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"WHAT DOES THE CUSTOMER WANT TO TELL US?" AN AUTOMATED CLASSIFICATION APPROACH FOR SOCIAL MEDIA POSTS AT SMALL AND MEDIUM-SIZED ENTERPRISES

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Research paper

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Abstract

Social media posts created by customers capture a lot of business relevant information for decision-makers, e.g., current consumer expectations on products and services. For that purpose, the social media posts need to be analyzed thoroughly. In this respect, a topic-related classification facilitates managerial decision-making because business relevant topics, social media users discuss about, immediately become obvious and the need for action can be derived. For instance, it may get obvious that the majority of a company's negative customer posts refers to a particular product or a specific campaign. However, such a classification of social media posts is particularly challenging for small and medium-sized enterprises (SMEs). This is because human resources for a manual examination of posts are missing and an automatic analysis is error-prone due to particularities of customer posts such as the occurrence of regional dialect or branch-specific expressions. We thus develop a tool, which enables the automatized topic-related classification of social media posts and matches the particular requirements of SMEs in southern Germany. Our solution is evaluated by using a data set stemming from three collaborating companies.

Keywords: Social Media, Classification, Small and Medium-Sized Enterprise.

1 Motivation

The number of active social media users has been steadily increasing over the last couple of years (e.g., Chaffey, 2016). It is estimated that 90% of all American young adults (18-29 years) use social media for private communication purposes while even the number of elderly users (above 65 years) has tripled since 2010 (currently 35%) (Perrin, 2015). Social media user records are equally high for Europe, with 63.2% of Internet users participating in social media networks on an average (eMarketer, 2016). According to current studies, Facebook counts 1.6 billion users worldwide and the microblogging service Twitter has 313 million subscribers for instance (Statista, 2016a; Statista, 2016b). In this regards, the wide dispersion of social media has not only influenced peoples' private communication behaviour but also the way customers interact with enterprises (Hanna et al., 2011). Hence, a lot of consumers are contacting firms via social media these days shifting away from traditional communication channels such as telephone, email or fax (cf. Hanna et al., 2011). Besides large companies, also small and me-

dium-sized enterprises (SMEs) have increasingly begun to use social media, e.g., to improve the bidi-rectional communication with consumers or to positively impact the company culture amongst others (Meske and Stieglitz, 2013; Lee et al., 2008; Durkin et al., 2013).

In that context, customer posts in social media platforms (e.g., a company's Facebook page) contain a lot of information about current expectations regarding products, services or a company in general (cf. Sigala, 2012a; Sigala, 2012b; Hienerth et al., 2011). The expectations – also entitled as "voice of the customer" in literature (e.g., Lunau et al., 2008) – capture the current assessment of the "value" (cf. Womack and Jones, 1996) consumers ascribe to a firm's offerings (cf. Keil, 2010) and point out *"what's important to customers"* (Pande et al., 2000, p. 190), e.g., an innovative product design. A topic-related classification of corresponding posts facilitates managerial decision-making because business relevant topics, social media users discuss about, immediately become obvious and the need for action can be derived. For instance, it may get clear that the majority of a company's negative customer posts refers to a particular product or a specific campaign. Management may then trigger according initiatives to counteract reasons for consumer dissatisfaction (e.g., product redesign) and increase customer loyalty (e.g., Chua and Banerjee, 2013). Such countermeasures may comprise process improvement projects (cf. Thawesaengskulthai, 2010) or the specification of new products and services (cf. Sigala, 2012a) amongst others. The classification of customer posts thus is a helpful means to systematically structure a disorganized set of posts extracted from social media channels and to prepare the ground for management decisions (cf. Huang et al., 2013).

However, due to lacking resources, the classification of social media posts is challenging for SMEs in case it is performed manually and a large amount of data is to be analyzed (cf. Capgemini, 2015). Employees at SMEs often do not find the time to screen the social media channels besides their daily routines. Although several social media analysis tools are available on the market (e.g., Brandwatch, Radian6, etc.), none of them support a topic-related and company-specific classification of posts (cf. Wozniak, 2016). Further, commercial tools are not affordable for many SMEs due to a restricted IT-budget (cf. Kasper and Kett, 2011; Stavrakantonakis et al., 2012). Some tools are available as "free versions" but these do not include technical support, multilingual analyses for languages others than English or functionalities for data extraction from multiple social media platforms (cf. Stavrakantonakis et al., 2012; Wozniak, 2016). Hence, their applicability in an entrepreneurial context is limited. This holds particularly true for applications at SMEs located in non-English speaking countries. Further, because of the limited regional presence of SMEs (cf. Durkin et al., 2013), customer posts in the corresponding social media channels are usually characterized by regional slang as well as branch-specific product names and expressions amongst others (e.g., Laboreiro et al., 2010; Naaman et al., 2010; Petz et al., 2013). Such peculiarities are not considered by current commercial tools leading to a low accuracy of social media analysis results (e.g., Waltinger, 2010; Wozniak, 2016).

SMEs play a pivotal role considering the German economy. In 2015, there were about 3.62 million SMEs in Germany and, currently, more than 60% of all people in paid work are being employed by this company type (Söllner, 2014; Statista, 2016c). Especially in southern Germany, a large majority of employees is engaged at SMEs (cf. Söllner, 2014; Handelskammertag BW, 2015). In Bavaria this number even amounts to 99.6% of the employees in the private sector (Statistisches Bundesamt, 2015). However, southern Germany is also imprinted by a lot of underdeveloped rural counties (cf. Bavarian Ministry of Agriculture and Forestry, 2006), which makes this region highly interesting for analyzing the impact of information technologies on business performance.

