ASSESSING THE ACCURACY OF SENTIMENT ANALYSIS OF SOCIAL MEDIA POSTS AT SMALL AND MEDIUM-SIZED ENTERPRISES IN SOUTHERN GERMANY

Completed Research

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Abstract

In recent years, small and medium-sized enterprises (SMEs) have increasingly adopted Social Media technologies with the purpose of fostering the bidirectional communication with customers or to facilitate the collaboration between employees amongst each other. Thereby, customer posts in a company's Social Media channels capture consumers' current attitude towards product and service offerings or the enterprise as a whole. An automatic analysis of these posts does not only provide a firm with valuable knowledge on the customer relationship, but also frees up human resources in case the posts were screened by employees manually hitherto. However, posts in Social Media channels of SMEs are characterized by certain peculiarities such as regional slang or off-topic discussions amongst others. The study at hand investigates the impact of such characteristics on the accuracy of results received from an automatic sentiment analysis of corresponding posts. In this context, we revert to Social Media posts of five SMEs from southern Germany. The results show that an adaption of approaches used for sentiment analysis to the specific language of customers and firms is mandatory for achieving a high level of accuracy.

Keywords: Social Media, sentiment analysis, small and medium-sized enterprises.

1 Introduction

With affordable and reliable internet service for everyone and information technology evolving quickly, Social Media began to emerge massively at the turn of the millennium (Heidemann et al., 2012). According to current studies (cf. Statista, 2015a; PWC, 2012), the number of active Social Media users is estimated to be 2.44 billion worldwide in 2018. This is an increase of 37% compared to user statistics for 2015. In January 2015 alone, the social network Facebook had about 1.36 billion users and the microblogging service Twitter counted 284 million subscribers for instance (cf. Statista, 2015a).

As Social Media had developed into being a major part of communication in the private life of the majority of the young generation (PWC, 2012), many larger scale companies decided to join Social networks and microblogging platforms (cf. Gallaugher and Ransbotham, 2010). Literature presents a variety of benefits that companies may achieve by the purposeful introduction of Social Media technologies with either the individual, a team or the organization as a whole profiting (Lehner and Fteimi, 2013). For example, van Zyl (2009) points out that Social Media helps to find experts and business partners, to increase staff motivation, to accumulate organizational knowledge, to develop innovations, and to strengthen customer relationships. Further, the creation of customer adapted services and products is emphasized frequently (cf. Mitic and Kapoulas, 2012; Ramaswamy, 2010). This is particularly important as customer requirements are rapidly changing these days due to increased market transparency (cf. Goodrich and de Mooij, 2014; Sharma and Baoku, 2013). Social Media offers the opportunity to gain insights into customers' attitudes, supports brand building and thus contributes to establishing long-term customer loyalty (Chua and Banerjee, 2013; Chikandiwa et al., 2013; Parveen, 2012).

Lately, small and medium-sized enterprises (SMEs) have increasingly started to apply Social media, too (Meske and Stieglitz, 2013; Lee et al., 2008; Durkin et al., 2013). In this context, the improved bidirectional communication with consumers, the easy access to company knowledge, and a positive impact on the company culture are particularly accentuated (cf. Meske and Stieglitz, 2013; Lee et al., 2008). Besides these benefits, the introduction of Social Media in a company is reported to be comparatively easy (Bell and Loane, 2010), which increasingly tempts SMEs to apply corresponding technologies for supporting the day-to-day business.

Though, many of the benefits associated with the external use of Social Media (e.g., strengthened customer relationship, customer co-creation of services and products) (cf. Sigala, 2012; Ramaswamy, 2010) can be traced back to a deeper understanding of customer concerns and expectations gained by applying corresponding technologies. Social Media posts, e.g., on an enterprise's Facebook page, represent the "voice of the customer (VOC)" (cf. Pande et al., 2000) and capture current customer attitudes towards products, services or the company in general. The analysis of these posts can provide valuable information on consumers' behavior and serve as a base for triggering word-of-mouth (WOM) efforts (cf. Oh et al., 2016), product development projects or business process improvement (BPI) initiatives for example. As customer posts in Social Media platforms become visible without any delay, companies can immediately analyze them and retrieve a customers' current sentiment (cf. Liu, 2012). This is a clear advantage over the collection of secondary data (e.g., quality reports), which is often outdated, or the costly and elaborate conduction of customer surveys (cf. Meran et al., 2013).

However, to fully utilize the information captured in Social Media posts, all posts have to be analyzed and interpreted. Since the amount of posts quickly rises when a company establishes a Social Media strategy, enormous human efforts are required in case the analysis is performed manually. This is a major challenge for SMEs regarding limited human resources and the lack of time available to monitor Social Media channels besides the daily routines. Contrary to large enterprises that usually create own positions for Social Media responsibles, SMEs often charge employees of their operational divisions (e.g., marketing) with Social Media efforts. As a result, these employees cannot dedicate a lot of time into monitoring Social Media channels without sacrifizing their daily routine. Against this background, the necessity for an automated sentiment analysis of Social Media posts becomes evident. Several approaches (cf. Liu, 2012) and tools have been developed to fulfill this purpose in recent years (e.g., Brandwatch, SocialBench, etc.), anyway, it is a market still in the process of maturation (cf. Paltoglou, 2014). Additionally, customer posts in Social Media channels of SMEs are characterized by colloquial language, consumers' regional dialects and an industry-specific terminology amongst others. What is missing yet are profound insights regarding the accuracy of automatic approaches for conducting sentiment analyses in comparison to manually performed analyses of corresponding posts at SMEs. Due to the lack of grammatical structure and industry-related language encountered in Social Media posts we consider dictionary-based approaches as particularly well suited for the analysis. We thus post the following research questions:

- RQ1: What accuracy does an automatic sentiment analysis using a dictionary-based approach provide for posts in SMEs' Social Media channels in southern Germany in comparison to the results of a manual classification?
- RQ2: What peculiarities of the customer posts can be reverted to for explaining a potential inaccuracy of the analysis results?

