. by controlling the warranty issues), subjective quality is very hard to measure.

Establishing a successful product or service requires a detailed analysis of customer needs and expectations. Therefore the voice of the customer is taken into account using various survey techniques (e.g. KANO analysis [4]) and customer visits. In several publications however it was shown that this process is highly critical [5,1,6]. The difficulties are based on the fact that customers are explicitly asked. A data source is needed which does not influence the respondents. The Internet is such a data source. With the growing number of customers using

social networks, the World Wide Web provides unsolicitedly written customer feedback. A manual analysis of 1,196 discussions in Internet fora has shown that most of these discussions deal with quality related data (Fig. 1). A carefully selected data source of Internet fora and trustworthy weblogs is the base for the proposed analysis system.

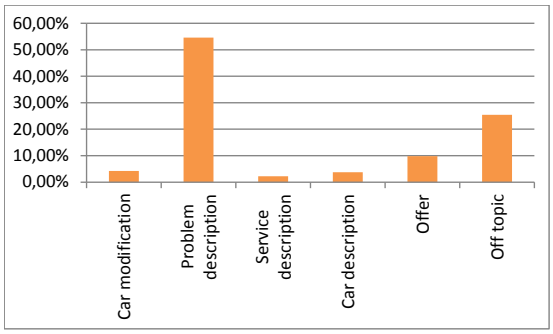


Fig. 1. Abstract topic analysis on 1,196 entries of the automotive forum benzworld.org. Nearly 50% of the posts deal with technical or conceptual problems in which the author asks for advice. 25% of the entries do not deal with any car-related problem at all and can be disregarded for quality analysis.

In the following section a method is proposed which makes it possible to get relevance and satisfaction information without explicitly asking the customer. Analyzing the unsolicitedly provided data of users in the World Wide Web makes it possible to detect topics being relevant for customers along with the degree of the customer's satisfaction. Our approach is realized within a prototype in the automotive domain and aims to obtain knowledge about how to improve the customer's product perception.

2 Satisfaction Analysis

2.1 Data Pre-Processing

User generated content is generally not thought for automated quality related analysis. The data has to be pre-processed to obtain structured quality related information. This is done by data cleaning, natural language processing and information extraction algorithms (Fig. 2). The main steps – *topic detection* and *sentiment analysis* – are discussed in the following.

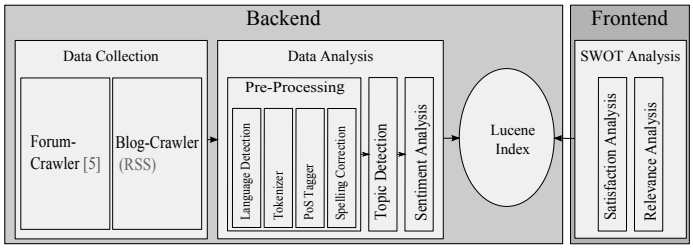


Fig. 2. Prototype architecture for the proposed analysis system: The prototype tracks different Internet fora and weblogs and analyzes the downloaded data. The extracted information is stored in a Lucene index for fast access and incremental updates, which is used by the frontend for interactive analysis.

Topic Detection Topics — in this case product features — can be easily defined in a survey. User generated content instead is not limited to predefined topics. Therefore it is necessary to extract discussed topics out of unstructured textual data. Schierle and Trabold proposed to use a taxonomy based approach [7]. In order to label each comment with related topics they propose to organize the terminology of the given product domain in a taxonomy providing the possibility to store multi-lingual synonyms for each concept. Adding context information and part-of-speech tags facilitates the disambiguation of terms that are associated with different concepts. Using simple token matching algorithms, each user comment can be labeled with its contained concepts. Thanks to the large amount of available data we can afford to discard unconfident classifications and still maintain enough user comments. The taxonomy structure itself groups different concepts to topics. In the following, these topics are called "product features" because it is not important if the analysis focuses on specific features or abstract topics.