Against this background, the paper's aim is to design, implement and evaluate a social media analysis tool, which considers the peculiarities and specific needs of SMEs. Building on a prior work of ours (cf. Schwaiger et al., 2016), which focuses on the sentiment analysis at SMEs in particular, the main emphasis of this research is on the automated topic-based classification of customer posts. Hence, the contribution of the paper is as follows: first, we provide a solution – consisting of a classification approach and a corresponding tool – that explicitly takes into account the characteristics of social media posts at SMEs (e.g., regional dialect, slang, etc.), which is a prerequisite to receive high accuracy levels

for social media analysis. Existing tools show drawbacks in this respect (cf. Wozniak, 2016) and our research strongly contributes to the field of social media analysis at SMEs paying attention to their particular requirements, which is an under-researched topic yet. Second, our research provides a starting point for the development of generally valid dictionaries enabling social media analyses at SMEs. Hence, we pose the following research question (RQ):

How can an approach for classifying social media posts at SMEs, considering the inherent characteristics of these posts, look like? How can the approach be realized in form of a software tool?

The structure of the paper is as follows: in section 2, foundations on social media and peculiarities of posts at SMEs are presented. Afterwards, the procedure of the research is described. Section 4 deals with the development and evaluation of a social media analysis tool for SMEs. The tool development follows the Design Science (DS) approach (Peffers et al., 2007; von Alan et al., 2004). Subsequently, the benefits of the research are emphasized. The paper is rounded off with a conclusion and an outlook.

2 Foundations

In literature, social media is described as *"a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of User Generated Content (UGC)"* (Kaplan and Haenlein, 2010, p. 61). Examples for internet-based applications entail blogs, social networks (e.g., Facebook or Twitter), enterprise social networks (ESN) (e.g., Yammer), collaborative projects (e.g., Office 365) as well as tools supporting social networking applications (e.g., MS Share_Point) (Turban et al., 2011). In its early stages, social media was used as a solution for individuals, mostly students, to maintain long-distance friendships or relationships. Many social networks like MySpace (2003), Facebook (2004) and Twitter (2006) emerged, providing a simple and direct way to communicate and to inform friends and "followers" about your daily life activities.

Aside from private usage, social media technologies are also increasingly adopted by enterprises integrating them for supporting value-creation. In this regards, not only large enterprises invest into the adaption of social media technologies but also SMEs become more and more engaged (e.g., Meske and Stieglitz, 2013). Especially when it comes to SMEs, the introduction of social media technologies is quite simple as costs are minimal and the required level of IT-expertise is low (Abed et al., 2015). Against this background, companies are becoming more and more engaged in using social technologies like Facebook, Twitter, Instagram or YouTube to strengthen the customer relationship, to support communication with consumers (e.g., Heidemann et al., 2012; Stobbe et al., 2010) and to integrate upcoming social technologies with their business processes and the IT-landscape (cf. Trainor et al., 2014). With the help of social media channels, companies can easily and efficiently handle customer inquiries (e.g., Culnan et al., 2010), share marketing material widely (e.g., Gallaugher and Ransbotham, 2010) or solve customer complaints quickly (e.g., Pinto and Mansfield, 2012). However, with the extended usage of social media channels, the number of posts is also rising quickly and to fully utilize the information captured in social media posts, all data has to be analyzed and interpreted. Particularly at SMEs, which are characterized by limited financial and human resources, an error-prone and a resource-intense manual analysis process is often found.

Besides the general characteristics of social media posts, as described by *Laboreiro et al.* (2010), *Naaman et al.* (2010) or *Zhao and Rosso* (2009), there are some additional peculiarities which are particularly evident at SMEs in southern Germany. Usually SMEs show a limited regional presence, which typically implicates a more direct communication between company employees and their customers (Durkin et al., 2013; Lee et al., 2008). Hence, also corresponding social media posts reflect this tight relation and often address specific products, services or local company-hosted events. By interviewing several social media representatives at SMEs in southern Germany, we were able to retrieve further characteristics. Thus, SMEs tend to be niche players in their industries, which results in a very special language that includes specific expressions as well as product-related and company-related terms. Furthermore, we perceived different aims of using social media among the interviewed SMEs. Some SMEs

use social media channels exclusively for marketing campaigns to emphasize new product launches or upcoming events. Additionally, some SMEs strengthen their customer loyalty by offering prize competitions and free product trials. In contrast, others try to involve their users in general discussions and, by doing so, keep their social media channels populated and vivid.

The term "classification" is defined as the assignment of data towards a predefined set of categories (Feldman and Sanger, 2007). Because of the abovementioned various types of social media usage an approach for an automatic classification of social media posts needs to be highly customizable. Social media posts need to be classified in a company-specific way (e.g., product-related or event-related posts) and the object addressed in a post needs to be precisely determined (cf. Maynard et al., 2012).

3 Procedure of the Research

To develop a tool, called "UR SMART (UR Social Media Analysis Research Toolkit)", for the automated classification of social media posts, which is customized for SMEs in southern Germany, we follow the Design Science (DS) approach (Peffers et al., 2007; von Alan et al., 2004). DS has gained high popularity and has become a legitimate IS research method (Alturki et al., 2013; Buckl et al., 2013; Gregor and Hevner, 2013). A widely recognized suggestion on how to conduct DS projects was introduced by *March and Smith* (1995) and *Peffers et al.* (2007). In this respect, DS research represents a synthesis of the activities "build/development" and "justify/evaluate" with the main goal of developing an IT-artifact to address an organizational problem (Cleven et al., 2009; von Alan et al., 2004).
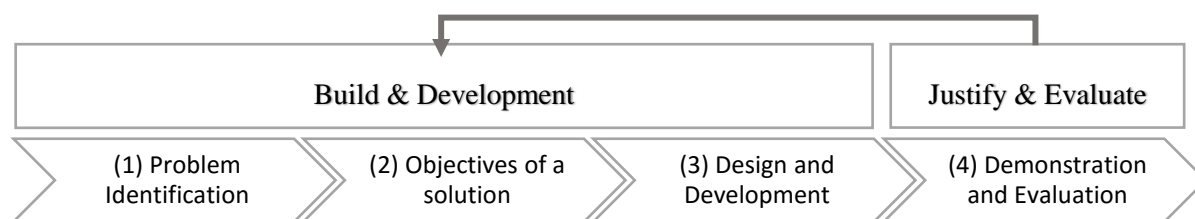