By the first research question, we aim to provide a better understanding for the capabilities of established approaches for the automatic sentiment analysis to correctly assess customers' current attitudes towards a company. In this context, we investigate Social Media posts of five SMEs from southern Germany. Generally, SMEs play a decisive role in the German economy (cf. Söllner, 2014) with 99.3% of all companies being assigned to this enterprise category in 2013 (Statistisches Bundesamt, 2015a). Especially in southern Germany, SMEs employ a majority of the workforce (cf. Söllner, 2014; Handelskammertag BW, 2015); e.g., in Bavaria 99.6% of the employees in the private sector work for SMEs (Statistisches Bundesamt, 2015a, 2015b). Neverthless, from an economic perspective, southern Germany is also characterized by a vast amount of underdeveloped rural regions (cf. Bavarian Ministry of Agriculture and Forestry 2006). Consequently, the region of southern Germany is particular interesting for studies dealing with the application of information technology at SMEs to raise business performance. The second research question aims to uncover deficiencies of the automatic sentiment analysis and to investigate the causes for these drawbacks reverting to the characteristics of customer posts. These insights help SMEs to decide whether an automatic sentiment analysis is worth the investment of resources. Therefore, our findings are particulary interesting for practitioners disussing the potentials of Social Media introduction.

The paper unfolds as follows: in section 2, foundations on Social Media, sentiment analysis and peculiarities of customer posts at SMEs are introduced. Afterwards, the procedure of our research is presented (section 3). Section 4 highlights the result of the investigation. The results are discussed and interpreted in section 5. The paper is rounded off with a conclusion, limitations and an outlook.

2 Foundations

2.1 Social Media and Peculiarities of Posts in SMEs

Social Media entails *„…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“* (Kaplan and Haenlein, 2010, p. 61). These Internet-based applications incorporate blogs, social networking sites, collaborative projects, content communities, virtual social worlds as well as virtual game worlds (Kaplan and Haenlein, 2010). At first, Social Media was used as a way for individuals, mostly students, to maintain long-distance friendships or relationships. Many social networking sites like Six Degrees (founded 1997), Friendster (2002), MySpace (2003) and Facebook (2004) emerged by providing a solution for this need to its users. Microblogging platforms like Twitter (2006) provided additional ways to inform your friends or “followers” about your daily life events.

In today’s market, Social Media technologies are increasingly adopted by enterprises integrating them with their business processes to support value-creation. SMEs can easily engage in Social Media as costs are minimal and the level of IT skills needed is low (Abed et al., 2015). For example, SMEs can benefit from using social networks like Facebook to gain positive impact, e.g., by reducing costs for customer service, by improving customer relations, or by improved information accessibility (Ainin et al., 2015). Alongside, recent studies revealed that one of the main strategic goals of German SMEs is to improve customer service (Statista, 2015b). To support this goal, direct access to customer data is required and *“…social media usage has a positive influence on information accessibility. Organizations can get information about their potential customers, their tastes, their wants easily from the conversations in the social media sites such as Facebook pages, twitter sites etc.”* (Parveen et al., 2015, p. 11). However, the use of Social Media in SMEs is very diverse since the owner-managers are a heterogeneous group, e.g., in regards to their preference for face-to-face interaction with customers, or the knowledge and skills in the e-Business context (Derham et al., 2011). A major driver for Social Media adaption in organizations is identified as institutional pressure from the external environment, e.g., customers, or competitors (Parveen et al., 2015). Especially for customers Social Media is a quick and easy channel of communication that enables them to interact with a company publicly.

Social Media data commonly consists of the following elements: a username, the shared content, the time and date of the post, the self-reported location of the user, references to other users or sites, and the network of the user (Murphy et al., 2014). Posts in Social Media distinguish from other communication in three points. First, the posts are by default either accessible by the public or at least by several members of a personal network. Hence, Social Media posts usually address more than one person. The second characteristic of Social Media posts is the shortness of the post, triggered by either technical limitations of the platform (e.g., 140 characters on Twitter) or by constraints of the user (e.g., typing a post on a mobile device on the subway). In either case posts need to be concise (Zhao and Rosson, 2009). Consequently, text economy increases, e.g., whitespaces are spared as well as words are replaced by numbers of similar pronunciation (Laboreiro et al., 2010; Petz et al., 2013). Additionally, there is a high usage of emoticons to express emotions (Pak and Paroubek, 2010; Petz et al., 2013). A third differentiation point of Social Media posts results from the meshed structure of a social network. Posts reflect this structure by adapting it, for example by allowing users to provide direct feedback to other users' posts or by offering the possibility to add references into posts (Naaman et al., 2010).

Aside from these aspects, Social Media posts show several specifics in regards to the language used. Especially non-standard language elements like emoticons (see section 4.2), "internet slang" (e.g., the expression "4u"), multiple languages within one posts, or spelling errors (e.g., "Helllllooooo") typically occur and should thus be regarded (Laboreiro et al., 2010; Petz et al., 2013). As Social Media posts can be created on many different devices without the ability of spellchecking, an increase of spelling mistakes can be observed (Laboreiro et al., 2010; Naaman et al., 2010).

