Understanding Social Media Marketing: A Case Study on Topics, Categories and Sentiment on a Facebook Brand Page

Irena Pletikosa Cvijikj
Information Management, ETH Zurich
Scheuchzerstrasse 7
8092 Zurich, Switzerland
+41 44 632 8624
ipletikosa@ethz.ch

Florian Michahelles
Information Management, ETH Zurich
Scheuchzerstrasse 7
8092 Zurich, Switzerland
+41 44 632 7477
fmichahelles@ethz.ch

ABSTRACT
Social networks have changed the way information is delivered to the customers, shifting from traditional one-to-many to one-to-one communication. Opinion mining and sentiment analysis offer the possibility to understand the user-generated comments and explain how a certain product or a brand is perceived. Classification of different types of content is the first step towards understanding the conversation on the social media platforms. Our study analyses the content shared on Facebook in terms of topics, categories and shared sentiment for the domain of a sponsored Facebook brand page. Our results indicate that Product, Sales and Brand are the three most discussed topics, while Requests and Suggestions, Expressing Affect and Sharing are the most common intentions for participation. We discuss the implications of our findings for social media marketing and opinion mining.

Categories and Subject Descriptors
H.3.1 [**Information Storage and Retrieval**]: Content Analysis and Indexing

General Terms
Human Factors

Keywords
Facebook, social media marketing, social media mining, opinion mining

1. INTRODUCTION
Marketing has recently undergone significant changes in the way information is delivered to the customers [8]. Social networks, as a part of Web 2.0 technology, provide the technological platform for individuals to connect, produce and share content online [7]. They are becoming an additional marketing channel that could be integrated with the traditional ones as a part of the marketing mix.

Social media marketing, also known as word-of-mouth marketing, viral marketing, buzz, and guerilla marketing is the intentional influencing of consumer-to-consumer communications by professional marketing techniques. Manufacturer and retailers, from food to electronics, are starting to understand the possibilities offered by the social media marketing. They have evolved their approach to the customers, shifting from traditional one-to-many communication to one-to-one approach, offering direct assistance to individuals at any time through the social media sites such as Facebook, Twitter, MySpace, etc. In turn, companies can learn about customers' needs through users' feedback or by observing conversations, resulting in involvement of members of the community in the co-creation of value through the generation of ideas [26].

Recent growth in the fields of opinion mining and sentiment analysis enables automatic identification and extraction of attitudes, opinions, and sentiments from the content shared on the social networks [34]. These tools aim to analyze the large amounts and diversity of generated data. User content shared on social networks introduces additional challenges for analysis due to the lack of sentence structure and the use of informal Internet language specific to these settings that differ from the formal written language [35]. These challenges might be overcome through investigation of the form and topics used on the social networks.

This paper focuses on the analysis of the user posts shared on a Facebook brand page ok.-[1], launched by the Swiss company Valora[2] in March, 2010. The company focuses on the fast moving consumer goods, i.e. products that are sold quickly and at relatively low cost. The Facebook brand page targets the younger customers with a social network marketing approach and counts 43,656 fans[3].

In this paper, we examine the topics, categories and sentiment shared on this brand page. Based on our results, we discuss the implications for social media marketing and opinion mining.

MindTrek'11, September 28-30, 2011, Tampere, Finland.

[1] http://www.facebook.com/okPunktStrich

[2] http://www.valora.com/

[3] Obtained on May 12, 2011

2. RELATED WORK

Social networks (SN) have a mediating effect between individuals and society in the virtual world [32]. As such, they represent a natural technological platform for marketing since they provide access to a large number of users, who group themselves into communities, based on a structured set of social relationships, e.g. among admirers of a brand, i.e. a brand community [23].

According to Harris and Rae [16] social networks may play a key role in the future of marketing; they may increase customers' engagement, as well as help to transform the traditional focus on control into a collaborative approach more suitable to the modern business environment. Traditional advertising techniques are not applicable to the social network platforms, resulting in companies experimenting with many different approaches, thus shaping a successful social media strategy based on their personal experiences [11].

Previous studies have focused on the users by trying to identify the most influential target group [21] or explain their relationship to social media [2]. Others have addressed the challenges of social marketing such as aggressive advertising, lack of e-commerce abilities, invasion of user privacy and legal pitfalls [6][30], over-commercialization and transparency [16].

Apart from the challenges, many opportunities have also been recognized, such as building brand awareness and raising public awareness about the company, finding new customers, community involvement and conducting brand intelligence and market research for gathering insights and knowledge for future steps [6][33]. In addition, Javitch [18] argues: free social marketing is a good alternative to the costly traditional marketing campaigns.