Sentiment Analysis Sentiment analysis extracts emotions out of user generated content. In our prototype, we apply a phrase-level polarity analysis as described in [8]. A sentiment lexicon containing polar terms [9] and intensifiers (e.g. negations, strengthening and weakening itensifiers) is used. Contrary to the well-established polarity analyses of complete sentences, our applied deep-level approach allows the extraction of relations between concepts and emotions. Hence, we annotate concepts with the corresponding sentiment value $\in [-1; 1]$ employing a suitable relation extraction algorithm (cf. [10]).

2.2 Quality Analysis

Users do not write about things they have nothing to do with. They are writing about things they (dis-)like or about unexpected behaviors. A product feature that is not discussed is not necessarily dispensable. It could just work as expected. A product feature discussed heavily in social networks is not implicitly

an indication for malfunction, it could just be an attractive feature the users are proud of. That means if you use user generated content as data source for quality analysis you only can analyze features relevant for the customers in the customers' point of view. These features can be analyzed for relevance and satisfaction.

Relevance Analysis All analysis types based on the World Wide Web have to deal with one very important problem: It is not possible to consider all available user comments. The usage of absolute numbers as a measure is doomed to fail because they depend on the selected data sources. Instead, relative calculations are necessary. The relevance for a given feature y_i regarding a product x_j is calculated as the probability $p(y_i|x_j)$ that depends on the frequency f of both concepts relative to the product itself:

$$p(y_i|x_j) = \frac{f(y_i, x_j)}{f(x_j)}$$

Satisfaction Analysis A satisfaction index $s(y_i, x_j)$ for a given product x_j is based on the number of positive user comments concerning a product-feature combination $f^+(y_i, x_j)$ and the number of negative comments $f^-(y_i, x_j)$. Intuitively, one might assume that this index can be calculated as ratio of both frequencies and that the satisfaction will be neutral if the ratio is equal to 1. But this presupposes to have a balanced lexicon and a balanced language. Both conditions are very unlikely. Therefore it is necessary to take the expected satisfaction ratio into account. This can be done in two ways: relative to the market or relative to the product.

1. *Market Ratio:* In the first case, the expected satisfaction ratio is based on the frequency of all products $f^+(y_i)$ and $f^-(y_i)$. The satisfaction index therefore measures whether the product x_i realizes a feature better or worse than the average of all products:

$$\begin{aligned} f_{\text{positive}} &= \frac{f^+(y_i,x_j)}{f^+(y_i)} \\ f_{\text{negative}} &= \frac{f^-(y_i,x_j)}{f^-(y_i)} \end{aligned} \tag{1}$$

2. *Product Ratio:* In the second case, the satisfaction index measures whether a feature is realized better or worse than the overall product satisfaction by using $f^+(x_j)$ and $f^-(x_j)$ instead of $f^+(y_i)$ and $f^-(y_i)$. This makes it possible to learn features in need of improvement in the customer's point of view.

Instead of using the ratio of positive and negative frequencies, the satisfaction index $s(y_i, x_j)$ is now calculated using a case distinction to guarantee a symmetric satisfaction value with 0 for neutral.

$$s(y_i, x_j) = \begin{cases} \frac{f_{\text{positive}}}{f_{\text{negative}}} - 1 & \text{if } f_{\text{positive}} \leq f_{\text{negative}} \\ 1 - \frac{f_{\text{negative}}}{f_{\text{positive}}} & \text{else} \end{cases} \quad (2)$$

3 Prototype

3.1 Implementation

The proposed analysis system has been realized as a prototype in the automotive domain. It tracks 20 automotive Internet fora and 103 weblogs. In sum, the analysis system has downloaded 13 million German and English user comments. The taxonomy for topic detection contains 2,081 automotive-related multilingual concepts (e.g. components, service terms) with 5,392 synonyms. These terms have been extracted from different automotive lexica in addition to co-occurrences found in forum data. The sentiment lexicon was created based on [9] in addition to English translations. User comments are preprocessed using the OASIS Unstructured Information Management Architecture (UIMA) [11,12]. All analysis results are stored in a Lucene[1] index for fast data access so that incremental data updates are possible (Fig. 2).