Beside these general characteristics of Social Media posts, there are some additional peculiarities of posts relating to SMEs in southern Germany that influence the content and structure of the posts. SMEs usually show a limited regional presence (Durkin et al., 2013; Lee et al., 2008). This typically results in a more direct communication between the companies and their customers and employees (Durkin et al., 2013). This stronger relation can also be observed in corresponding Social Media posts, which often address specific products, services or local events hosted by the companies. While little research has been focusing on this topic, we were able to retrieve some peculiarities by interviewing several Social Media representatives of SMEs in southern Germany. We received multiple feedback from our interviewees that pointed out that their target audience uses a very specific language. As SMEs tend to be niche players in their industries, their customers tend to use very special language and expressions as well as product and company names. Additionally, customers may use the Social Media channel as a first approach for complaints and customer service requests since SMEs usually do not maintain call centers or local service centers. Thus, we expect a lot of posts carrying service requests and therefore have a rather negative annotation. Furthermore, we identified a difference in usage of Social Media among the SMEs interviewed. While some use Social Media channels strictly as a marketing channel to present new products or upcoming events, others try to involve their users in general discussions. We also identified open innovation as a potential usage scenario of Social Media for SMEs. As SMEs account for the majority of companies in a nation, the individual companies differ vastly in size and public recognition. As a result, we also expect customer involvement in Social Media channels to be very heterogeneous and very dependent of the popularity of the product or service offered.

2.2 Approaches for Sentiment Analysis in Social Media

Automated sentiment analysis of specific text is an interdisciplinary research field. In consequence, there are a variety of publications in the areas of Natural Language Processing, Text Mining, Web Mining and Information retrieval (Liu, 2012). Sentiment analysis consists of different subareas, such as subjectivity detection, sentiment classification and opinion summarization (Kumar and Sebastian, 2012).

Approaches with reference to sentiment analysis can be categorized into three different classes. At first, document-based approaches aim towards the classification of the sentiment of a whole text corpus, for example newspaper articles. The second category focuses on sentence-based approaches, which analyze whether a single sentence can be classified as having a positive, negative or neutral sentiment. The third category considers aspect-based approaches which focus on entities and their aspects. For example, in product reviews the attributes (aspects) of the reviewed products (entities) could have different characteristics (Vohra and Teraiya, 2012; Feldman, 2013; Liu, 2012).

Considering the research questions, the focus of the study was to analyze Social Media posts in SMEs. Accordingly, we focused on sentence-based approaches, namely *dictionaries, corpus-based approaches, syntactic patterns, artificial neural networks* and *treebanks* (Medhat et al., 2014). When using *dictionaries,* the sentiment of each entity (e.g., each word) from a text is classified into a positive or negative class using dictionaries. The dictionaries annotate opinion carrying words. The sentiment of the whole text is determined by considering the sum of the combined scores of all its entities (Turney, 2002; Kundi et al., 2014). *Corpus-based approaches* determine the sentiment based on a domain specific text corpus regarding the context of the sentence, which can be recognized by particular adverbs (Liu, 2012). *Treebanks* disassemble the sentence into a hierarchical grammatical structure (tree). With respect to the purpose of sentiment analysis, this structure could be used either to identify recursively restraining negations or to determine the semantic orientation of the sentence by means of adverbs and adjectives (Turney, 2002; Sadegh et al., 2012). *Artificial neural networks* consist of parallel operating units (neurons) to classify the sentiment of a sentence. The words that need to be classified traverse the network through weighted branches. The network can be trained by adjusting the weights of the branches (Sebastiani, 2002).

Although sentiment analysis is a lively discussed field of research, the available approaches and solutions do not reach satisfactory accuracy levels for practical applications yet (Collomb et al., 2014). This is particularly true when it comes to German Social Media posts. The German language contains a vast amount of complex language-specific grammatical rules and thus many approaches initially designed to interpret English fail in delivering acceptable accuracy levels (cf. Waltinger 2010). Challenges for the approaches especially occur in case the posts capture regional slang or irony. For the purpose of irony detection, knowledge about the topic addressed, the events related to ironic statements (e.g., special incidents), and correctly identified emotions, e.g., expressed by emoticons, are important factors (Carvalho et al., 2009; Davidov et al., 2010; Derks et al.,2008; Gonzales-Ibanez et al., 2011). To identify slang, current sentiment analysis approaches build on dictionaries covering branch-specific or topic-related expressions for instance (Asghar and Zubair, 2014; Nielsen 2011). However, generally valid cross-industry dictionaries do not exist yet. Accordingly, a case-dependent adaption of current approaches for sentiment analysis or a value-adding combination of them is required in practice (cf. Gonçalves et al., 2013). To sum it up, sentiment analysis research still is in a maturing phase with commercial social monitoring tools requiring further improvements to be beneficially applied at SMEs (cf. Sponder, 2010).

3 Procedure of the Research

For answering the research questions, we followed the procedure as shown in figure 1. The steps are part of a larger Design Science project (cf. Hevner et al., 2004), aiming at the development of a Social Media monitoring tool adapted to the needs of SMEs in southern Germany in particular.

