Differentiated Sentiment Analysis of Corporate Social Media Accounts

Full Paper

Marten Risius
Goethe University Frankfurt
risius@wiwi.uni-frankfurt.de

Fabian Akolk
Goethe University Frankfurt
fabian.akolk@gmail.com

Abstract

Social media managers as well as analysts use social media messages as an additional channel to manage and measure opinions towards brands. Currently, however, sentiment tools have been predominantly focused on the binary positive-negative valence of emotions and thereby neglected the multi-dimensional structure of human emotions. Moreover, while practitioners try to address the issue of undifferentiated customer requests towards a brand by operating more interest group-specific accounts, research still lacks understanding regarding the impact of different account types. We approach this research gap by developing a classification of social media accounts and, subsequently, deploy a sentiment analysis that differentiates between seven emotions within 532,363 thousand tweets towards 641 accounts from 33 S&P 100 companies. Our results confirm the assumed necessity of considering different account types when studying corporate social media presence and assessing differentiated emotions in social media analytics.

Keywords

Differentiated Sentiment Analysis, Social Media Analytics, Corporate Social Media Accounts, Twitter

Introduction

Social media platforms such as Twitter or Facebook have experienced an unprecedented growth in user numbers over the past decade, causing a proliferation of data regarding opinions, relations, and behavior (Lin et al. 2014). Companies use social media data in general for different purposes such as market research, recruiting, public relations, and reputation management (Kaplan et al. 2011; Zhou et al. 2014). In this regard, social media analytics provide viable solutions for supporting respective corporate activities to generate leads and to relate to their customers on social media (Stieglitz et al. 2014). Consequently, most marketers report to use social media for marketing purposes and recent estimates approximate a rapidly increasing annual worldwide social media spending of $10 billion (Clark et al. 2013).

Through corporate communication on social media companies intend to create positive awareness for its brand and products as well as improve its perception among the customers (and other stakeholders like private persons prior to their buying decision, competitors, or suppliers) (Larson et al. 2011). The web-based interaction provides the opportunity for companies to reduce costs and at the same time increase the efficiency of marketing. Due to the bidirectionality of these interactions, they differ from the traditional public relations and customer services, which were primarily conceptualized as unidirectional ‘customer notification’ (Krüger et al. 2012).

In this regard, social media analytics research supports companies, for example, by measuring success of corporate communication in terms of online word of mouth through sentiment analysis (Rui et al. 2010). Benthaus et al. (2013) were able to show an equal and partially even superior validity of sentiment-based word of mouth measures compared with reputation indices assessed with established questionnaires. Libai et al. (2010) explain the ever-increasing importance of word of mouth through the growing connectivity between users via social networking sites as one of the driving factors. At the same time brand awareness is positively affected by greater emotionality towards a company (Jansen et al. 2009). Consequently, it is imperative for companies to use social media platforms to manage word of mouth by
Differentiated Sentiment Analysis of Corporate Social Media Accounts

supporting positive and addressing negative user generated content (Kozinets et al. 2010; Söderlund et al. 2007; Trusov et al. 2009).

Apart from the advances in social media analytics, companies are still struggling to develop effective practices of successful interaction with their stakeholders (Rui et al. 2010). Developing appropriate strategies for communication on social media and linking these activities to the organizations' goals remains challenging for companies (Culnan et al. 2010). Research shows that gaining positive effects in firm performance from social media platforms requires companies to develop a successful social media management in terms of interacting with the community and monitoring user communication (Larson et al. 2011). However, Aral et al. (2013) describe the undifferentiated customer perspective as one of the key challenges of organizational social media management. In this sense, customers often do not distinguish with their requests (spanning from service problems, expressing brand enthusiasm, offering advice for product improvements, or needing answers for technical questions) between functional divisions within a company. Companies have begun to address the issue of broad customer requests by operating multiple accounts separately e.g., for each country, for specific interest groups and services (Krüger et al. 2012).

However, there is currently little understanding regarding the best ways in which companies should organize and manage social media accounts (e.g., allocation of responsibility, service outsourcing decisions, leadership) and how the multitude of accounts affects a company's word of mouth (Aral et al. 2013). Moreover, common sentiment tools only consider the average sentiment based on the unidimensional assessment of positive vs. negative emotionality. This analysis neglects research from psychology that established different emotional states (e.g., Ekman et al. 1969; Izard 1993) or emotion dimensions (e.g., Larsen et al. 1992; Russell 1980; Watson et al. 1985). Sentiment tools that analyze differential emotions do neither consider the strength of the emotions (Porshnev et al. 2013) nor the exclusiveness of emotional states (Baccianella et al. 2010) or withhold detailed insights into the classification of emotions (Bollen et al. 2011).