Based on exploratory findings and practical examples scholars try to generate guidelines for successful social marketing. Guidelines that apply for online word-of-mouth [9] also apply to Facebook marketing: (1) sharing the control of the brand with consumers and (2) engaging them in an open, honest, and authentic dialog. In addition Kozinets et al. [20] argue that classification of different types of content is the first step towards understanding the conversation, and that the communication is affected by the type of offered product or service.

Li [21] recommends that companies need to build a plan before diving into the social marketing in order to appropriately approach the frequent users who are most likely to virally spread their enthusiasm for a new product or service. He suggests (1) focusing on a conversation, (2) developing a close relationship with the brand through "friending" with the social marketing pages, and (3) building a plan for engagement and finding out what interactions, content, and features will keep users coming back.

Related to the understanding of the conversation within the social media platforms is the field of opinion mining and sentiment analysis. The term opinion mining was coined by Dave et al. [13] to describe a tool that would "process a set of search results for a given item, generating a list of product attributes (quality, features, etc.) and aggregating opinions about each of them (poor, mixed, good)". Approximately at the same time the term sentiment was used in reference to the automatic analysis of evaluative text and the tracking of predictive judgments [12], thus the two disciplines are interconnected.

Early studies in opinion mining focus on the interpretation of narrative points of view in text. The growth of Web 2.0 with its content sharing platforms revealed the opportunity for further expansion in the direction of machine processing and machine learning algorithms [4]. Today there are numerous papers investigating different research problems and opportunities derived from opinion mining and sentiment analysis [27].

The importance of opinion mining for social media marketing has been recognized [24]. Opinion mining allows companies to conduct analyses of user-generated comments to determine how the population perceives a given brand, product or feature, i.e. for market analysis and rumor detection. This resulted in a research on analyzing long structured text discussions from blog posts [22][19], as well as utilizing such communication for the prediction of user behavior, sales, stock market activity, etc. [1][10][22].

The change in social media towards short commentary, as introduced by Twitter or Facebook, results in a significant difference in the comment structure and language that may affect the accuracy of opinion mining techniques [29]. This has motivated research into text analysis and application of the opinion mining techniques to social media in order to understand the activities and identify the specific issues with the relevance to the specific language used in this noisy environment.

Recent studies focus on applying the opinion mining techniques on short comments from the SN Twitter to investigate the value of tweets as online word-of-mouth [17], possibilities for movie revenue prediction [3] and opportunities for television broadcasters [14], to identify topics [25], perform sentiment analysis [5], etc. However, the studies regarding Facebook and the usage of brand pages in particular are still relatively limited [28].

Our study analyses the content of the posts shared on a Facebook brand page. We focus on identification of the topics, referred to within the posts, categories of the posts, as an indication of intention for participation and emotions that people share through the posts. We discuss the implications of obtained results for social media marketing and opinion mining.

3. DATA ANALYSIS

3.1 Data Collection

The dataset used for this study consists of posts from the ok.- Facebook brand page. The data collection was performed over one year, from the official launch of the ok.- page in March, 2010 to March, 2011. To guarantee accuracy of the data and ensure independence from potentially changing Facebook policies, post were fetched on a daily basis, using a script utilizing the Facebook Graph API[4].

The Graph API provides access to Facebook social graph via a uniform representation of the objects in the graph (e.g., people, pages, etc.) and the connections between them. For purpose of this study we have used the Feed connection of the Page object. Feed connection represents a list of all Post objects containing the post details, i.e. the message, post type, likes, comments, time of creation, etc. The elements extracted from the Facebook Graph API were stored in a relational database for further investigation.

[4] http://developers.facebook.com/docs/reference/api/

From the total of 759 shared posts, we have removed 134 posts published by the site moderator, leaving 625 posts published by the page fans. Of those 3 were removed due to the difficulty in recognizing the used language and an additional 11 after being labeled as spam, leaving 611 user posts for qualitative analysis.

3.2 The Method

The ok.- brand is present only in the German speaking part of the Switzerland. Although German is the official language in this part of the Switzerland, in daily conversation a dialect is used, know as Swiss German. The challenge of applying automatic opinion mining to the textual content written in Swiss German is increased by the fact that not only does it differ significantly from High German, but there are also large variations within different parts of Switzerland, with no standardized rules for the written form. Therefore, we have performed a manual analysis of the data.

In order to analyze the content we have followed two methods used in [19] for analysis of Twitter data. We have applied the action-object approach [35] for post classification by following the coding development strategy [17]. The process consisted of two steps:

- **Tagging**: Each of the posts has been assigned one or more tags to identify the key concepts in the content, e.g.

  > "*my favorite: ok.- Branchli - when will there be a jumbo pack?*",

  was tagged as 'product', 'positive affect', 'information inquiry', 'suggestion' and 'package'.