Figure 1. Procedure of the research

To identify existing approaches for sentiment analysis, the first step was to *review the state of the art*. For this purpose, we examined 196 relevant publications resulting in 17 identified approaches potentially suitable for automatic sentiment analysis of textual elements. Social Media posts represent a specific area of application, for which only a limited number of algorithms are applicable. Thus, a main task was to identify a suitable approach for the given area of application.

Within the *construction of the scenario,* we cooperated with five SMEs from southern Germany. Each company operates at least one Facebook page and is heavily engaged in the field of Social Media. In a discussion with representatives of the five companies we defined the further elements of our scenario (e.g., languages analyzed, timespan of the data extraction).

For the next phase, the *application of the approach*, we used a well-established text-mining procedure (cf. Aggarwal and Zhai, 2012). Its first step is the extraction of the Social Media data from every company's Facebook page. For this objective, we developed an extraction tool based on public API libraries. Our extraction tool connects to existing Facebook and Twitter developer interfaces and stores the extracted data in a universal file format. The extracted data is then used for further data preprocessing and analysis. Due to the linguistic and structural characteristics of Social Media posts, we had to adjust the existing sentiment analysis algorithms to fit our specific requirements. Aside from customizing the algorithms for the shortness of Social Media posts (Zhao and Rosson, 2009), we focused on the integration and detection of emoticons, media-specific words and multiple languages in a single text (Laboreiro et al., 2010). As a result, we created a software application that can automatically conduct a sentiment analysis on Social Media posts in German language, specifically aimed at the peculiarities of SMEs.

The last step of our research procedure is the *presentation and interpretation of the results.* For the evaluation of the results generated by the automated application, it was necessary to first assess the test data manually. For this purpose, the sentiment of every single extracted post was determined by a group of six researchers and discussed with at least one representative of each participating company. The agreed-upon sentiments served as a comparative value for our automatic sentiment analysis. As we eliminated subjectivity as much as possible, we considered the manual sentiments identified as "reality". To determine the accuracy of the automated analysis, we used the commonly accepted metrics *precision, recall* and *f-measure* (Christen, 2012). The results were then discussed and evaluated at a workshop with representatives of all participating companies.

4 Identification of Peculiarities in the Application of Sentiment Analysis in the Context of SMEs in Southern Germany

4.1 Construction of the Scenario

As mentioned earlier, we generally considered 17 algorithms for sentiment analysis as appropriate for our research. With regards to the stated peculiarities of Social Media posts in the context of SMEs (see section 2.2), the implementation of a dictionary-based algorithm was seen as the most promising approach for multiple reasons: first, Social Media posts do not provide a precise grammatical structure; much more they often contain a set of "fuzzy" text fragments. Second, we expected a lot of specialized resp. industry-related language to occur in Social Media posts of SMEs. Hence, algorithms for sentiment analysis requiring a correct grammar or orthography of the texts to be analyzed will not achieve a convincing classification. Therefore, the algorithm to be selected needs to be able to cope with these circumstances by taking into account every single entity (e.g., word) of the post. Additionally, the dictionary-based approach allows for a simple customization and thus enables its application for the different requirements of the cooperating companies (Liu, 2012).

After selecting the approach for further evaluation regarding the quality of the sentiment analysis, we defined a structured evaluation scenario. To gain valuable insights into the specifics of Social Media posts in SMEs in general, we selected the Facebook sites of five SMEs for our data collection. For this purpose, a company search was performed. Freely available online databases with addresses of German companies and the internet were analyzed in that context. The search was directed at enterprises of small and medium sizes across all industries, openly declaring their commitment to Social Media. The commitment could be shown by a link to Social Media channels on the firm's website, by inviting visitors to become "fans" on Facebook, or by encouraging them to follow the company's Twitter account.

The Social Media presence for each firm identified was then analyzed to see whether up-to-date content was regularly pronounced by the company (e.g., announcement of events, etc.) or not. Further, the number of followers of a company's Social Media channels was drawn upon to judge its online visibility, and only those enterprises that continuously updated their Social Media presence were further considered. In these cases, the companies' dedication to Social Media could be acknowledged from an external perspective making them potential candidates for our evaluation. Relevant firms were then contacted and asked if they were willing to participate in our evaluation. A total of five companies from various industries and different target audience decided to join our study (see table 1). The companies mentioned the vast amount of posts generated by the high number of followers as their main reason for the need of an automatic analysis and thus for joining our study. To generate comparable results for all companies, we agreed on only analyzing the companies‘ Facebook pages and focusing on posts in German language.

Company	Industry/Description	# of Employees (approx.)	# of FB fans (approx.)
Company A	Market leader in fun sport equipment for watersports	80	4,000
Company B	Online Store for children's fashion, baby fashion, toys and children's furniture	400	85,000
Company C	Manufacturer and distributor of high-quality toys, games & room decor for kids of all ages	1,200	30,000
Company D	Leading manufacturer and distributor of equipment for day-care centers, kindergartens, and schools	200	2,000
Company E	Leading manufacturer of RVs, mobile homes and caravans	1,200	1,500

Table 1. Participating companies in our evaluation

First, we extracted all posts from the Facebook pages for a ten week timespan (July 25th to October 6th 2015), providing us with a total of 1,554 initial posts (see table 2). However, the extracted posts also entailed posts by the companies' own Social Media teams as well as posts in non-German languages. Thus, we had to eliminate these from our dataset which subsequently shrank to exactly 1,000 posts to be analyzed. We continued our research by conducting a workshop with Social Media representatives from the five companies. In this workshop, we selected approx. 40 eye-catching posts per company and discussed the specifics of these in regards to special expressions and meanings of the corresponding industries. After this valuable input from practice, six researchers were able to determine the sentiment for each of the 1,000 posts individually. The results were then discussed and aggregated to the sentiment agreed upon (402 positive, 455 neutral, and 143 negative). The resulting list of 1,000 posts and their corresponding sentiment were the foundation for the evaluation of the algorithm in regards of its accuracy to estimate sentiments in Facebook posts for SMEs in German language.