In this study, we address this research gap by applying a self-adapted open source emotion-specific dictionary which we derived from the established SentiStrength lexicon (Thelwall et al. 2012). This enables us to measure the emotion strength of seven different emotions whose conceptualization is based on the psychological model of the hierarchical structure of the affective domain from Ekkekakis (2013). Moreover, we develop a categorization of company social media accounts based on the virtual customer environment classification from Culnan et al. (2010) and the brand communication genres by Krüger et al. (2012) to gain insights into corporate social media management practices. Subsequently, we apply the sentiment analysis to 532,363 thousand Twitter messages on 641 accounts from 33 S&P 100 companies collected over a three-month period. We conduct multivariate analyses of variance of the differentiated emotion strength and the company account set-ups. Thereby, we address calls for IS research regarding a more comprehensive understanding of social media management practices (Aral et al. 2013) and advance the field of social media analytics by providing access to a more sophisticated sentiment analysis. Overall, in this study we explore how differential emotions vary across various social media company accounts.

The remainder of this paper is organized as follows. After the introduction, we explicate the theoretical background of the differentiated emotion and account typologies. Subsequently, we describe our empirical research approach with the corresponding results. Concluding, we integrate and discuss our findings in the light of the existing body of knowledge, their theoretical and practical implications, and links for future research as well as the study’s limitations.

Theoretical Background

Differentiated Sentiment Analysis in Social Media Analytics

Psychology of emotion generally distinguishes between emotions as distinct-states or dimensions. State-theorists consider each emotion as unique and distinct from all others (e.g., Ekman et al. 1969; Izard 1993) while advocates of the dimensional approach position emotions along elemental dimensions which account for similarities and differences among affective states (e.g., Larsen et al. 1992; Russell 1980; Izard 1993). However, Aral et al. (2013) describe the undifferentiated customer perspective as one of the key challenges of organizational social media management. In this sense, customers often do not distinguish with their requests (spanning from service problems, expressing brand enthusiasm, offering advice for product improvements, or needing answers for technical questions) between functional divisions within a company. Companies have begun to address the issue of broad customer requests by operating multiple accounts separately e.g., for each country, for specific interest groups and services (Krüger et al. 2012).

However, there is currently little understanding regarding the best ways in which companies should organize and manage social media accounts (e.g., allocation of responsibility, service outsourcing decisions, leadership) and how the multitude of accounts affects a company's word of mouth (Aral et al. 2013). Moreover, common sentiment tools only consider the average sentiment based on the unidimensional assessment of positive vs. negative emotionality. This analysis neglects research from psychology that established different emotional states (e.g., Ekman et al. 1969; Izard 1993) or emotion dimensions (e.g., Larsen et al. 1992; Russell 1980; Watson et al. 1985). Sentiment tools that analyze differential emotions do neither consider the strength of the emotions (Porshnev et al. 2013) nor the exclusiveness of emotional states (Baccianella et al. 2010) or withhold detailed insights into the classification of emotions (Bollen et al. 2011).

In this study, we address this research gap by applying a self-adapted open source emotion-specific dictionary which we derived from the established SentiStrength lexicon (Thelwall et al. 2012). This enables us to measure the emotion strength of seven different emotions whose conceptualization is based on the psychological model of the hierarchical structure of the affective domain from Ekkekakis (2013). Moreover, we develop a categorization of company social media accounts based on the virtual customer environment classification from Culnan et al. (2010) and the brand communication genres by Krüger et al. (2012) to gain insights into corporate social media management practices. Subsequently, we apply the sentiment analysis to 532,363 thousand Twitter messages on 641 accounts from 33 S&P 100 companies collected over a three-month period. We conduct multivariate analyses of variance of the differentiated emotion strength and the company account set-ups. Thereby, we address calls for IS research regarding a more comprehensive understanding of social media management practices (Aral et al. 2013) and advance the field of social media analytics by providing access to a more sophisticated sentiment analysis. Overall, in this study we explore how differential emotions vary across various social media company accounts.

The remainder of this paper is organized as follows. After the introduction, we explicate the theoretical background of the differentiated emotion and account typologies. Subsequently, we describe our empirical research approach with the corresponding results. Concluding, we integrate and discuss our findings in the light of the existing body of knowledge, their theoretical and practical implications, and links for future research as well as the study’s limitations.

Theoretical Background

Differentiated Sentiment Analysis in Social Media Analytics

Psychology of emotion generally distinguishes between emotions as distinct-states or dimensions. State-theorists consider each emotion as unique and distinct from all others (e.g., Ekman et al. 1969; Izard 1993) while advocates of the dimensional approach position emotions along elemental dimensions which account for similarities and differences among affective states (e.g., Larsen et al. 1992; Russell 1980;

---

1 We provide open access to the differentiated sentiment lexicon for the sentiment analysis here: [http://bit.ly/1BpecLL](http://bit.ly/1BpecLL)
Watson et al. 1985). Ekkekakis (2013) integrated both understandings in a recent reconsideration into the model of the hierarchical structure of the affective domain. Based on the models of Nesse (2004) and Shaver et al. (1987), this framework understands the affective domain to have a hierarchical structure with basal dimensions (i.e., valence and activation) as an evolutionary basis for seven more differentiated emotional states.