- **Integrating**: Based on the tagging results, grouping of similar tags was performed in order to define groups of topics and categories. For the previous example, the resulting group descriptors were: (1) '*Product: Affect: Positive*', (2) '*Sales: Availability: Launch Date: Information Inquiry*' and (3) '*Product: Feature: Package: Suggestion*'.

The tagging captured the following aspects of the posts: (1) topics referred to within the posts, (2) actions related to different posts, further denoted as post categories, and (3) sentiment present in the content. In the continuation of the paper we present the obtained results.

4. RESULTS

4.1 Post Topics

The post topics describe what is being talked about. Our analysis identified seven major topic groups. Table 1 shows the number of occurrence for each of the identified topic groups as well as the results from the statistical analysis corresponding to the comparison of a topic with the "following" topic, e.g. Product vs. Sales.

Table 1. Topic groups (*p < 0.0001, **p < 0.005, ***p < 0.05)

Topic Group	Occurrences	Percentage	z
Product	318	52%	14.539*
Sales	79	13%	3.02**
Brand	46	8%	2.306***
Competitor	26	4%	0.759
Facebook Contest	20	3%	1.452
Company	11	2%	1.883
Environment	3	0%	
TOTAL:	**489**	**80%**	

The results of the statistical analysis have shown that there is a significant difference ($z = 14.539$, $p < 0.0001$) in the proportion of Product posts (52%) compared to the Sales (13%). Furthermore, the proportion of posts regarding Sales is significantly larger ($z = 3.02$, $p < 0.005$) compared to the proportion of Brand posts (8%), while the number of Brand mentions is significantly larger ($z = 2.306$, $p < 0.05$) compared to the number of Competitor (4%) posts. Thus, proportions of Product, Sales and Brand topic groups are larger compared to all of the topic groups with the smaller number of mentions. For the remaining topic groups, no significant difference was found to exist ($p > 0.05$).

Each of the topic groups is further divided into sub-topics as presented in Table 2. The percentages of occurrence are given in relation to the number of posts within a topic group.

Table 2. Topics subdivision

Topic	Sub-topic		N	%
Product	Suggestion		149	47%
	Affect		99	31%
	Feature	Technical details	18	6%
		Package	12	4%
		Price	9	3%
		Quality	8	3%
		Ingredients	2	1%
		Taste	4	1%
		Calories	1	0%
	Complaints		16	5%
Sales	Availability	Supply chain	24	30%
		Launch date	23	29%
	Retail channels	Store	25	32%
		Online	1	1%
	Warranty		4	5%
	Discounts		1	1%
	Loyalty cards		1	1%
Brand	Affect		43	94%
	History		1	2%
	Manufacturer		1	2%
	Inventor		1	2%
Competitor	Product features		11	42%
	Price		8	31%
	Affect		4	15%
	Product range		3	12%
Facebook Contests	Outcome	Winner	13	65%
		Prize	5	25%
	Participation details		2	10%
Company	Praise		5	45%
	Customer service		4	36%
	Facebook	Strategy	1	9%

		Moderation	1	9%
Environment			3	100%

In the following text we explain the topic groups and discuss the most frequent subtopics and their value from the marketing perspective.

Product is the most frequently referred to topic group. Within this group, the two most common subtopics are Product Suggestion with 149 (47%) and Product Affect with 99 (31%) occurrences, e.g.:

> *"I want ok.- Apfelsaftschorle!"*, *"i love ok.- bier!!!^^"*.

From the marketing perspective understanding both of these subcategories is important, the first one for sensing the needs of the customers and the second one as an indicator of product acceptance. From the remaining subtopics, Technical details are present in 18 (6%) posts in the form of information inquiry, while the Price is referred to in 9 posts (3%), usually in the context of comparison with the competitor brands.

Sales: The three most discussed topics within the Sales group are Stores (25), Supply chain (24) and Launch date (23), e.g.:

> *"will you soon open one/more ok.- stores?"*, *"when comes a new ok.- energy drink??"* .

The Stores subtopic relates to opening specialized brand stores and new stores or store locations, both within Switzerland and abroad. The Supply chain topic refers to the product availability and product delivery at particular location. These topics can be used for evaluation of the interest in the brand and can be mapped to the geographical location.

Brand: Affect is the most common subtopic (43, i.e. 94%) within the Brand topic group, e.g.:

> *"i <3 ok.-"*.

Since this is where users express their emotions, it can be perceived as the measure of the brand awareness and strength.

Competitor: References to competitors occurred in 4% of the posts in total. This topic was used to express positive/negative Affect, but also to compare the features, price or product range to those offered by different brands, e.g.:

> *"*Red Bull is not ok.-"*.

This topic is of importance to the company since it allows identification of the perceived similarities and differences. It also indicates the specific aspects of the products that users compare and expect to get from the brand, such as price or taste.