company	# of extracted posts	# of relevant posts
Company A	325	125
Company B	416	260
Company C	351	316
Company D	90	34
Company E	372	265
total	**1,554**	**1,000**

Table 2. Number of extracted and relevant Facebook posts per company

4.2 Application of the Approach

For the evaluation of the approach for analyzing the sentiment, the application follows the general method of text analysis as shown in figure 2 (cf. Aggarwal and Zhai, 2012).

Figure 2. Selected approach for sentiment analysis

As a starting point, data (e.g., posts or tweets) is extracted from Social Media channels and converted to a consistent data format for further effective processing (Akaichi et al., 2013; Feldman, 2013). Even though we focused on the companies' German Facebook pages, one of the main problems during our evaluation was the mixture of English and German language in the extracted Social Media posts. As many of the preprocessing techniques are language dependent and we focused on posts in German only (see section 4.1) this issue needed to be addressed. Thus, we implemented a language detection prior to the other steps to determine the language of every single post and eliminated non-German posts.

Subsequently, data preprocessing, including various techniques like tokenization, stop word reduction, stemming and normalization, is required (Aggarwal and Zhai, 2012). Tokenization describes the decomposition of posts into smaller parts, e.g., single words. Additional symbols, punctuation and special characters are removed (Carstensen et al., 2010). Afterwards, stop word reduction is performed. Hereby, words that do not carry opinions are removed (Angulakshmi and ManickaChezian, 2014). To identify these, publicly available stop word lists are applied. The next preprocessing technique used is called stemming. During the stemming process, prefixes and suffixes are eliminated and words are reduced to their stem or basic form. For example, the verb “walking” is stemmed to its base form “to walk” (Akaichi et al., 2013). Normalization is the last of the mentioned preprocessing techniques. Thereby, all remaining text is transformed to lower case characters (Angulakshmi and ManickaChezian, 2014).

Despite the mentioned preprocessing techniques, most approaches for sentiment analysis cannot handle some special content immediately. Therefore, a feature extraction composed of defining feature types and selecting specific features (e.g., emoticons, part of speech, sentiment carrying expressions) is necessary (Selvam and Abirami, 2009). Due to the frequent occurrence of these features in our dataset, we integrated particular dictionaries to meet this specific characteristic of Social Media posts. To establish a proper feature resource, we examined our dataset and extracted the most common features. A collection of examples is presented in table 3.

<table>
<tr><th>Features indicating a positive sentiment</th><th>Features indicating a negative sentiment</th></tr>
<tr><td>(y) | :-) | ;-) | =) | :-D | XD | (x | (=| ^^ | *O* | :-* :') | <3 | :-P | :o)
„Yeeha“| „rock&roll“| „Bang!“ | „wow“</td><td>:-(| /: | :' | :'(| :_(| T_T | ;-; | Dx | 'n' | :\ | :/ | >:o D:
„#soEinShice“ | „das macht betroffen“</td></tr>
</table>

Table 3. Examples for features found in our dataset

After completing the steps data extraction, data preprocessing and feature extraction the act of *knowledge extraction* follows. As presented in section 2.2, a variety of algorithms for conducting this task exists. Due to the emphasized characteristics of Social Media posts, as mentioned, dictionary-based approaches represent a generally accepted approach for the automated sentiment analysis of such textual content. Dictionaries represent lexical resources with annotated words (Feldman, 2013). Depending on the sentiment of each word, the annotated value is either positive, neutral or negative. It is expressed by a number within a predefined range (a higher value is more positive) (Feldman, 2013). For example, given a value range of [-2;+2], the word “fantastic” would be annotated with a value close to +2, while the word “horrific” would be annotated with a value close to -2.

A widely accepted implementation of a dictionary-based approach is SentiWordNet 3.0. SentiWordNet 3.0 represents a lexical resource for automated sentiment classification (Baccianella et al., 2010). However, SentiWordNet 3.0 only provides a lexical resource for English. To support German Social Media posts as well, we used SentiWS, a German language resource for analyzing the sentiment of German texts (Remus et al., 2010). As SentiWS did not match the structural requirements of the SenitwordNet 3.0 approach, we adapted SentiWS by converting the structure of the German dictionary to fit the one of SentiWordNet 3.0 (Remus et al., 2010). Both resources contain lists of positive and negative opinion carrying words.

For acknowledging irony and slang the dictionary was extended with expressions pointing to special events (e.g., product launch) of the branches considered. Also we classified the appearing emoticons into positive and negative ones to identify the expressed emotions within the posts. Further, a manual screening of posts on the companies’ Facebook sites was performed to extend the dictionary by words capturing slang expressions.

4.3 Presentation and Interpretation of the Results

To measure the accuracy of our approach, we used the commonly accepted metrics *precision, recall* and *f-measure* (Christen, 2012). To calculate these metrics, we had to define the underlying variables. The approach allocates the analyzed posts to three different sentiments (S), namely positive, negative, or neutral. For each sentiment we thus needed to define a differentiation between the two categories for the true and false allocation of the relevant posts. Consequently, we identified six categories which oppose the results of the automated approach to the real world data mentioned earlier (see table 4). Based on these categories, the accuracy of the implemented approach could be measured.