The valence dimension describes the evaluative character of an emotion which determines whether something is perceived as pleasant (also termed positive) or unpleasant (also termed negative) (Elster 1998). So far IS research has been predominantly focused on assessing the bipolar valence dimension of positive-negative emotionality with automated sentiment analyses (e.g., Li et al. 2014; Sprenger et al. 2014b). However, the predominant undifferentiated dimensional approach provides lower specificity compared with the assessment of distinct emotional states (Ekkekakis 2013). Recent findings show, for example, the higher predictive validity of a more differentiated microblogging sentiment on company-specific stock market reactions compared with an average sentiment score (Smailović et al. 2013; Sprenger et al. 2014a). Evolutionary theory states that negative emotions are more decisive for survival while positive emotions serve rather social purposes. In this regard, negative emotions are provoked in situations that are threatening, have an increased risk of loss or after a loss has occurred. Whereas positive emotions are triggered in situations that offer opportunities or unexpectedly advance a goal attainment progress (Nesse 2004). On social media platforms negative messages have been found to spread more easily (Kimmel 2010), receive more attention (Luo 2007), and are even more strongly associated with stock price movements than positive information (Li et al. 2014; Oh et al. 2011; Tirunillai et al. 2012). Our recent emotion specific analysis of company-specific tweets showed a significant association between depression and happiness with stock prices while other emotions were unrelated to stock movements (Risius et al. 2015). Considering the distinct evolutionary qualities, communicative purposes, and information processing characteristics of the different emotions, we generally expect users to express various emotions differently depending on the situation.

To analyze emotion-specific effects, we developed a sentiment lexicon that includes more refined individual emotional states instead of just the bipolar valence and also considers the activation dimension by measuring the strength of each emotion (Risius et al. 2015). Existing sentiment tools which measure differential emotions do not consider the strength of emotions (Porshnev et al. 2013), the mutual exclusiveness of emotional states (Baccianella et al. 2010) or have only poor inter-annotator agreement (Thelwall et al. 2010). Due to the comprehensiveness of the framework, we considered the descriptions from the model of the hierarchical structure of the affective domain to define the emotion states (Ekkekakis 2013; Nesse 2004; Shaver et al. 1987). Based on these descriptions (table 1), we classified the emotion words from the lexicon of the established sentiment tool “SentiStrength 2” (Risius et al. 2015; Thelwall et al. 2012).

**Affection** encompasses the generic form of companionate love which applies to friendship, family relationships, marital relationships, etc. which promotes a personalized feeling of well-being that is attributed to a particular person or object (Shaver et al. 1987). A word was classified as affection when it described admiration (e.g., *worry, graceful*) or personal appreciation (e.g., *handsome, liking, pretty, wonderful*). Also more passionate appraisals (e.g., *beloved, warmheart, cutie*), trustful expressions of consideration (e.g., *care, compassion, support*), and positive estimates of relationships (e.g., *homie, friend, mate*) were coded into this category. **Happiness** resembles the conceptual counterpart of depression (see below). It is triggered in situations where a positive outcome in the achievement (e.g., task success) or social domain (e.g., receiving esteem or affection) has been realized by attaining something desired or desirable (Shaver et al. 1987). An emotion word was coded as happiness whenever someone expressed joyful excitement (e.g., *overjoyed, terrific, thrilling*), a high level of activity (e.g., *lively, dynamism, ecstatic*) or a positive attitude (e.g., *optimistic, carefree, easygoing*). Similarly to affection, words of appreciation were included (e.g., *delightful, fabulous, wicked*) while for happiness these were less personalized and prolonged. The understanding of the emotion **satisfaction** draws heavily on work from positive psychology as it describes the acknowledgement and contentment when reaching a goal. This goal may be long striven for, predictable, or just predetermined as the level at which it provides satisfaction (Selgman 2002). Thus, satisfaction applied to achievement oriented emotion words that described reaching a goal (e.g., *accomplish, triumph, success*) and the associated intrinsic (e.g., *confident, content, pride*) as well as extrinsic consequences (e.g., *compliment, glory, reward*).
<table>
<thead>
<tr>
<th>Emotion Valence</th>
<th>Emotion</th>
<th>Description</th>
<th>Emotion Word</th>
<th>Example from data sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>Affection</td>
<td>Genuine fondness and liking that is attributed to a particular person or object.</td>
<td>Love, Longing, Adoration</td>
<td>I'm loving the new @DukeEnergy logo. Well done! <a href="http://t.co/CrelUK9WdY">http://t.co/CrelUK9WdY</a></td>
</tr>
<tr>
<td></td>
<td>Happiness</td>
<td>Amplified enthusiasm and excitement about attaining something desired or desirable.</td>
<td>Joy, Terrific, Amusement</td>
<td>I think it’s awesome that @CVS_Extra is removing tobacco products from their stores. Makes me happy that they are my pharmacy!</td>
</tr>
<tr>
<td></td>
<td>Satisfaction</td>
<td>Proud acknowledgement of and contentment with reaching a predetermined goal.</td>
<td>Pride, Success, Contentment</td>
<td>RT @AccentureCAS Over 80 delegates from 20 leading CG companies attended the hugely successful Accenture CAS User Forum in Atlanta.</td>
</tr>
<tr>
<td>Negative</td>
<td>Fear</td>
<td>Anticipatory horror or anxiety in unpredictable or potentially harmful situations.</td>
<td>Terror, Horror, Anxiety</td>
<td>@officialknewton @newtonrw have you ever put a penny in some coca cola? Frightening what it could be doing to our insides.</td>
</tr>
<tr>
<td></td>
<td>Anger</td>
<td>Animated animosity towards malevolence that can motivate rectification.</td>
<td>Hate, Outrage, Irritation</td>
<td>I hate Texas Instruments and all of their evil creations.</td>
</tr>
<tr>
<td></td>
<td>Depression</td>
<td>Impeding sadness evoked by an aversive event that may hinder activity.</td>
<td>Sadness, Hopeless, Disappointed</td>
<td>Sad day for all of the @UnionPacific family. Sad to see such a good man and CEO be taken by a vicious disease but he's in a better place</td>
</tr>
<tr>
<td></td>
<td>Contempt</td>
<td>Revulsion to something considered socially offensive or unpleasant.</td>
<td>Guilt, Shame, Disgust</td>
<td>Don't work for Bank of America ever. They have no loyalty to their employees. Absolutely despicable.</td>
</tr>
</tbody>
</table>