Figure 1.   Procedure of the research

As a first step (1), we **identified the problems** in analyzing social media posts at SMEs by choosing three cooperating partners located in southern Germany, which openly declared their commitment to social media and provided us with detailed problem descriptions. Based on that, we derived the need to develop a software solution, which considers the peculiarities and specific needs of SMEs and enables an automatized sentiment analysis and classification of customer posts. Second (2), we **defined the objectives of a solution** by collecting requirements on a corresponding tool via several interviews with business intelligence managers, social media managers, online marketing managers as well as marketing staff of our collaborating partners. In this regards, the technical realization of the sentiment analysis was done in a previous work of ours (cf. Schwaiger et al., 2016), while the focus of this paper is on the realization of the classification functionality to provide a more detailed perspective on customer attitudes. Hence, for the identification of existing approaches aiming at the automatized classification of customer posts, we conducted a literature review. For this purpose, we examined 130 relevant publications leading to 20 approaches that are potentially suitable for the automated classification of textual social media content. The next step was the **design and development (3)** of our IT-solution. In this regards, we conceived and developed a web based tool enabling the sentiment analysis and classification of social media posts in close cooperation with our collaborating partners. For the **demonstration and evaluation** (4) of our artifact, we chose the combined evaluation method "prototype and action research", as suggested by *Peffers et al.* (2007). The evaluation was realized by a real world deployment of the artifact at our collaborating partners. Additionally, we assessed the accuracy of the developed tool in terms of classifying posts by reflecting the results of an automatized classification against the outcomes of a manually performed classification of a specific data set, which was provided by our cooperating partners. To reduce subjectivity, the manual classification was performed by three researchers. To

measure the accuracy of our artifact, we applied the commonly accepted metrics *precision, recall* and *f-measure* (Christen, 2012). Conclusively, the results of the evaluation were **communicated and discussed** at workshops and audio conference with representatives of all participating companies.

4 A Tool for the Automatized Classification of Customer Posts

4.1 Selection of collaborating partners

For the development of our tool, we collaborated with three partners as indicated in Table 1. For that purpose, a company search was performed in a prior step. We focused on SMEs across all industries who were openly committed to social media usage, e.g., by presenting a link to social media channels on their website or by suggesting visitors to become followers on Twitter or fans on Facebook. In this context, online databases with addresses of German companies and the internet were drawn upon to delimit our search to those companies located in the region of southern Germany. The social media presence of potential candidates was closely investigated to see whether the content was updated on a regular base (e.g., product launch) or not. For our study, only SMEs that were actively engaged in social media use and continuously shared new content were further considered. More, the number of followers on Twitter and Facebook was used for judging the online visibility of a firm. Three firms finally decided to join our study and the conjoint development of a social media analysis tool. By the tool, the SMEs expected to get more profound insights into customers' attitudes by the analyses of posts.

Company	Industry/Description	# of employees (approx.)	# of Facebook fans (approx.)
Company A	Market leader in fun sport equipment for watersports	80	89000
Company B	Online Store for children's fashion, baby fashion, toys and children's furniture	400	85000
Company C	Manufacturer and distributor of high-quality toys, games & room decor for kids of all ages	1200	38000

Table 1.   Collaborating partners

4.2 Collection of requirements

To identify existing problems within social media analysis, we conducted several interviews with our collaborating partners. Thereby we identified their requirements on a tool supporting the analysis of social media posts, which guided its development. To get an overall view, we interviewed business intelligence managers, social media managers, online marketing managers as well as marketing staff. That way, specific expectations from various representatives of SMEs in southern Germany were uncovered supplementing commonly established requirements from literature (cf. Maynard et al., 2012).

The interview partners reported that users of their social media channels used a very specific language imprinted by slang and branch-related expressions due to the niche position of the companies in the market. Some companies exclusively used social media as a communication path to reach customers ("megaphone perspective", e.g., to pronounce campaigns and product launches) whereas others actively invited customers to engage in a bidirectional dialogue ("magnet perspective", e.g., to solve complaints, identify their personal preferences or answer service requests) (cf. Gallaugher and Ransbotham, 2010). In this respect, the monitoring of customer-to-customer dialogues and the automatized classification of posts was strived for, to unveil business relevant topics of great interest to customers (e.g., design of products) and to react quickly ("monitor perspective") (cf. Gallaugher and Ransbotham, 2010). Nevertheless, the analyses supported by available commercial tools tend to be more rudimentary in nature, e.g., number of followers reached by a post, and the required level of detail to trigger improvement or redesign initiatives is not reached by these (cf. Wozniak, 2016). In addition, more nuanced and localized analyses to adequately consider local "slang" or topics of "regional interest" are required to meet the particular needs of SMEs in southern Germany, which however are not supported by the standard functionalities of common tools yet (cf. Wozniak, 2016).

General requirements on the tool to be developed were the ability to extract data from Twitter and Facebook *(requirement 1)* and the automatized sentiment analysis of each customer post *(requirement 2)* at first. As the partners operated on an international level, the tool was supposed to support the analysis of English and German posts *(requirement 3)*. Particular negative or positive posts were to be highlighted by the tool separately *(requirement 4)*, while the user should be able to disable additional functionalities (e.g., spell-checker) upon request *(requirement 5)*. For example, – regarding *requirement 4* – one interview partner (company C) stated *"it would be important to recognize negative developments by help of the posts immediately"*. The ability to filter customer posts (e.g., by creation time) *(requirement 6)*, to modify automatically generated reports *(requirement 7)* and the implementation of a user administration *(requirement 8)* were demanded by our partners as well. More, a key requirement on the tool was the option to automatically classify customer posts *(requirement 9)* and to define new categories on demand *(requirement 10)*. All these requirements were rated as equivalent in importance.