Sentiment (S)	Category	Description
Positive	true positives	posts, which are correctly assigned to the sentiment *positive*
	false positives	posts, which are assigned to the sentiment *positive*, but are not positive in real world data
Negative	true negatives	posts, which are correctly assigned to the sentiment *negative*
	false negatives	posts, which are assigned to the sentiment-category *negative*, but are not negative in real world data
Neutral	true neutrals	posts, which are correctly assigned to the sentiment *neutral*
	False neutrals	posts, which are assigned to the sentiment *neutral*, but are not neutral in real world data

Table 4. Sentiments and related categories

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 sentiment S:

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

For example, a high value for *precision* (e.g., close to 1) predicates that a very high number of posts that are assigned to the sentiment S by the algorithm are classified correctly. Contrary, a low value of *precision* (close to 0) indicates that a high number of posts are not classified correctly. When looking at our dataset (see table 5), 48 posts of company A were classified positive by the algorithm, but only 45 of them are truly positive and thus classified correctly. Consequently, the *precision* for the sentiment *positive* for company A is 45/48 = 0.94, resulting in a *precision* of 94 percent.

In comparison, the metric *recall* calculates the amount of correctly assigned posts in relation to all posts classified in the real world data for a given sentiment S.

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

Hence, a high value (close to 1) for *recall* for positive posts indicates that most of the truly positive posts are also classified correctly as being positive. A low value for *recall* indicates that the share of the automatically and correctly classified posts for a sentiment in relation to all posts of this sentiment is low. For example, the *recall* for the sentiment *positive* for company A in our dataset in table 5 is calculated by dividing 45 correctly classified positive posts by all 52 positive posts in the real world (0.87).

Since *precision* and *recall* aim at different objectives, there is a third metric called *f-measure*. It 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).

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

In our example, *f-measure* of company A for the sentiment *positive* is 2*0.94*0.87/0.94*0,87 = 0.90.

The following table 5 shows all results of our application of the dictionary-based approach on the extracted dataset provided by the five Facebook pages of the cooperating companies.

The first column (“real # of posts”) represents the number of positive, neutral and negative posts, agreed upon by the six independent researchers and verified with the responsible experts from each company. The second column (“classified # of posts”) represents the number of automatically classified posts into positive, neutral and negative sentiments. The numbers for true positive, true neutral and true negative posts are written in bold. Consequently, the other numbers in this column represent the false positive, false neutral and false negative numbers of posts. For example, company E has a total of 95 positive posts in the “real world”. The dictionary-based approach classified a total of 89 posts as positive, whereas 70 were true positive (classified correctly) and 19 were classified incorrectly (false positive).

		real # of posts			classified # of posts				precision			recall			f-measure		
		+	o	-	+	o	-	∑	+	o	-	+	o	-	+	o	-
company A	+	**52**			**45**	1	2	48	0.94			0.87			0.90		
	o		**64**		6	**61**	2	69		0.88			0.95			0.92	
	-			**9**	1	2	**5**	8			0.63			0.56			0.59
	∑				52	64	9								Ø 0.80		
company B	+	**73**			**58**	37	10	105	0.55			0.79			0.65		
	o		**135**		13	**78**	9	100		0.78			0.58			0.66	
	-			**52**	2	20	**33**	55			0.60			0.63			0.62
	∑				73	135	52								Ø 0.64		
company C	+	**165**			**140**	14	4	158	0.89			0.85			0.87		
	o		**124**		22	**101**	3	126		0.80			0.81			0.81	
	-			**27**	3	9	**20**	32			0.63			0.74			0.68
	∑				165	124	27								Ø 0.79		
company D	+	**17**			**17**	1	1	19	0.89			1.00			0.94		
	o		**12**		0	**10**	0	10		1.00			0.83			0.91	
	-			**5**	0	1	**4**	5			0.80			0.80			0.80
	∑				17	12	5								Ø 0.88		
company E	+	**95**			**70**	9	10	89	0.79			0.74			0.76		
	o		**120**		20	**107**	16	143		0.75			0.89			0.81	
	-			**50**	5	4	**24**	33			0.73			0.48			0.58
	∑				95	120	50								Ø 0.72		
total	+	**402**			**330**	62	27	419	0.79			0,82			0.80		
	o		**455**		61	**357**	30	448		0.80			0.78			0.79	
	-			**143**	11	36	**86**	133			0.65			0.60			0.62
	∑				402	455	143								Ø 0.74		

Table 5. Results of the application

As the results shown in table 5 demonstrate, the implemented dictionary-based approach achieved an aggregated *f-measure* of 74 percent. Although, the particular results for the different companies and sentiments vary significantly. Most of these differences can be explained by the peculiarities of Social Media posts for SMEs as described earlier in section 2.1.

For example, there are consistently high *f-measure* values (avg. 88 percent) for company D, the leading manufacturer and distributor of equipment for daycare centers, kindergartens, and schools. These high values can be explained by the very structured, clear and correct language within the posts of company D (e.g., see table 6 example #1). We see the fact that the target audience are mainly business customers as the underlying reason for this observation.