Table 1. Overview of the Seven Different Emotions and Their Operationalization

Regarding the negative emotions, *fear* is the interpretation of events as potentially dangerous or threatening to the self (physical harm, loss, rejection or failure) which is formed in unfamiliar and unpredictable situations (Shaver et al. 1987). Fear was coded when a sentiment addressed an unpleasant apprehension (e.g., anxious, concern, distraught) of a potentially harmful event (e.g., complication, chaos, catastrophe). Also words that revolved around possible consequences (e.g., doom, threat, danger) or rudimentary coping mechanisms (e.g., avoid, doubt, fright) of these dreaded occasions were included. *Anger* is experienced when faced with interferences of the execution of plans or attainment of goals (e.g., by reducing the individual’s power, violating expectations, frustrating or interrupting goal-directed activities) (Shaver et al. 1987). The emotion anger applied to words that express aversion ranging from animated antagonism (e.g., furious, detest, antagonize) up to agonized rail (e.g., bloody, crappy, shoddy) or personal insults (e.g., bastard, fool, jerk). Moreover, the category included descriptions of the inclined attitude towards the aggravating object (e.g., animosity, grudge, hate). *Depression* constitutes the prototypical form of sadness where a person feels powerless, helpless, or impotent to change an aversive situation and cognitions ruminate about these unhappy circumstances (e.g., suffering, disappointment, neglect) (Shaver et al. 1987). Depression comprised the communication of the experience of a saddened condition (e.g., cheerless, bitter, crushing) and of its evoking event (e.g., burden, calamity, misfortune). Words that express diminished coping capabilities (e.g., apathy, breakdown, resignation) and dismal prospects (e.g., aimless, discourage, futility) were also included in this coding category. *Contempt* is the emotional response of revulsion to something considered offensive or unpleasant. In our understanding,
it forms the core emotion of shame and represents the social correspondence of biological disgust (Tybur et al. 2009). Ultimately, contempt was classified for socially offensive actions (e.g., adultery, bribe, affectation), the personal evaluation of the respective behavior (e.g., amoral, deceitful, despicable), and the sentiment following the contemptible event (e.g., awkward, guilt, shame). Expressions signaling consequent punitive behaviors were also incorporated (e.g., condemn, detract, evade).

Considering the different qualities of emotions, we expect that users express different emotions depending on the context. In the case of social media platforms, we hypothesize:

H1: The strength of the users’ sentiment expressions differ between the various emotions.

Differentiated Consideration of Social Media Accounts

Social media platforms generally facilitate direct communication with customers. Thereby, companies can keep users regularly informed and demonstrate appreciation for the users which is a necessary prerequisite for building strong relationships with a community (Wulf et al. 2001). Twitter offers companies the opportunity to operate different accounts to reach different target groups and ultimately build strong virtual communities around their brand (Krüger et al. 2012).