Considering *requirement 10*, the general categories as shown in Table 2 were principally considered to be promising for classifying customer posts and were worked out in a first conjoint workshop with all practice partners participating. Hence, posts should be allocated to the most appropriate category:

No.	Category	Description
1	Product	Praise or complaints about the company's products
2	Service	Remarks about the service portfolio
3	Processes	Posts concerning processes, e.g., the handling of orders or claims
4	Suppliers	Information about the delivery (delayed shipment…)
5	Competitors	Information about goods and services from competitors
6	Retailers	Information about retailers
7	Campaigns	Feedback about campaigns, e.g., raffles
8	Brand	Verdicts about the company
9	Experience / event	Posts about experiences at events
10	User generated content (UGC) / emotional post	Videos, pictures or other content created by users
11	Contests	Posts sharing emotions about contests
12	Topics related to provincial specifications	Posts capturing experiences about provincial specifications

Table 2.   Proposed categories

However, to quickly receive a first version of the tool for the collaborating partners, the participants prioritized these categories and only those with the highest priority were supposed to be implemented in a first shot. For that purpose, the partners selected those categories in a follow-up workshop, which best matched with their major aims for using the social media channels. For instance, companies applying social media to support "product advertisement" considered the categories "campaigns" and "experience/event" as most important. The suitability of the chosen categories was validated by reflecting them against a sample set of representative posts gained from the social media channels of each collaboration partner in addition. The categories to be realized in the first version of the tool thus were: "product", "service", "campaigns", "processes", "experience/event" and "UGC/emotional post".

4.3 Approaches for classifying social media posts

To identify objectives of a solution, we conducted a literature review on social media analysis. The automated analysis of textual data is a widely distributed research field. In general, the computer-assisted analysis of text documents to identify specific patterns within large collections of data is described as *text-mining* (Feldman and Sanger, 2007; Heyer et al., 2006). A main field of text mining is defined as Machine-Learning (ML). ML characterizes a set of approaches and algorithms to identify the earlier mentioned specific patterns to predict future data (Murphy, 2012). When it comes to the automated grouping of large data sets, different research areas can be found in literature. To identify suitable approaches for the automatized classification of customer posts, a literature search on the databases ACM Digital Library, EBSCOhost, Emerald Insight, IEEE Xplore Digital Library, ScienceDirect and SpringerLink was performed (cf. vom Brocke et al. 2009). For this purpose, we examined 130 relevant publications leading to 20 identified approaches potentially suitable for the automatic clustering or classification of textual social media content. On the one side, there are unsupervised approaches which focus

on the assembly process of data to achieve automatically defined homogenous groups by identifying statistical structures and patterns (Dayan, 1999). The best-known techniques in the field of unsupervised ML are *clustering* and *topic modeling*, which both aim at different objectives (Aggarwal and Zhai, 2012b). *Topic modeling* approaches like "probabilistic latent analysis" (pLSA) (Hofmann, 1999) or "latent dirichlet allocation" (LDA) (Blei et al., 2003) try to identify specific topics within huge sets of textual data by reducing the dimensionality and attaching different weights to the specific data set (Crain et al., 2012). *Clustering* approaches like k-means (MacQueen, 1967), expectation maximization (Dempster et al., 1977) or agglomerative hierarchical clustering (Tan et al., 2005) renounce a reduction of dimensionality and try to group matching elements of the dataset on base of their structure (Feldman and Sanger, 2007; Heyer et al., 2006). In contrast to unsupervised approaches, which focus on the assembly of data to come to automatically defined, unlabeled and homogenous groups, there are also supervised ML techniques that provide the automated mapping of data. These techniques are summarized by the term *classification* and use labeled training data to determine the affiliation towards previously defined categories (Feldman and Sanger, 2007; Heyer et al., 2006). Considering the aim of this research, namely the development of a solution for the automated classification of posts, which focuses on the assembly of data towards predefined classes (Feldman and Sanger, 2007; Heyer et al., 2006), 11 of the earlier mentioned 20 approaches were not further considered because they only support an unsupervised clustering. So consequently, we ended up with a total of 9 potentially suitable approaches. Typical approaches in the research field of *classification* are k-nearest-neighbor (Cover and Hart, 1967), naïve bayes (NB) respectively multinomial naïve bayes (MNB) (McCallum and Nigam, 1998; Tuarob et al., 2014) or support vector machines (SVM) (Gunn, 1998). Especially when it comes to textual data, SVM and NB/MNB deliver convincing results (Jin et al., 2013). Hence, we focused our research on 4 remaining approaches in this field. NB assumes that every categorizing attribute is equally consequential and independent from one another (Feldman and Sanger, 2007). A special variant of NB, which implements the NB Algorithm for multinomial spread data, is MNB. It is often used when it comes to textual data like social media posts and delivers better outcomes than NB, particularly for large data sets with specialized event models (McCallum and Nigam, 1998; Tuarob et al., 2014; Kibriya et al., 2004). As the simultaneous analysis of English and German posts is one of the requirements of our cooperating partners, we choose a multilingual supervised classification approach (e.g. Giannakopoulos et al., 2012) to be most suitable for our research.