However, we also identified cases where the application of the automatic approach resulted in indifferent values. Considering company B, an Online Store for children's fashion, baby fashion, toys and children's furniture, the *f-measure* for positive posts is 65 percent and the *f-measure* for neutral posts is 66 percent, both significantly lower compared to all other companies. We analyzed the respective posts and noticed a high level of off-topic discussions that do not relate to the company’s products or services (see table 6 example #2). During the initial manual classification, the researchers agreed upon that these off-topic discussions belonged to the *neutral* sentiment. In contrast, the automatic approach processes all posts word by word without knowing the context of the post. Thus, it classified these posts *positive* or *negative*, based on the annotation of the containing words.

Another peculiarity of Social Media posts we observed in the posts of company A is industry-specific language. As company A is a market leader in fun sport equipment in the watersports industry, we noticed industry-specific components (e.g., slang, jargon) to be commonly used in positive posts of our dataset (see table 6 example #3). Based on these observations, we enhanced the existing feature libraries and included several generally known expressions of the fun- and watersports industry. After integrating these industry-specific items, we achieved a recognition rate of about 90 percent for positive posts.

A lot of times Social Media posts demonstrate a network character by addressing more than one person, for example when fans congratulate a company for winning a certain award or when they provide general feedback to certain events, e.g., sweepstakes or giveaways (see table 6 example #4). This could be repeatedly observed in the posts of company C, a manufacturer and distributor of high-quality toys, games & room decor for kids of all ages.

Generally, it is noticeable that positive posts are classified very well. Especially companies whose posts are written in a certain language that is typical to the relevant industry or region (company A / company E) or directly address specific products or services (company C) achieve high values for *f-measure* for positive posts. Additionally, the frequent use of emoticons to express sentiment within Social Media posts contributes to a higher accuracy of the algorithm (see table 6 example #5). We see these two reasons as a main driver resulting in an aggregated *f-measure* value of 80 percent for all positive posts.

However, there is a discrepancy in negative posts. The classification of negative posts resulted in an aggregated *f-measure* of 62 percent for all posts, which is significantly lower than the average *f-measure* value of positive posts. This gap can be explained by two factors. On the one hand, several customer complaints about malfunctions contain company-specific expressions and are written in a neutral way, which makes it impossible for the approach to identify them as negative posts (see table 6 example #6). This results in low *f-measure* values of 59 percent for company A and 58 percent for company B. On the other hand, we identified a number of posts that contain negation and irony, which results in comparatively lower *f-measure* values for negative posts.

#	Example (in German language)	Translation to English / Explanation
1	*Es wäre schön wenn es auch was für die unterstützte Kommunikation nicht sprechender Kinder gäbe, solche Kinder gibt es ja auch in Kindergärten und Krippen.*	It would be nice if you offered products to support the communication of not speaking children, as they also visit kindergartens and nurseries.
2	*Unser 4-jähriger schläft immer bei uns und ich genieße es. Vergeht ja viel zu schnell die zeit.....*	Our four-year-old still sleeps at our place and I´m appreciating it. Time is running too fast…
3	*Schon ausprobiert, 9er bei 32 Knoten: So hoch war ich noch nie!!! Yeehaa*	Already tried it, 9’s at 32 knots: I´ve never jumped so high!!! Yeehaa
4	*Wann erfährt man denn, ob man dabei ist, wenn schon die erste Spielefamilien testen können? Hatte mich am 10. September schon beworben.*	When do I get informed if I´m involved, since the first families are already testing the products? I already applied on September the 10^{th}.
5	*:D*	:D
6	*An wen wende ich mich, wenn mein Van einen Konstruktionsfehler hat bezogen auf die Scheibenwischer.*	Who should I contact if my Van has construction errors concerning its windshield wipers.
7	*gefelt mir*	Spelling error (correct would be “gefällt”)

Table 6. Examples for peculiarities identified

Additionally we identified that spelling mistakes are widely spread in our dataset. Due to the diversity of users within social networks, spelling mistakes reoccur constantly in Social Media content (Agichtein et al., 2008). This fact also lowers accuracy as misspelled expressions cannot be identified by the approach (see table 6 example #7).

In summary, regarding research question 1 (RQ1), the highest value for the *f-measure* received was 88 percent for company D while the lowest value was 64 percent for company B. Correspondingly, dictionary-based approaches provide a high level of accuracy in case the Social Media posts have a structured, clear and correct language. With an increase of off-topic discussions, slang, spelling errors or industry-specific expressions the accuracy decreases which clearly becomes evident in table 5. Considering our second research question (RQ2), we observed a strong variation among the investigated companies' posts. This is justified through several peculiarities of Social Media posts in SMEs: by specialized industry- and product-specific language, by off-topic discussions that do not cover company-specific topics, by industry specific components (e.g., slang, jargon) and company-specific expressions (e.g., surfer jargon in fun- and watersports or dedicated vehicle parts). It also is notable that the correct classification is highly influenced by the usage of emoticons to express sentiment.

5 Discussion

Generally, the sentiment analysis as performed above provides valuable insights into customers' current attitude towards a company. For example, a high number of posts classified as "negative posts" can be seen as an indicator for consumer dissatisfaction requiring a firm to trigger corresponding countermeasures such as product or service campaigns. Further, a high number of positive posts may indicate a generally optimistic mood amongst customers, positively shaping the company image. From that point of view, the sentiment analysis serves as a valuable indicator as to whether a company's efforts to meet customer requirements (e.g., by the current product and service portfolio, etc.) are successful or get out of hand. All participating SMEs of the study agreed that the automatic analysis will lead to a tremendous cutback of human efforts as the assessment of the posts' sentiment was usually done manually by the companies hitherto which is a time-consuming and error-prone task. As shown in table 5, the accuracy of the analysis varies for different companies, but the f-measures generally were above the expectations of the firms participating *(see RQ1)*. In this regard, the data also confirmed the strong use of Social Media channels for the bidirectional communication between SMEs and customers as described in literature (cf. Meske and Stieglitz, 2013) because a large number of company posts (e.g., answer to requests, support for common problems) mixed with posts from the customer side.