Facebook Contest refers to the responses by users to the entertainment actions undertaken by the moderators of the Facebook brand page, e.g.:

> *"…will there soon be another ok.- Photo Contests? ;-)"*.

The goal of organizing contests is to engage the users, thus increasing the level of activity on the page. However, since it does not directly reveal the sentiment about the product, this topic is not of specific interest from the marketing perspective.

Company is an umbrella topic for the posts related to customer service. It includes praise for the company itself, as well as for the Facebook strategy and moderation style, e.g.

> *"Valora is cool", "I think it's cool that you always write back to answer or ask. I call that interest for customers:)"*

Although rare, it is an indication of the "job well done" for the page moderator and the company in overall.

Environment topic occurred in only 3 posts. Still, the intensity of the posts was quite strong indicating that they should be taken seriously, e.g.

> *"Why doesn't one emerging brand like ok.- focus on environment friendly material right from the beginning??? Dos it has something to do with the money or with the lack of intelligence??? Other reasons I can't imagine except maybe yet merciless ignorance."*

Not all of the posts were classified as belonging to a topic. Some of them (20%) were written in a form of a "word play" or slogan, thus belonging to no particular topic. e.g.

> *"ok...in the end."*

This analysis revealed additional possibility for presentation and interpretation of the same results, centered on categories that might serve as indication for the participation intentions.

4.2 Post Categories

Within this paper, post category refers to the posting intention. A reverse reading of the initially assigned group descriptors resulted into the discovery of eight post categories. The categories and their frequencies of occurrence, as well as the results from the statistical analysis are given in the Table 3.

Table 3. Post categories (*p < 0.0001)

Post Category	Occurrences	Percentage	z
Suggestions & Requests	170	28%	-0.001
Affect Expression	169	28%	0.195
Sharing	165	27%	4.592*
Information Inquiry	98	16%	7.09*
Complaints & Criticism	23	4%	-0.003
Gratitude	22	4%	3.111*
Praise	5	1%	
Competitor Reference	22	4%	
TOTAL:	674	N/A	

In this case all the posts were assigned to one or more categories, e.g.:

> *"The Mango Drink is really cool, the taste really promises a mango for everyone, thanks! Yellow can, also cool! Is there already something new on the way?"*

was labeled as belonging to (1) 'Affect: Positive: Feature: Taste', (2) 'Gratitude: Product', and (3) 'Information Inquiry: Sales: Product: Launch'.

The most common intention for posting was found to be Suggesting & Requesting something (28%), followed by expressing Affect (28%) and sharing Statuses (27%). Between these three categories there was no significant difference in terms of their proportions. Still, when compared to the Information Inquiry (16%), Sharing occurs in a significantly larger number ($z = 4.592$, $p < 0.0001$). Thus, Sharing also occurs in a significantly larger number compared to all of its "following" topics. Since

Suggestions & Requests and Affect Expression have a slightly larger number of occurrences compared to Sharing, the same reasoning applies also for them. Furthermore, the proportion of Information Inquiry (16%) is significantly larger ($z = 7.09$, $p < 0.0001$) compared to Complaints & Criticism (4%), thus also compared to the remaining categories with smaller number of occurrences. Finally, the proportion of Gratitude (4%) is significantly larger ($z = 3.111$, $p < 0.0001$) compared to the proportion of least occurring post category, i.e. Praise (1%). For the remaining post categories, no significant difference was found to exist ($p > 0.05$).

Each of the identified categories is explained and discussed in the following text.

Suggestions and Requests: Within suggestions and requests, two related topic groups that occur are Sales and Product. Fans tend to give suggestions for products, new ones as well as improvements of specific features of existing products, e.g.:

> *"please an ok.- energy drink pineapple".*

Affect Expression occurs both in positive and negative context. It was targeted toward the ok.- brand, a product or a specific feature of a product, e.g.

> *"I don't like the ok.- mango, but that is the matter of taste"*

Affect was also expressed for competitors, often in a relation to the specific feature, e.g. the amount of carbonation in the drinks. Posts belonging to this category are of particular interest from a marketing perspective. They give clear indication on how is the brand is perceived by the users, what the popular products are and which specific features are the ones that are favored by the customers.

Sharing: Our study indicates that within a sponsored Facebook brand page fans share (1) activity, (2) advice, (3) opinion, (4) intention, (5) need, (6) information, (7) feelings, (8) reflection on specific events and (9) rhetorical questions. A very common form of expression was a word play and/or a slogan (92 posts, 15%), e.g.