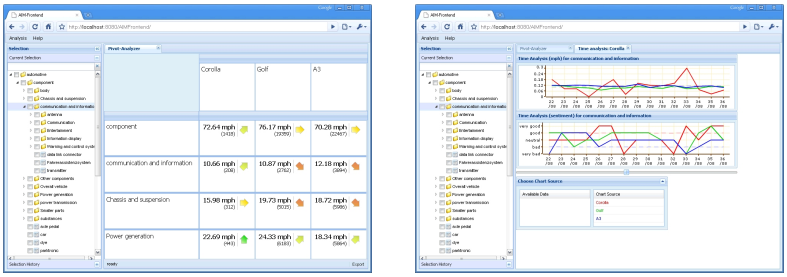
The frontend, the user interacts with, is a Rich Internet Application (RIA) based on GWT[2]. The user can drag products and product features to an analysis table in which the system automatically calculates all necessary frequencies using Lucene search queries. The analysis system additionally classifies each satisfaction value to five different groups based on empirically determined borders. Each class is represented by one of five different arrows in order to give a quick quality impression (Fig. 3a).

Next to the abstract overview, the user can analyze the satisfaction and relevance indices over time and on different abstraction levels including the original user comments (Fig. 3b).

3.2 Market Ratio vs. Product Ratio

In section 2.2 two different normalization methods have been proposed for calculating a satisfaction index. The market ratio is usually used in SWOT analyses that compare one product to others. It has already been shown that market ratio provides quality relevant information [13]. Unfortunately, it could result in an above-average satisfaction index although customers may be dissatisfied with specific features especially for high quality products. Using the product ratio solves this problem as it analyzes the product itself and compares each feature with the overall product satisfaction. Features above or below the expected

[1] `http://lucene.apache.org/`
[2] `http://code.google.com/webtoolkit/`



(a) satisfaction analysis (b) time analysis

Fig. 3. Prototype use case: A potential customer wants to compare customer satisfaction for three different car models. After selecting features relevant to the user, the prototype calculates the satisfaction and the relevance index (a). Each product-feature combination can be analyzed over time (b).

product satisfaction can be identified as strength and weaknesses of the product. The advantages can be shown in real world examples (Fig. 4).

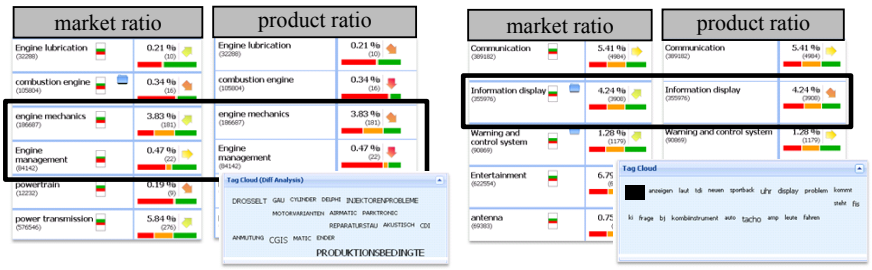


Fig. 4. Market ratio versus product ratio: Although specific product features could be realized above market average, it is possible that customers are dissatisfied. A classical SWOT analysis (market ratio) that compares product features according to the market could hide problem areas. A product driven analysis (product ratio) instead exposes these areas.

Tag Clouds visualizing the most significant words of the analysis subject help to identify problem areas while the original entries offer problem details. Hence, the ranking of approaches to product improvements according to their influence on the customer's product perception is facilitated.

4 Conclusion

User generated content is an impressive alternative to conventional survey methods used for quality analysis. Unsolicited user comments provide a direct and

mostly unbiased insight to product perceptions. We presented a simple method that analyzes this data by extracting topics and calculating relevance and satisfaction measures. An analysis engineer can use these measures to identify critical product features and therefore to control product improvements.

We have demonstrated that classical SWOT analyses could hide problem areas especially for high quality products. It is necessary to additionally analyze products on its own and to identify the best and worst product features in the customer's point of view. This is also the original intention of Kano et al.: Identify these product features that are worth to improve.

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