Nevertheless, the study also showed that the accuracy of the sentiment analysis at SMEs, using a dictionary-based approach, strongly depends on a proper extraction of features inherent to consumers' Social Media posts as well as a decent adaption of the dictionaries regarding the terminology used by enterprises and their customers *(see RQ 2)*. Accordingly, slang as well as industry- and product-specific expressions need to be adequately considered for instance as shown in section 4.3.

From this point of view, our investigation does not only provide beneficial insights for SMEs using Social Media, but also contributes to the current body of knowledge on sentiment analysis. In our study, we used a dictionary-based approach, which is widely established in literature (e.g., Turney, 2002; Kundi et al., 2014). Many freely available lexical ressources for automatic sentiment analysis exist (e.g., SentiWordNet 3.0). However, these are not customized for certain industries or types of companies in the region of southern Germany. Furthermore, the amount of lexical resources in German language is limited. Thus, for raising the accuracy level of dictionary-based approaches, the lexical ressources need to be translated from English into German and enhanced by the peculiarities of Social Media posts at corresponding companies.To our best knowledge, a systematic uncovering of such characteristics for firms in southern Germany has not been performed yet.

Language-specific peculiarities that could be deducted from research refer to expressions capturing slang at first. These can be used to revise existing dictionaries. Further, we were able to identify expression related to special events (e.g., new product launch) for the branches considered, which is a prerequisite to unveil irony (e.g., Davidov et al., 2010). Thereby, the selection of companies was helpful for finding expressions related to slang and irony, since the customer base of the five different SMEs was rather diversified. Contrary to a very homogeneous customer group, e.g., as given for direct banks, a strong variation in the use of language was observed. This positively affected the extraction of a set of expressions supporting irony and slang identification (e.g., 'incredible customer service ;)'). Additionally, a large set of branch-specific jargons was identified, with detailed findings for the toy, children fashion and child equipment industry as companies B, C, and D came from that particular field. By enhancing existing dictionaries accordingly, the accuracy of the sentiment analysis could be further improved significantly. The results as presented are the base for the development of a dictionary for SMEs in southern Germay, which we will pursue in future work.

More, six researchers were engaged in assessing the sentiment of the posts in our database to mitigate subjectivity and conduct the assessment. In practice, such a use of human resources is unrealistic, especially for SMEs with a limited number of employees. Thus, an automatic sentiment analysis with adapted dictionaries, leading to precise results, is a great support for SMEs as confirmed by the participating companies.

6 Conclusion and Outlook

In the research at hand we conducted an automatic approach for sentiment analysis using Social Media posts from five SMEs. Therefore, posts from the companies' Facebook sites were extracted with help of a prototype, preprocessed and then classified using SentiWordNet 3.0 and SentiWS as a combined dictionary. The results show that a considerable level of accuracy was reached. Nevertheless, to receive results that are more precise, an adaption of the dictionaries to the specific terminology of a company and its customers alike is required.

By the sentiment analysis as described, practitioners are given means to determine consumers' current attitude by an automatic approach. This is highly beneficial for SMEs who usually do not have the resources to monitor their Social Media channels on a regular basis besides the day-to-day business. Based on the insights into customers' mood, a company may start initiatives to clarify misunderstandings or to restore customer satisfaction for example.

The findings of this study are also beneficial for research as the impact of peculiarities of customers' Social Media posts at SMEs are investigated more profoundly. There still is a vague understanding of how the characteristics of Social Media posts influence the accuracy of the automatic analyses using dictionary-based approaches. The research at hand addressed this gap by explicitly focusing on SMEs in southern Germany. Thereby, the peculiarities of according posts were uncovered in detail. It became evident, that adapting the dictionary to a firm's terminology – determined by the product and service portfolio – as well as customers' language use is mandatory to receive a high-level of accuracy.

There are some limitations to this study: at first, we focused on SMEs from southern Germany which is a restriction in terms of the generalization of the results. Though, the focus on a particular geographic region allows to draw more detailed results for that particular area. Second, the number of SMEs participating in the study is limited to five. Considering additional enterprises might have provided further peculiarities of posts not explicated yet. Third, the manual sentiment analysis which was used to judge the accuracy of the automatic approach underlies subjectivity to a certain degree. We mitigated this by having six researchers perform the analysis and consolidate the results. Posts were further discussed with representatives of the affected companies. However, complete objectivity cannot be assured.

As this research is part of a larger Design Science project, we will further develop the aforementioned prototype to better match the requirements of SMEs in future work. This includes the company-specific adaption of freely-available dictionaries amongst others. Thereby, based on the findings, mechanisms to identify slang and irony more precisely will be pursued reverting to the knowledge gained on industry-specific topics for instance. Further, the creation of algorithms for automatically clustering customer statements, e.g., based on keywords identified within posts, is to be done. Currently, such in-depth insights are usually gained by manually screening data collections of customer statements, using techniques such as the CTQ-Matrix for example (cf. George et al., 2005), which is time-consuming and resource-intense revealing the necessity for automatic clustering approaches.

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