> *"One ok.- a day, keeps the dok.-ter away"*

Information Inquiry is an important category from the organizational aspect of the Facebook brand page. It identifies possible domains of interest of the page fans, e.g.:

> *"Who actually invented the ok.- brand?"*

Since running a successful Facebook page requires full dedication and round-a-clock interaction with the fans, these insights reveal a need for different sources of information or a structure of the team behind the page moderator. Topics referred in this category include (1) Brand, (2) Product, (3) Sales, (4) Company and (5) Contests.

Complaints and Critics are painful, yet valuable part of social media marketing. As users feel very free to express themselves in this medium, they offer the possibilities for improvement that would result in greater customer satisfaction. The most complaints were after the launch of a mobile phone product line which had several technical problems at the beginning, e.g.

> *"Today I bought a ZTE San Francisco: dead on arrival. The touch screen feels nothing. The hotline number also does not work…"*

Within the same Product topic, there were also a few price complaints, usually in relation to the price offered by the competitor. Product availability, i.e. Sales was the second most referred topic in form of asking for a product delivery to a given location.

Gratitude was mostly shown in case of winning a prize in one of the Contests organized within the Facebook page. However, those of interest from the marketing perspective expressed gratitude toward product launch (Sales) providing initial insight into the acceptance of the product, e.g.:

> *"I am happy that there is now an energy drink in the light version! Thank you ok.- :-)"*

Praise was targeted towards the discussed subtopics within the Company topic group.

Topics and categories are interconnected. Table 4 shows the frequencies of combination occurrences. Apart from Sharing, Product Requests and Suggestion (24%) and Expressing Affect towards the Products (20%) are the most common topic-category combinations.

4.3 Sentiment Analysis

Understanding how people feel about the brand or specific product is one of the key elements for social media monitoring. Facebook brand page offers the required platform to gather such information and undertake an appropriate respond if needed.

For the analyzed dataset, sentiment was shared within the posts from the Affect Expression category. Table 5 shows the sentiment frequency of occurrence in terms of positive and negative sentiment towards brand and a specific product. The results show that positive sentiment is shared far more often compared to the negative sentiment.

Table 4. Topic-category combinations and co-occurrence frequencies

	Product	Sales	Brand	Competitor	Contests	Company	Environment	General
Requests & Suggestions	149 (24%)	20 (3%)					1 (0%)	
Expressing Affect	122 (20%)		43 (7%)	4 (0%)				
Sharing								165 (27%)
Information Inquiry	29 (5%)	49 (8%)	3 (0%)		10 (2%)	3 (0%)		4 (0%)
Complaints & Criticism	16 (3%)	4 (0%)				1 (0%)	2 (0%)	
Expressing Gratitude	2 (0%)	6 (1%)			10 (2%)	2 (0%)		2 (0%)
Praise						5 (1%)		
Comparison				22 (4%)				

Table 5. Sentiment analysis

Sentiment	Occurrences (all)	Percentage (all)	Percentage (sentiment only)
Positive	150	25%	93%
Negative	11	2%	7%
Neutral	450	73%	
TOTAL:	611	100%	161 (27%)

Apart from the sentiment distribution, we were interested in analyzing how people express emotions. We have identified that emotions are displayed either via adjectives or through the usage of the following elements of internet slang: (1) emoticons, (2) interjections and (3) intentional misspelling.

Emoticons were used in 226 (37%) of the posts; 22% of those contained more than one emoticon. Table 6 illustrates the emotions that can be assigned to the used emoticons:

Table 6. Emoticons and expressed emotions

Emoticon	Emotion
:) :-) =) x) (:	Joy (smiling)
:D	Excitement
;) ;-) ;D ;P (;	Wink
xD =D ^^ ^.^	Happiness (laughing)
<3 ♥ *_* *.* **	Love
:P	Playfulness (tong out)
:O	Surprise
:S	Skepticism
(Y)	Support (thumbs up)
:(=(	Sadness
-.-	Annoyance

An interesting form of emotion display was the usage of the “*<emotion>*” notion (6 occurrences), e.g.

> *“I want the new Ok.- Cookie and an Energy…But no kiosk near...*sniff*”.*

Interjections (29; 5%) that have occurred within the analyzed dataset and the enclosed emotions/meanings are listed in Table 7.

Table 7: Interjections and their emotional meaning

Interjections	Emotion
Mmm	Pleasure
Hmm	Wondering
Mhmm	Confirmation
yeah, uee, juhu, jipi, wuhu, boah	Excitement
haha, hihi	Laughter
jum jum, njam njam	Tasty
Wow	Surprise

Intentional misspelling and punctuations marks are interesting from the perspective of sentiment analysis as indication of emotion intensity. The recognized patterns include (1) Capital letters, (2) Repeating vocals and (3) Punctuation marks, e.g.:

> *“YOU ARE SUPER!”, or “That is sooooo fine!!!!”*

The usage of misspelling and punctuations was not as common as the usage of emoticons. Repeating vocals were present in 19 posts (3%), capital letters in 27 (4%), while punctuation in 105 posts (19%). Still they are to be taken in account for the automatic sentiment analysis.