4.4 Design and development of a supervised classification approach

As mentioned, we focus on the automated classification of social media posts for SMEs in southern Germany in this research, to provide more substantial insights into posts that were already classified by help of a sentiment analysis (positive, negative, neutral, etc.). In this respect, the ability to adapt the classification algorithm to fast changing contexts (e.g., upcoming product trends) is crucial (Read et al., 2012). Especially in terms of sectoral characteristics, several statements can have a meaning which is different to the "common sense". An example for such sectoral characteristics are first names (female or male) occurring in social media posts. Considering company "A", posts including first names like "Clara" unambiguously address human beings, while for companies "B" and "C" such posts may also refer to "dolls" that are retailed by them. In addition, the structure of the investigated posts is decisive. Two aspects need to be considered: at first, social media posts are usually written in a short, succinct way (Zhao and Rosson, 2009). Many social media posts are thus created without a circumscription of the expressed statement. For instance, a typical product review is usually articulated as a combination of the reviewed product and the experiences or feelings associated with it. An exchange of a single entity (e.g., name of the product) may lead to a completely different classification. Consequently, the meaning of every single entity (e.g., word) of the post is relevant for a correct classification. Second, social media posts typically do not follow grammatical rules (e.g., Laboreiro et al., 2010). As a consequence, approaches presupposing correct grammatical structures are not applicable at hand. While these content-related issues are important in terms of the classification, also a company's purpose of using social media needs to be considered. Due to dissimilar target groups (e.g., customers or fans), the appearance

of company-specific or branch-specific issues in social media posts may differ massively. In this regards, company "A" mainly aims at relating its products with joyful emotions by publishing many posts including photos or event reports. In contrast, company "B" intends to maintain a sense of "togetherness" by fostering discussions about topics of interest for their target group.

Considering this, we chose an approach, which combines MNB with a dictionary-based seed word library. Posts are analyzed regarding these seed words (e.g., Carroll, 2008), which allows to assign them to predefined classes. Furthermore, as an additional advantage, the dictionary-based approach enables to customize the classification of posts considering the specific needs of our cooperating partners by enhancing the seed word dictionary by company-specific expressions (cf. Liu, 2012).

Our classification approach is based on the general method of text analysis by *Aggarwal and Zhai* (2012a). Subsequently to the pre-processing step, which uses several techniques like tokenization, stop word reduction as well as normalization to eliminate irrelevant parts, the data is categorized by help of a dictionary. The dictionary contains the most frequently used and relevant seed words (up to 4000 pre-trained words) to enable the assignment of a post to the specific categories of our cooperating partners (see section 4.2). To trigger the classification of a post its core entities (so called tokens) are drawn upon. At first, these tokens will be processed by a stemming algorithm, which transforms the entities to a normative shape, e.g., by cutting designated word endings (Porter, 2001). Afterwards, matching word candidates from the post are being identified and reflected against the seed words from the dictionary. If an entity matches with a seed word from the dictionary, the post will be assigned to the designated category. This task is iterated until all matching word candidates are identified. For example, the post *"wow! Eine Kullerbühkugelbahn[1]!! "* (company "C") is reduced to *"wow! ~~Eine~~ **k**ullerb**ue**hkugelbahn"*. During pre-processing, the language "German" is detected by identifying typical German language features, e.g., umlauts. Afterwards, all letters are transformed to lower case. Subsequently, all umlauts are exchanged. Finally, appropriate word candidates for the entities *"wow" (UGC/emotional post)* and *"kullerbuehkugelbahn" (product)* are searched for. As a result, the post is classified according to the categories *"UGC/emotional post"* but also "product".

A classification of posts, according to the process as described, highlights those topics customers are vividly discussing about in the social media channels. In combination with a sentiment analysis of the posts their tonality gets evident as well. Hence, conclusions can be drawn whether customers have a positive attitude towards particular issues (products, campaigns, services, etc.) or not. This prepares the ground for management decisions (e.g., product redesign initiatives). While the main focus of this paper is on the classification of posts – after a sentiment analysis was already performed – the sentiment analysis functionality of our tool was realized and validated in a previous work (cf. Schwaiger et al., 2016).

4.5　Demonstration and evaluation

In the following, the realization of the major requirements on our tool "UR SMART", as introduced in section 4.2, is briefly described. Considering *requirements 1 and 2* the ability to extract data from Twitter and Facebook as well as the sentiment analysis of customer posts, were implemented (see Figure 2). The ability to analyze German as well as English posts was realized by including a language detection functionality as part of the pre-processing phase *(requirement 3)*. During sentiment analysis, the tonality of posts is determined by the detection and reconciliation of specific words with annotated features (seed words, smileys, etc.). Particular negative or positive posts are highlighted separately *(requirement 4)*. Additional functionalities (e.g., spell-checker) can be enabled or disabled upon request *(requirement 5 – lower check box in the right graphic of Figure 2)*. A filtering function for customer posts *(requirement 6)* by features like category, message, score (sentiment analysis) or timestamp is implemented as well. To manage user access a user administration *(requirement 8)* was realized. The ability to automatically classify customer posts *(requirement 9)* is described in this paper in detail. Figure 3 shows an exemplary

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[1] The expression refers to the wooden marble run "Kullerbüh", which is offered by company "C".

classification of posts for company "C" (within an observation period of three months). It gets obvious, that the topic-related classification of posts further details the results of the sentiment analysis. For instance, it gets obvious that 263 negative customer posts refer to the category "product", whereas also 547 positive posts exist in this respect. (see Figure 3)
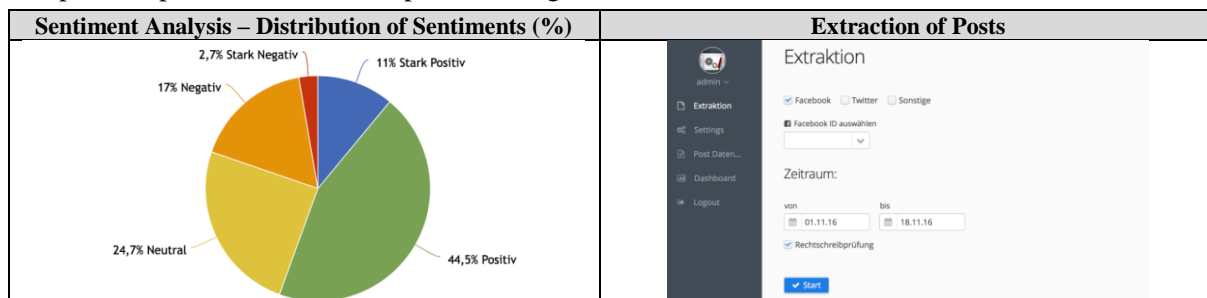