<table>
<thead>
<tr>
<th>Primary Category</th>
<th>Sub-Category</th>
<th>Description</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Branding</td>
<td>Advertising</td>
<td>Providing product promotions and special offers in local stores.</td>
<td>Get head-turning hair with Herbal Essences NEW Moroccan My Shine line, available at your local CVS/Pharmacy! [link]</td>
</tr>
<tr>
<td></td>
<td>Public Relations</td>
<td>Informing about corporate social responsibility endeavors such as community service.</td>
<td>Wounded veteran gets new home, mortgage-free</td>
</tr>
<tr>
<td></td>
<td>News Releases</td>
<td>Delivering news and announcements about the company and its products.</td>
<td>Exxon Mobil Corporation announces estimated fourth quarter 2013 results [link]</td>
</tr>
<tr>
<td>Sales</td>
<td></td>
<td>Distributing products and services with direct links to special offers online.</td>
<td>No one likes overpaying for a service. Same goes for electricity. Get a fixed rate. [link]</td>
</tr>
<tr>
<td>Customer Service &amp; Support</td>
<td></td>
<td>Responding to user questions, offering advice, or directing towards helpful contacts.</td>
<td>Tim, pls email us at <a href="mailto:CareTW@lowes.com">CareTW@lowes.com</a> with ur question, contact info &amp; we’ll be glad to assist you. Put TW-4424 in subj line.</td>
</tr>
<tr>
<td>Product Development</td>
<td></td>
<td>Information on product innovations, research, and future development trends.</td>
<td>Learn how IBM #UrbanCode solutions work with cloud technologies at IBM Innovate 2014. [link]</td>
</tr>
<tr>
<td>Human Resources</td>
<td>Jobs &amp; Career</td>
<td>Posting job offers and career opportunities.</td>
<td>We’re hiring electrical #engineers in electrophysics, design &amp; analysis and avionics. View #jobs: [link]</td>
</tr>
<tr>
<td></td>
<td>Academy &amp; University</td>
<td>Publishing recruiting activities at universities and jobs for academics.</td>
<td>#JNJ campus ambassadors will be hosting an interview workshop at 425 Shillman tomorrow 6PM @JNJUniversity @NU_Coop</td>
</tr>
</tbody>
</table>

Table 2. Overview of the Social Media Account Typology

Singular social media accounts have been shown to successfully support organizational divisions like advertisement (Guglielmo 2009), human resources (Li 2010), customer service and public relations (Weinberg 2009). Thereby, social media engagement is not restricted to the provision of information...
about services or the promotion of products but also enables to incite user emotions about brands (Bernoff et al. 2008). Moreover, companies now have the opportunity to enhance their conventional marketing efforts by specifically addressing different target groups (Richter et al. 2011). So far, however, social media analytics has neglected the role of the different accounts when assessing the company’s public perception (e.g., through sentiment analysis) on social media platforms. Preliminary qualitative research that compared different types of accounts has found that accounts differ in their communicative behavior (e.g., number of questions asked or answers given, unidirectional vs. bidirectional interaction) and, in turn, are addressed differently by the users (e.g., statements about the brand in general, special product lines or company strategies) (Krüger et al. 2012). Considering the varying tasks, target groups, and interactive behavior of the different accounts, we generally expect various accounts to also attract dissimilar emotions.

Dependent on the account name and the message content, we developed a classification of company social media accounts in reference to the virtual customer environment classification from Culnan et al. (2010) and the brand communication genres by Krüger et al. (2012) (table 2). The Branding accounts provide different forms of brand-related information. The subcategory Advertising alerts users about temporary product discounts and invitations to events at local shops. Public Relation distributes charitable information about a company’s community service, content from other media (e.g., TV commercials) and directs attention to users showing brand-committed behavior. The third and most common subcategory is News Releases which disseminate news about the company and its products (e.g., press releases). The Sales genre is related to advertising except that it refers customers directly to a product or service in an online store or on a company homepage. The Customer Service and Support accounts engage in bidirectional dialogue with the users to answer questions from the community and offer advice regarding individual brand-related issues. With a Product Development account companies provide updates on product innovations and point users towards future developments. Accounts from the Human Resources category address different personnel management aspects. A Jobs and Career account publishes general job openings and directs users towards further information on the application. Finally, companies also operate Academy and University accounts which specifically target academic candidates and inform about university engagements.

Thus, we assume that different accounts attract and address different target groups and interactions which ultimately translate into different sentiment expressed towards these accounts. Regarding the general social media set-up, we hypothesize:

\[ H_2: \text{The strength of the users’ sentiment expressions differ between the various account types.} \]

Method

We conducted an empirical study in order to address our research question of identifying different emotions in user tweets and the way in which this message sentiment varies across different corporate social media accounts (see figure 1).