5. IMPLICATIONS

The results presented in this paper are interesting from two perspectives (1) social media marketing and (2) opinion mining.

5.1 Implications for Social Media Marketing

In order to successful run a Facebook brand page as a part of the social media marketing approach, marketing departments needs to understand what people share and why. As discussed in the previous section, posts reveal (1) perception of the brand, (2) acceptance of new product, (3) most favored products and features, (4) required products and features, (5) problems, (6) locations with great volume of sales, and also may serve to (7) generate ideas and (8) identify competitors.

In addition, knowing what people talk about on a brand page can be valuable input for those companies just starting with the social media marketing. Organizationally, the topics can be used to understand what different sources of information need to be available to moderators to successfully run a Facebook brand page, i.e. members of the support board behind the moderator that can be addressed when a specific question is posed. This study indicates the need for following experts: (1) sales, (2) logistics, (3) company/brand information (producer, founder, history, etc.), (4) product information and (5) environmental issues.

Our results indicate that Product, Sales and Brand are the three most discussed topics, while Requests and Suggestions, Expressing Affect and Sharing are the most common intentions for participation, each of them with significantly larger number of occurrences compared to the remaining topics/categories with the lower number of occurrences in posts. Furthermore, we show that the topics and categories are interconnected. Our results show that Product Requests and Suggestion (24%) and Expressing Affect towards the Products (20%) are the most common topic-category combinations. This confirms that Facebook can be used as a suitable platform for social media marketing. Facebook brand pages support the social media marketing opportunities and goals for building brand awareness, gathering insights and knowledge for future steps, community involvement and engaging in open and honest dialog, as presented in the related work section. Marketing practitioners could use the topic-category frequency of occurrence as a measure for successful social media marketing utilization over time.

5.2 Implications for Opinion Mining

Manual post analysis has given us an understanding of the format of the content that fans/users share on the Facebook brand page. However, in order to provide the possibility to perform such analysis on a larger datasets and to create a tool that could track the changes in content and sentiment over time, an algorithm for automatic text analysis is required.

To enable automatic text analysis, the results show the need to create a standardized lexicon for the internet slang including: (1) Internet slang abbreviations that helps replace them within text content and/or assigned emotions, (2) an emoticon lexicon and (3) a translation of interjections to emotions. Further, the results show the need for the following steps: (4) use number of emoticons and punctuation marks as a measure for the intensity of the displayed emotion, (5) apply a mechanism for recognizing repeating vocals in the words to (a) understand the meaning of the word and (b) measure the intensity of the displayed emotion.

In addition, incorrect punctuation usage should be taken into consideration, i.e. some posts do not have any punctuation, although manual inspection reveals separate sentences within one post. An effective algorithm for sentence recognition that is not based on the punctuation marks is needed. This algorithm would need to differ for different languages, and should be based on sentence structure recognition.

For the specific domain of Swiss German language there are still many open questions: (1) to which extent can German lexicon be applied for automatic analysis and (2) how and if it is possible to overcome the challenge of not having rules for written form.

The tagged dataset from this study could further be used as training set for the machine learning algorithms for automatic opinion mining for the content shared on brand pages from the Swiss German speaking region.

6. CONCLUSIONS AND FUTURE WORK

This study presents an analysis of the posts shared on a Facebook brand page. We have identified the topics and categories of posts and have explained their interconnections. Based on our results we have drawn implications social media marketing.

We are aware of the limitations of our study in the sense of a relatively small dataset extracted from only one Facebook page. Still, we believe that the long period of time for data collection offers more insights in terms of variety of addressed topics, since certain subtopics occur only within a limited number of posts (e.g. Environment) and during a limited period of time (e.g. the subtopic Technical Details occurs for the first time on December 4th, 2010). Furthermore, we provide a detailed analysis for the specific domain of sponsored Facebook brand page, managed by the company offering fast moving consumer goods for young customers.

Our future steps would include (1) expanding the analysis on post comments, (2) comparison of our results with other Facebook brand pages, and (3) evaluation of possibilities for opinion mining automation for the Swiss German language, using the tagged dataset as a training set for machine learning algorithms.

7. REFERENCES

[1] Adar, e., Weld, D. S., Bershad, B. N., and Gribble, S. S. 2007. Why We Search: Visualizing and Predicting User Behavior. In *Proceedings of the 16th International Conference on World Wide Web* (Banff, Alberta, Canada, May 8-12, 2007). WWW'07. ACM, New York, NY, USA, 161-170. DOI= http://doi.acm.org/10.1145/1242572.1242595

[2] Agozzino, A. L. 2010. *Millennial Students Relationship with 2008 Top 10 Social Media Brands via Social Media Tools*. Doctoral Thesis. Bowling Green State University, United States - Ohio. Dissertations & Theses: A&I. (Publication No. AAT 3405748).