Figure 2.   Sentiment analysis and extraction of posts

Because of that, the classification of posts specifies the results gained via the sentiment analysis in more detail. While the sentiment analysis only indicates whether posts have a "positive", "negative" or "neutral" tonality, the classification allows to uncover those topics, the customers are actually discussing in a positive, neutral or negative way. In Figure 3, the sentiment analysis of our tool distinguishes between "strong positive", "positive", "neutral", "negative" and "strong negative" posts.
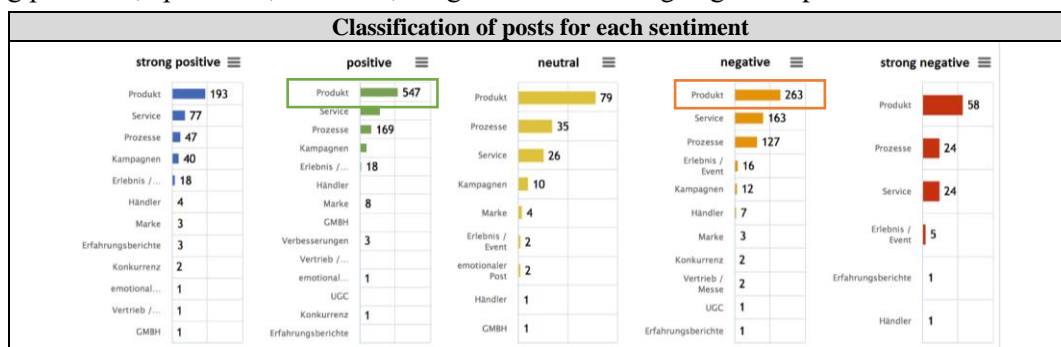

Figure 3.   Classification of posts

UR SMART was implemented as a client-server solution. CPU-intensive and time/power consuming operations, which are necessary for realizing the classification of posts, are thus processed by the server (java-based) and can be visualized by web-enabled devices. A major field of application for UR SMART is to identify and visualize trends or to detect weaknesses regarding particular categories (e.g., "product", "service", etc.) based on feedback captured in social media posts. The importance of each category for a company was ranked based on a joint decision achieved in workshops with the cooperating partners (see section 4.2).

To evaluate the quality of the classification, a set of approx. 2000 posts from the Facebook sites of our partners was provided considering a time frame of three months. The extracted posts were screened and manually classified by three researchers to come to a manual classification of the posts. The results of the manual classification served as a base for evaluating the accuracy of the automatic classification later on. Posts that were not German or English were not further considered. Accordingly, a data set of 1200 posts was drawn upon for the manual classification. The classification of a post was seen as unambiguous, in case two of three researchers assigned the post to the same category independently from one another at least. This process resulted in a set of 612 posts that were unambiguously classified in a manual way and were drawn upon to evaluate the automatic classification as generated by UR SMART. During evaluation, several challenges came up. A major challenge concerned the appropriate delineation of categories. As an example, the post *"I have a Kite Rebel 2015 12 M. Have to change the hoses. Can't find spare parts in Brazil. I am waiting for your help. Thanks!"* (company "A") can be assigned to the

categories "product" or "service". At first glance, this post is a clear candidate to be classified as a *"service"* post. However, at a second glance, the post is relevant for the category "product" as well. Besides the information about the lack of Brazilian dealers offering spare parts ("service"), the post also captures information that "hoses" are a vulnerable product component *"Rebel 2015 12M"* ("product"). This provides valuable hints to raise customer satisfaction. First, there is the necessity to improve the availability of repair parts in Brazil and second to optimize the quality of the product component "hoses". If the post would be assigned to one category only, crucial information about either the product quality or the service infrastructure would get lost. Thus, an assignment to both categories was done.

To measure the accuracy of our approach, we used the commonly accepted metrics *precision, recall* and *f-measure* (Christen, 2012). To calculate these metrics, the underlying variables are to be defined.

Category (C)	Group	Description
main	true appendant	posts, which are correctly assigned to a category
	false appendant	posts, which are assigned to a category, but are not appendant in real world data

Table 3.   Categories and related groups

The metric *precision* focuses on the implemented approach. It calculates the amount of correctly assigned posts in relation to all automatically classified posts for a given category C (see Table 3):

$$precision(C) = \frac{|true\ (C)|}{|true\ (C)| + |false\ (C)|}$$

When looking at the category "product" of our cooperating partner company "C" (see Table 4), 90 posts were assigned to the category by the algorithm, but only 67 of them are truly product-related and thus classified correctly. Consequently, the *precision* for the category "product" for company "C" is 67/90 = 0.74 (74%). In comparison, the metric *recall* measures the amount of correctly assigned posts in relation to all posts classified in the real world data for a given category C.

$$recall(C) = \frac{|true\ (C)|}{all\ posts\ classified\ in\ the\ real\ world\ data\ for\ (C)}$$

For example, the *recall* for the category "experience/event" for company "A" in our dataset in Table 4 is achieved by dividing 18 classified posts, which matched with the manual classification, by all 21 posts that were unambiguously classified by the researchers by hand (85.71%). To sum up, a high value for *precision* (e.g., close to 1) predicates that a very high number of posts that are assigned to the category C by the algorithm are classified correctly. In contrast, a high value (close to 1) for *recall* for posts of a specific category indicates that most of the truly assigned posts are also classified correctly. Hence, a low value for *recall* indicates that the share of the automatically and correctly classified posts for a category in relation to all posts of this category is low. *Precision* and *recall* aim at different objectives. Therefore, we use a third metric called *f-measure. F-measure* merges *precision* and *recall* to their harmonic mean and gives an overall view of the accuracy of the used approach (Makhoul et al., 1999; Hripcsak and Rothschild, 2005). For example, the *f-measure* for company "B" for the category "processes" is 2*0.89*0.56/0.89+0.56 = 0.69.