![Figure 1. Overview of the Steps to Analyze the Differentiated Sentiment Expressed towards Various Company Accounts](image-url)
Differentiated Sentiment Analysis of Corporate Social Media Accounts

Data Collection and Preparation

In the first step, we randomly selected a sample of 33 companies from the S&P 100 Index encompassing various industries with generally well-known companies which are of considerable public interest and thereby trigger sufficient social media messages (e.g., Sprenger et al. 2014b). During the second step of data collection we collected tweets in English from a certified Twitter data provider without the common rate limits. We collected all tweets from the identified 641 company accounts and all messages explicitly addressing one of these accounts (keyword sample) in English over a three month period. Thereby, we avoid the biases of the common data collection approach of tracking hashtagged tweets (e.g., incomplete stream of conversation) (Bruns et al. 2013). In the last cleaning step, to exclude spamming users we considered the individual share of followers and tweets as an exclusion criterion. Based on a rule of thumb we deleted all tweets sent from users with zero followers and more than 50 messages as well as messages from users with fewer than 100 followers and a tweets-to-followers-ratio of 1000 or higher. Next, we removed tweets that simultaneously mentioned several accounts in order to ensure proper appropriation of the sentiment. Afterwards, we excluded all user tweets that were mere retweets of company messages, since these do not express the user sentiment towards the account (Sul et al. 2014). Lastly, a manual screening of the remaining tweets showed that 1,261 users’ messages were wrongfully collected as their username nonsensically corresponded to one of our keywords (e.g., Citi_media) and another 1,146 terms caused data noise as they were not related to the company itself (e.g., containing the name of a company sponsored sports arena). Tweets containing these 2,407 terms were consequently removed. In total we identified 641 different company accounts which sent 181,917 and were directly mentioned in 532,363 user-generated tweets over the period from January to March 2014. Messages from the company accounts were used to classify the accounts according to the developed social media account typology (see above) while the user-generated messages were subjected to the differentiated sentiment analysis.

Differentiated Sentiment Analysis

Subsequently, we assessed the differentiated emotions of every tweet with an automated unsupervised sentiment analysis. Therefore, we deployed the previously developed emotion specific lexicon (for more details see Risius et al. 2015) originally build for the SentiStrength tool (Thelwall et al. 2012). A descriptive overview of the sentiment dictionary can be found in table 3. SentiStrength was developed by Thelwall et al. (2012) and is specialized in analyzing the sentiment of short informal texts that also contains abbreviations, emoticons, and common informal formulations. In comparison to other popular word lists (e.g. ANEW or AFIN) it has been shown to be the most elaborate approach for the analysis of microblogs (Nielsen 2011). Nonetheless, we further adapted the lexicon for the purposes of this study (e.g., removing the word “talent” to prevent a systematic bias for human resource accounts or “lowe” and “gamble” as these were company name components). By providing validated scores between 1 and 5 separately for the strength of each emotion word, SentiStrength enables to also measure the activation dimension of each emotion (Ekkekakis 2013). Afterwards, we computed the average scores separately for each account type by dividing the emotion-specific sum of strengths through the total number of tweets towards the account. The remaining steps of data analysis are described in the following.

<table>
<thead>
<tr>
<th>Descriptive Statistics</th>
<th>Positive</th>
<th>Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Affection</td>
<td>Happiness</td>
</tr>
<tr>
<td>Absolute [x]</td>
<td>163</td>
<td>123</td>
</tr>
</tbody>
</table>

Table 3. Descriptive Statistics of the Differentiated Sentiment Dictionary.

Results

We conducted two multivariate analyses of variance (MANOVA) as well as the corresponding a-posteriori univariate analyses of variance (ANOVA) and Tukey-Kramer tests to test our hypotheses. This approach enabled us to simultaneously compare the different account types regarding multiple outcome variables.
Differentiated Sentiment Analysis of Corporate Social Media Accounts

(i.e., emotion categories) while controlling for any empirical biases through an alpha inflation (Creswell 2013). The first MANOVA included the primary account categories as unit of analysis while the second MANOVA assessed the account subcategories to provide more detailed insights. The descriptive results (table 4) reveal that companies use Twitter mostly for branding purposes by providing news releases about products and brands. The second most common account types provide jobs & career information for potential applicants. While companies are still cautious regarding the Prosumer-like product development, we find that on average every company operates a customer service & support account. Thus, companies increasingly expose themselves to public discussion through bidirectional interaction. Sales accounts were dropped from the further analysis as our sample only comprised one sales account.