[3] Asur, S., and Huberman, B. A. 2010. Predicting the Future with Social Media. In *Proceedings of the International Conference on Web Intelligence and Intelligent Agent Technology* (Toronto, Canada, August 31 – September 3, 2010). IEEE/WIC/ACM'10. IEEE, 492–499

[4] Baloglu, A., and Aktas, M. S. 2010. BlogMiner: Web Blog Mining Application for Classification of Movie Reviews. In *Proceedings of 5th International Conference on Internet and Web Applications and Services* (Barcelona, Spain, May 9 - 15, 2010). ICIW'20. IEEE, 77–84.

[5] Bermingham, A., and Smeaton, A. F. 2010. Classifying Sentiment in Microblogs: Is brevity an Advantage? In *Proceedings of the 19th ACM International Conference on Information and Knowledge Management* (Toronto, Canada, October 26-30, 2010). CIKM'10. ACM, New York, NY, USA, 1833-1836. DOI= http://doi.acm.org/10.1145/1871437.1871741

[6] Bolotaeva, V., and Cata, T. 2010. Marketing Opportunities with Social Networks. *J. Int. Soc. Netw. and Virtual Communities* 2010. DOI=10.5171/2010.109111

[7] Boyd, D. M., and Ellison, N. B. 2007. Social Network Sites: Definition, History, and Scholarship. *J. Comput.-Mediat. Comm.* 13, 1 (Oct. 2007), 210–230.

[8] Brandt, K. S. 2008. You Should be on YouTube. *ABA Bank Marketing*, 40, 6 (Jul. 2008), 28-33.

[9] Brown, J., Broderick, A. J., and Lee, N. 2007. Word of Mouth Communication within Online Communities: Conceptualizing the Online Social Network. *J. Interact. Mark.* 21, 3 (Summer 2007), 2–20.

[10] De Choudhury, M., Sundaram, H., John, A., and Seligmann, D. D. 2008. Can Blog Communication Dynamics be Correlated with Stock Market Activity? In *Proceedings of the 19th ACM Conference on Hypertext and Hypermedia* (Pittsburgh, Pennsylvania, USA, June 19-21, 2008). HT'08. ACM, New York, NY, USA, 55-60. DOI= http://doi.acm.org/10.1145/1379092.1379106

[11] Coon, M. (2010). *Social Media Marketing: Successful Case Studies of Businesses Using Facebook and YouTube with an In-Depth Look into the Business Use of Twitter*. M.A. Thesis. Stanford University, Stanford, CA.

[12] Das, S. R., and Chen, M. Y. 2007. Yahoo! for Amazon: Sentiment Extraction from Small Talk on the Web. *Manage. Sci.* 53, 9 (Sep. 2007), 1375-1388. DOI: 10.1287/mnsc.1070.0704.

[13] Dave, K., Lawrence, S., and Pennock, D. M. 2003. Mining the Peanut Gallery: Opinion Extraction and Semantic Classification of Product Reviews. In *Proceedings of the 12th International Conference on World Wide Web* (Budapest, Hungary, May 20-24, 2003). WWW '03. ACM, New York, NY, USA, 519-528. DOI= http://doi.acm.org/10.1145/775152.775226.

[14] Diakopoulos, N. A, and Shamma, D. A. 2010. Characterizing Debate Performance via Aggregated Twitter Sentiment. In *Proceedings of the 28th International Conference on Human Factors in Computing Systems* (Atlanta, GA, USA, April 10-15, 2010). CHI'10. ACM, New York, NY, USA, 1195-1198. DOI= http://doi.acm.org/10.1145/1753326.1753504

[15] Glaser, B., and Strauss, A. 1967. *The Discovery of Grounded Theory: Strategies for Qualitative Research*. Chicago: Aldine.

[16] Harris, L., and Rae, A. 2009. Social Networks: The Future of Marketing for Small Business. *J. Bus. Strat.* 30, 5 (2009), 24-31.

[17] Jansen, B. J., Zhang, M., Sobel, K., and Chowdury, A. 2009. Twitter Power: Tweets as Electronic Word of Mouth. *J. Am. Soc. Inf. Sci. Tec.* 60, 11 (Nov. 2009), 2169-2188.