$$f - measure\ (C) = \frac{2 * recall\ (C) * precision(C)}{recall(C) + precision(C)}$$

Once these metrics are applied to social media posts of our data set, large variations among the different companies can be observed (see Table 4). While the majority of posts regarding company "A" refers to products (103 posts) and experience/events (21 posts), only a minority of posts concerns services (7 posts), processes (2 posts) (delivery, orders, claims) or campaigns (1 post). This can be explained by considering the strategic orientation of company "A", which only operates in a B2B environment. Hence, the bidirectional communication (including campaigns) with end-customers is not desired and should be handled by the resellers instead. The aim of the Facebook presence of company "A" is to merchandise the products and connect them to positive emotions. Thus, product-related and experience-specific/event-specific posts were judged to be relevant. Product-specific posts are classified in an accurate way (recall: 88.35%; precision: 53.22%; f-measure: 66.42%). The high recall value states that a majority of relevant posts was identified. The precision of 53.22% can be explained by fast changing

trends within the market segment company "A" operates in. This becomes evident by continuously changing product labels amongst others. To enable the derivation of action recommendations by decision-makers, it was necessary to tolerate an extra classification of extraneous posts. An akin result could be observed for experience-specific/event-specific posts (recall: 85.71%; precision: 58.06%; f-measure: 69.23%). The high value for recall (85.71%) testifies that a majority of relevant posts was correctly detected. The precision value of 58.06% is justified by considering that company "A" operates in a market (fun sports), which is characterized by fast changing trends complicating the definition of seed words. Further, the corresponding posts are imprinted by slang expressions while also photos or videos are posted on the Facebook page of company "A". In contrast, the classification of posts concerning "service" is more inaccurate (recall: 42.86%; precision: 30.00%; f-measure: 35.29%). Posts regarding "processes" and "campaigns" were not considered because of their rare occurrence.

		Manual reference	Algorithm true	Algorithm false	Precision	Recall	F-Measure
company A	product	103	91	80	53.22	88.35	66.42
	service	7	3	7	30.00	42.86	35.29
	experience/event	21	18	13	58.06	85.71	69.23
	processes	2	2	1	66.67	100.00	80.00
	campaigns	1	1	1	50.00	100.00	66.67
company B	product	87	76	151	33.48	87.36	48.41
	service	75	63	100	38.65	84.00	52.94
	UGC/emotional	74	62	60	50.82	83.78	63.27
	processes	61	54	43	55.67	88.52	68.35
	campaigns	40	24	9	72.73	60.00	65.75
company C	product	79	67	23	74.44	84.81	79.29
	service	19	17	17	50.00	89.47	64.15
	UGC/emotional	32	21	27	43.75	65.63	52.50
	processes	4	3	2	60.00	75.00	66.67
	campaigns	7	6	4	60.00	85.71	70.59
total	product	269	234	254	47.95	86.99	61.82
	service	101	83	124	40.10	82.18	53.90
	processes	67	59	46	56.19	88.06	68.60
	campaigns	48	31	14	68.89	64.58	66.67
	Mean values				*53.28*	*80.45*	*62.75*

Legend: the colored lines hint at the categories that were most important for the companies

Table 4.   Results of the automatic categorization

The direct distributing company "B" put great emphasis on the bidirectional communication with customers. To increase the level of customer satisfaction, all posts dealing with product orders were to be monitored by the company in particular. To strengthen brand loyalty, company "B" started several campaigns like raffles or surveys. To create a feeling of "togetherness" and to associate the products with positive emotions, company "B" created posts regarding emotional topics (e.g., "merry to Christmas time"). Accordingly, the categories "processes" (61 posts), "campaigns" (40 posts) and "UGC/emotional" (74 posts) were selected to be the most relevant ones. The results of the automatic classification for processes bring about a recall value of 88.52% and a precision value of 55.67% (f-measure: 68.35%). The precision value of 55.67% can be explained by the challenging delineation of the category "processes" to other categories such as "service" or "product" via suitable seed words. "UGC/emotional" posts are categorized with a recall of 83.78% and a precision of 50.82% (f-measure: 63.27%). As "UGC/emotional" content is very difficult to identify, the moderate precision is to be judged in light of the subjective interpretation by humans in this respect. Campaigns are categorized with a recall of 60.00% and a precision of 72.73% (f-measure: 65.75%). The lower recall is justified by the usual lack of context information. A majority of posts regarding "campaigns" is written by directly referencing the context, however, without naming the context like "took part". The high precision of 72.73% states that the automatic approach had a well-adjusted set of training data to identify the most relevant posts regarding campaigns. Company "C" (just as company "A") operates as a B2B distributor. The intention of the social media presence of company "C" is to advertise its products and to strengthen brand loyalty. For that purpose, the bidirectional communication with consumers is crucial. Most posts

are product-related (79 posts) and correctly interpreted by the implemented algorithm at large (precision: 74.44%; recall: 84.81%; f-measure: 79.29%). The high number of service posts (19 posts) for a B2B company is striking. In this respect, the slightly lower precision value is owed to the complex delineation of the categories "service", "products" and "processes" for company "C".

Overall, the mean value for *precision* (53.28%) is much lower than the mean value for *recall* (80.45%). The reasons for that are the following: at first, the loss of valuable information by narrowing the range of possible seed word candidates for particular categories was to be avoided. Second, the subjective human interpretation is frequently imprinted by the given context, and thus, relevant information is blinded out. To enhance the precision of the classification, a further refinement of the general categories by the help of subcategories is advisable. For that purpose, we gathered partner-specific lists of the product and service portfolio, which served as a starting point to delineate subcategories regarding the general categories "product" and "service".