Both omnibus test MANOVAs revealed generally significant differences across all emotions between the primary accounts ($F_{28,1624}=1.943$, $p<.01$, $\eta^2=.03$) and the sub-category accounts ($F_{49,2274}=1.543$, $p<.01$, $\eta^2=.023$). In general, the results of the a-posteriori analysis (table 5) support our hypotheses as the different emotions’ strengths vary significantly across account types. Regarding Hypothesis 1, on the one side, we find that the emotion strength of affection ($F_{28,1624}=1.505$, $p<.05$, $F_{49,2274}=1.249$, $p<.05$) and fear ($F_{28,1624}=0.529$, $p<.05$, $F_{49,2274}=0.475$, $p<.05$) do not vary at all. These two emotions seem to have different qualities from the other five emotions in the sense that they are less targeted and account-specific but are rather broadly encompassing emotions. Satisfaction, on the other side, is most specific seeing that this emotion does not differ between the general primary account categories ($F_{4,456}=1.435$, $p<.05$) but between the sub-categories ($F_{7,453}=2.095$, $p<.05$). The other four emotions show significant differences between both primary and sub-category accounts. Thus, the results support our assumption that the emotions should be differentiated as the users express varying emotions to different degrees.

### Table 4. Descriptive Statistics of the Account Set-Up

<table>
<thead>
<tr>
<th>Descriptive Statistics</th>
<th>Social Media Account Set-Up</th>
<th>Human Resources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute [#]</td>
<td>Advertising</td>
<td>Public Relations</td>
</tr>
<tr>
<td>Rel. Freq. [%]</td>
<td>1.3</td>
<td>4.6</td>
</tr>
</tbody>
</table>

Notes. 641 English speaking company accounts of 33 companies
Statistics. Absolute number of accounts; Relative frequency of accounts within sample

Regarding Hypothesis 2, we find that happiness and anger as well as depression and contempt show similar patterns of results. Generally the customer service and support account receives the least happy and most angry, depressed, and contemptuous messages. The human resources accounts receive significantly more happy ($T=0.107$, $p<.05$) and less angry ($T=-0.042$, $p<.05$) messages than the branding accounts which in turn receive significantly more happy ($T=0.104$, $p<.06$) and less angry ($T=0.063$, $p<.01$) tweets than the customer service & support accounts. The emotions of depression and contempt differentiate less in the sense that the customer service accounts receive generally more tweets of contempt and depression than the branding ($T=0.049$, $p<.01$), human resources ($T=0.067$, $p<.01$), and product development ($T=0.059$, $p<.08$) accounts. While for depression this does not pertain to the advertisement ($T=0.065$, $p<.1$) and academy & university ($T=0.047$, $p<.1$) accounts on the sub-category level, the differences translate to public relations ($T=0.047$, $p<.1$) and product development ($T=0.059$, $p<.08$) accounts as well as to news releases ($T=0.049$, $p<.01$) and jobs & career ($T=0.073$, $p<.01$) accounts. The contempt scores, however, are significantly higher for customer service & support compared to all other account types. Satisfaction is most strongly expressed towards public relations and academy & university accounts. Thus, these results support our hypothesis that multiple accounts serve various purposes which attract different emotions from the users.
<table>
<thead>
<tr>
<th>Emotion</th>
<th>Primary Category</th>
<th>Descriptive Statistics</th>
<th>Test-Statistic</th>
<th>Sub-Category</th>
<th>Descriptive Statistics</th>
<th>Test-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Happiness</strong></td>
<td>Branding</td>
<td>0.214 (0.285)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Customer Service</td>
<td>0.11 (0.103)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Human Resources</td>
<td>0.322 (0.487)</td>
<td>$F_{4,456} = 2.52^{**}$; $\eta_p^2=0.022$</td>
<td>Jobs &amp; Career</td>
<td>0.256 (0.441)</td>
<td>$F_{7,453} = 2.748^{***}$; $\eta_p^2=0.041$</td>
</tr>
<tr>
<td></td>
<td>Product Development</td>
<td>0.182 (0.215)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Satisfaction</strong></td>
<td>Branding</td>
<td>0.209 (0.26)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Customer Service</td>
<td>0.114 (0.125)</td>
<td>$F_{4,456} = 1.43$; $\eta_p^2=0.023$</td>
<td>Jobs &amp; Career</td>
<td>0.196 (0.241)</td>
<td>$F_{7,453} = 2.095^{**}$; $\eta_p^2=0.031$</td>
</tr>
<tr>
<td></td>
<td>Human Resources</td>
<td>0.226 (0.24)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Product Development</td>
<td>0.135 (0.211)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Anger</strong></td>
<td>Branding</td>
<td>0.052 (0.111)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Customer Service</td>
<td>0.114 (0.169)</td>
<td>$F_{4,456} = 4.466^{**}$; $\eta_p^2=0.038$</td>
<td>Jobs &amp; Career</td>
<td>0.011 (0.029)</td>
<td>$F_{7,453} = 2.584^{**}$; $\eta_p^2=0.038$</td>
</tr>
<tr>
<td></td>
<td>Human Resources</td>
<td>0.009 (0.27)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Product Development</td>
<td>0.074 (0.14)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Depression</strong></td>
<td>Branding</td>
<td>0.028 (0.09)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Customer Service</td>
<td>0.077 (0.181)</td>
<td>$F_{4,456} = 2.436^{**}$; $\eta_p^2=0.021$</td>
<td>Jobs &amp; Career</td>
<td>0.004 (0.01)</td>
<td>$F_{7,453} = 1.49$; $\eta_p^2=0.023$</td>
</tr>
<tr>
<td></td>
<td>Human Resources</td>
<td>0.01 (0.049)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Product Development</td>
<td>0.018 (0.04)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Contempt</strong></td>
<td>Branding</td>
<td>0.019 (0.06)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Customer Service</td>
<td>0.08 (0.187)</td>
<td>$F_{4,456} = 5.735^{**}$; $\eta_p^2=0.048$</td>
<td>Jobs &amp; Career</td>
<td>0.011 (0.031)</td>
<td>$F_{7,453} = 3.312^{***}$; $\eta_p^2=0.049$</td>
</tr>
<tr>
<td></td>
<td>Human Resources</td>
<td>0.008 (0.03)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Product Development</td>
<td>0.001 (0.002)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes. Company sample size = 33; account sample = 461; standard deviations are in parentheses beside group mean. $p$-values. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$; n.s. = non-significant (two-tailed significance)