[18] Javitch, D. 2008. *Entrepreneurs Need Social Networking*. Entrepreneur.com. http://www.entrepreneur.com/humanresources/employeemanagementcolumnistdavidjavitch/artic le198178.html

[19] Kaltenbrunner, A., Gomez, V., and Lopez, V. 2007. Description and Prediction of Slashdot Activity. In *Proceedings of the 2007 Latin American Web Conference*, (Santiago, Chile, October 31-November 2, 2007). LA-WEB'07. IEEE, 57-66.

[20] Kozinets, R. V., de Valck, K., Wojnicki, A. C., and Wilner, S. J. S. 2010. Networked Narratives: Understanding Word-of-Mouth Marketing in Online Communities. *J. Marketing* 50, 3 (May. 2010), 140-89.

[21] Li, C. 2007. *How consumers use social networks*. Forrester Research Paper. http://www.eranium.at/blog/upload/consumers_socialmedia.pdf

[22] Liu, Y., Huang, X., An, A., and Yu, X. 2007. ARSA: A Sentiment-Aware Model for Predicting Sales Performance Using Blogs. In *Proceedings of the 30th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval* (Amsterdam, Netherlands, July 23-27, 2007). SIGIR'07. ACM, New York, NY, USA, 607-614. DOI=http://doi.acm.org/10.1145/1277741.1277845.

[23] Muniz, Jr., A. M., and O'Guinn, T. C. 2001. Brand Community. *J. Consum. Res*. 27, 4 (Mar. 2001), 412-432.

[24] Nasukawa, T., and Yi, J. 2003. Sentiment Analysis: Capturing Favorability Using Natural Language Processing. In *Proceedings of the 2nd International Conference on Knowledge Capture* (Sanibel Island, Florida, USA , October 23-25, 2003). K-CAP'03. ACM, New York, NY, USA, 70-77.

[25] Ostrowski, D. A. 2010. Sentiment Mining within Social Media for Topic Identification. In *Proceedings of the 4th IEEE International Conference on Semantic Computing* (Pittsburgh, PA, USA, September 22-24, 2010). ICSC'10. IEEE, 394–401.

[26] Palmer, A., and Koenig-Lewis, N. 2009. An experiential, social network-based approach to direct marketing. *Direct Marketing: Int. J.* 3, 3 (2009), 162-176.

[27] Pang, B., and Lee, L. 2008. Opinion Mining and Sentiment Analysis. *Foundations and Trends in Information Retrieval* 2, 1-2, 1-135. DOI= http://dx.doi.org/10.1561/1500000011.

[28] Richter, D., Riemer, K., and vom Brocke, J. 2010. Internet Social Networking: Research State of the Art and Implications for Enterprise 2.0 (State of the Art). *Wirtschaftsinformatik* 53, 2 (Apr. 2011), 89-103.

[29] Simm, W., Ferrario, M.-A., Piao, S., Whittle, J., and Rayson, P. 2010. Classification of Short Text Comments by Sentiment and Actionability for VoiceYourView. In *IEEE International Conference on Social Computing* (Minneapolis, Minnesota, USA, August 20-22, 2010). SocialCom'10. IEEE, 552–557. DOI= http://dx.doi.org/10.1109/SocialCom.2010.87.

[30] Skul, D. 2008. *Social Network Marketing – Legal Pitfalls*. Relativity Business Technology Solutions. http://www.relativitycorp.com/socialnetworkmarketing/article26.html

[31] Thelwall, M., Wilkinson, D., and Uppal, S. 2010. Data Mining Emotion in Social Network Communication: Gender Differences in MySpace. *J. Am. Soc. Inform. Sci.* 61, 1 (Jan. 2010), 190-199.

[32] Wasserman S., and Faust, K. 1994. *Social Network Analysis: Methods and Applications*. Cambridge University Press, Cambridge.

[33] Weston, R. 2008. *7 Social Networking Strategies*. Entrepreneur.com. http://www.entrepreneur.com/technology/bmighty/article191312.html

[34] Wilson, T., Wiebe, J., and Hwa, R. 2004. Just How Mad Are You? Finding Strong and Weak Opinion Clauses. In *Proceedings of the 19th National Conference on Artificial Intelligence* (San Jose, California, USA, July 25-29, 2004). AAAI'04. A. G. Cohn, Ed. AAAI Press 761-767.

[35] Yassine, M. and Hajj, H., 2010. A Framework for Emotion Mining from Text in Online Social Networks. In *IEEE International Conference on Data Mining Workshops* (Sidney, Australia, December 13, 2010). ICDMW'10. IEEE, 1136–1142. DOI= http://dx.doi.org/10.1109/ICDMW.2010.75.

[36] Zhang, M., and Jansen, B.J. 2008. Using Action-Object Pairs as a Conceptual Framework for Transaction Log Analysis. In *Handbook of Research on Web Log Analysis*, B. J. Jansen, A. Spink and I. Taksa, Eds. Hershey, PA: Information Science Reference, 414–433.