Afterwards, the subcategories as defined for "product" and "service" were validated by reflecting them against our abovementioned sample set. In so doing, subcategories could either be merged or further ones could be established. The results were discussed with the partners once again and modifications made until a consensus was reached. Table 5 shows an excerpt of the subcategories for the general category "product" for companies "A", "B" and "C". However, the precise implementation of our approach to enable a classification according to these subcategories is a topic we are currently working on.

Product	Company A	Company B	Company C
Subcategories	board, kite, bar, binding, apparel	games, books, children's room, outdoor, toys, baby care, bags	wood toys, wooden furniture, puppets, dolls

Table 5.   *Exemplary overview of subcategories for the general category "product"*

5   Discussion & Benefits

The dictionary-based approach used for classifying the posts is generally valid, however, the company-specific adaption of the dictionary is crucial for receiving a high level of accuracy in terms of the classification. Further, the delineation of the categories using seed words is challenging and may cause ambiguity during the application. For instance, a post created by a customer who complains about problems during product return, may contain seed words such as "terms of service" and thus address an unsatisfactory customer service (category "service") but also hint at problems of the "product return process" in general (category "processes") by including seed words such as "return process". Nevertheless, even in case of assigning posts to more than just one category, the topics captured by these get evident, while irrelevant categories remain unaffected. As becomes obvious, the classification is especially valuable in combination with the sentiment analysis. That way, negative and positive attitudes towards business relevant topics, such as products or campaigns, are revealed. However, the classification of social media posts and the definition of seed words is far more complex than the sentiment analysis, which may be achieved by the use of freely-available dictionaries, e.g., "SentiwordNet 3.0" (cf. Baccianella et al., 2010), and only analyzes posts in terms of their general tonality.

More, the tool was developed considering the requirements of three partners exclusively, which surely is a restriction considering the generalizability of the solution. However, as a first step to provide means to support SMEs in southern Germany to automatically classify posts, a number of three partners kept the development process manageable as the customer posts had particularities (e.g., regional dialect) that needed to be carefully analyzed and considered for the specification of the dictionary. In general, UR SMART may be applied at other firms without customization as well. Admittedly the lack of adjustment will come at the expense of decreased accuracy levels. However, UR SMART is also adaptable to other company settings. That adaption includes an adjustment of the dictionaries as well as the detection of more company-specific features for instance. With the rising number of adjustments to specific company settings, the generalizability of UR SMART stepwise increases. UR SMART is currently eagerly used to analyze the social media posts of our collaborating partners and several benefits emerge for these companies. Hence, the software is directly integrated in the daily workflows of our partners

and supports managerial decision-making for SMEs based on social media data at first. An important intended use of UR SMART thus is to detect weaknesses in current business operations and processes. Principally, the selection of improvement initiatives is a challenging task for many firms (e.g. Thawesaengskulthai and Tannock, 2008) and social media posts provide a valuable reference for decision-makers in this respect. Based on social media posts, critical processes can be identified and business process improvement projects triggered to avoid monetary and also reputational damage (cf. Pande et al., 2000; Snee and Hoerl, 2003). Generally, literature provides further examples on how social media analyses may influence decision-making, e.g., for deriving new service ideas or improving the existing service portfolio (cf. Sigala, 2012a; Sigala, 2012b).

More, the management is made aware of particular critical issues (e.g., problems with product quality), since UR SMART takes into account every single entity of a post during the analysis. This enables to filter exceptionally negative customer posts and to analyze them more closely for example. Subsequently, UR SMART delivers systematic guidance to overcome process weaknesses. Measuring and monitoring the effectiveness of actions taken to optimize process performance is a crucial task. UR SMART allows to analyze social media posts in terms of different timeframes. Based on this functionality, the management of the cooperating companies can determine whether the impact of redesigning a process (e.g., training of employees to increase service satisfaction) is reflected by customer posts in the corresponding social media channels. As an incidence, a decrease of negative posts about the customer service would be an indicator for the success of process improvement initiatives in this respect. Another important factor concerns customers' reaction. Many of our cooperating partners use their social media channels for social media marketing or advertising campaigns. As UR SMART enables a time-dependent analysis, customers' reactions to social media marketing or advertising campaigns become evident (e.g., Castronovo and Huang, 2012). Hence, campaigns favorably received by consumers (e.g., prize competitions or special offers) often entail discussions in the social media channels. With the information and topics captured in these posts, SMEs may purposefully design and plan future campaigns.

As a scientific contribution of our research, we show the applicability of an approach for the automated classification of textual social media content at SMEs from southern Germany. The automated analysis of social media posts is an emerging research field but when it comes to a practical application in a real world scenario we identified various challenges. Especially at niche representatives, like our cooperating partners, the company-specific adaption of the approach is crucial for receiving a high level of accuracy. With UR SMART, we provide a tool that is not only suitable to analyze German and English social media posts but also to specify the analysis towards regional dialect, slang as well as branch-specific language. Our tool supports the sentiment analysis and the classification of posts and allows to get deep insights into customers' current attitudes, needs and expectations.

6   Conclusion

In this research, we described the development of a tool supporting the classification of social media posts. Particular attention was paid to the specific needs of SMEs in southern Germany. For that purpose, we collaborated with three partners from industry by using a dictionary-based approach. The classification of posts provides the SMEs with profound insights into customers' attitudes and thus helps to derive measures for strengthening the customer relationship. As a limitation, the focus on three collaborating partners surely hampers the generalizability of the solution. Nevertheless, a thorough adaption of a dictionary-based classification approach requires to concentrate on few selected partners to receive a high level of accuracy of the classification. Further, the delineation of categories, based on seed words, is challenging as described above and thus a refinement of the dictionary is strived for.

In future, we aim at the creation of a generally valid dictionary applicable for classifying social media posts at SMEs in southern Germany. More, the development of a semi-supervised approach that automatically detects new seed words on base of social media data is a topic for further research as well. Additionally, we plan to automatically derive suggestions for process or product redesign initiatives based on the social media analyses results.

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