Table 5. Results of the A-Posteriori ANOVA Account Comparisons Regarding the Average Emotion Strength
Discussion & Conclusion
The goal of our study was to take an exploratory approach towards empirically analyzing differences between social media company accounts on Twitter and investigate the necessity of considering different emotions in sentiment analysis. We conducted multivariate analyses of variance based on 532,963 user tweets towards 641 different company accounts collected over a three month period. On first sight, our results show that companies most frequently follow traditional mass media strategies by operating large numbers of branding accounts. However, it needs to be considered that the majority of accounts revolve around news releases regarding the brands and barely around the simple advertisement of products or services. This shows that companies indeed try to make use of the marketing potential of social media regarding the promotion of feelings about brands instead of simply promoting products (Bernoff et al. 2008). Moreover, they increasingly use social media platforms to provide information on jobs & career services, and customer service & support, while explicit advertising and sales are very uncommon. The accounts also differ regarding the emotions expressed about them. Customer service accounts are subject to most angry, depressed and contemptuous messages (with contempt as the strongest differentiating emotion), while users express strong happiness towards the branding and especially human resources accounts. Satisfaction, however, seems to be a highly specified emotion which only differs significantly between low-level account categories, whereas expressions of fear and affection do not vary between account types. Thus, we provide evidence for the necessity of considering the account typology when studying corporate social media engagement and differentiated emotions in social media analytics.

Theoretical and Practical Implications
This study offers several contributions to researchers and practitioners alike. To the best of our knowledge, we are the first to systematically assess different social media account categories beyond single case studies (Krüger et al. 2012) and compare them regarding differentiated emotions. Thereby, our sentiment dictionary exceeds existing limitations of the few other differentiated sentiment analyses which neglect the strength of an emotion (Porshnev et al. 2013), the exclusiveness of emotion states (Baccianella et al. 2010), or withhold detailed insights into the classification of emotions (Bollen et al. 2011). On the contrary, we provide open access to the dictionary for others to refine and advance the differentiated sentiment analysis. Generally our results suggest that the common measurement of word of mouth through the sentiment of all company related messages without consideration of the companies’ account structure is biased. Companies operating a customer service and support account would be negatively affected compared to firms that refrain from bidirectionally interacting with users. Moreover, we contribute to current value measurement difficulties on social media (Fan et al. 2014; Kane et al. 2014b; Larson et al. 2011) by demonstrating the role of different sentiment dimensions. The greater relevance of satisfaction for public relations and academy & university accounts, for examples, indicates the importance of considering corresponding levels of measurement (i.e., satisfaction targets a specific goal as well as public relations and academy & university accounts which describe definite events).

Limitations & Future Research
The implications of this study must be discussed under consideration of its limitations which also provide a link for future research. The generalizability of the results is limited to microblogging platforms which differ functionally from other social media technologies (Kane et al. 2014a) and to the western culture because we only considered tweets in English. However, the expression and impact of emotions has been found to vary across cultures (Matsumoto et al. 2004). In future we intend to expand our respective line of research regarding further insights into the differentiated account and sentiment structure. First, we intend to evaluate account specific behavior to identify individually successful practices. Second, we will investigate implications of the different sentiments and how they affect other social media measures (e.g., followers, share of voice, retweets). Third, we propose to conduct a comparison of the sentiment expressed towards the individual accounts with the overall message sentiment towards the company and assess in how far these correspond or contribute to the company’s general image. Thereby, we intend to identify the accounts that are most decisive for the company’s public perception and see whether different sentiments are more or less important to consider for different accounts (e.g., contempt for customer service and support or satisfaction for public relations).
REFERENCES


Porshnev, A., Redkin, I., and Shevchenko, A. 2013. "Improving prediction of stock market indices by analyzing the psychological states of twitter users“, National Research University Higher School of Economics.


