Journal of Universal Computer Science, vol. 22, no. 5 (2016), 709-734
submitted: 16/9/15, accepted: 29/4/16, appeared: 1/5/16 © *J.UCS*

Applying Brand Equity Theory to Understand Consumer Opinion in Social Media

Evangelos Kalampokis
(University of Macedonia, Thessaloniki, Greece
Centre for Research and Technology Hellas, Thessaloniki, Greece
ekal@uom.gr)

Areti Karamanou
(University of Macedonia, Thessaloniki, Greece
Centre for Research and Technology Hellas, Thessaloniki, Greece
akarm@uom.gr)

Efthimios Tambouris
(University of Macedonia, Thessaloniki, Greece
Centre for Research and Technology Hellas, Thessaloniki, Greece
tambouris@uom.gr)

Konstantinos Tarabanis
(University of Macedonia, Thessaloniki, Greece
Centre for Research and Technology Hellas, Thessaloniki, Greece
kat@uom.gr)

Abstract: Billions of people everyday use Social Media (SM), such as Facebook and Twitter, to express their opinions and experiences with brands. Companies are highly interested in understanding such SM brand-related content. Consequently, many studies have been conducted and many applications have been developed to analyse this content. For analysis purposes, the main SM metrics used include volume and sentiment. Interestingly, however, brand equity theory proposes different metrics for assessing brand reputation. These include brand image, brand satisfaction and purchase intention (henceforth referred to as marketing metrics). The objective of this paper is to explore the feasibility of applying marketing metrics in Twitter brand-related content. For this purpose, we collect, study and analyse tweets that mention two brands, namely IKEA and Gatorade. The manual analysis suggests that a significant amount of brand tweets is related to brand image, brand satisfaction and purchase intention. We thereafter design an algorithm that classifies tweets into relevant categories to enable automatic marketing metrics computation. We implement the algorithm using statistical learning approaches and prove that its classification accuracy is good. We anticipate that this article will motivate other studies as well as applications' designers in adopting marketing theories when evaluating brand reputation through SM content.

Key Words: Social Media, brand reputation, brand equity, marketing
Category: H.3.3, M.0, M.7, M.9

1 Introduction

Social Media (SM) are part of our everyday lives. Ample evidence are the 1.65 billion monthly active Facebook users [Facebook 2016] along with the 320 million monthly active Twitter users [Twitter 2015] that produce large amounts of online content (e.g. posts or reactions). A significant part of this content regards opinions and experiences of consumers with brands that refer to companies, products and services [Mangold and Faulds 2009, Bambauer-Sachse and Mangold 2011, Laroche et al. 2013].

The potential of this SM content is huge. During the last years, numerous studies exploited SM content to explain or even predict the behaviour of consumers towards a brand [Asur and Huberman 2010, Jansen et al. 2009, Moe and Trusov 2011]. These studies quantified consumer opinion by computing *SM metrics* through the analysis of SM content. The metrics that they usually employ are based on the *volume* of distinct SM content that refer to a brand and the *sentiment* expressed through them [Peters et al. 2013, Kalampokis et al., 2013].

However, the idea of quantifying consumer opinion is not new. On the contrary, it has been heavily studied by marketing theorists - far before the appearance of the SM trend - in the context of measuring customer-based brand equity. Customer-based brand equity occurs when consumers are aware of a brand and hold positive associations in their memory about it [Keller 1993, Esch 2006]. In this context, the opinion of consumers is quantified using *marketing metrics* such as brand image, brand satisfaction and purchase intention.

There is, hence, a gap between the metrics that traditional marketing theories use to quantify consumer opinion and the metrics that are currently computed using SM brand-related content. This gap hampers academia and businesses to fully understand and appreciate the role of SM in marketing [Mangold and Faulds 2009, Hanna et al. 2011, Hoffman and Fodor 2010].

The objective of this article is to explore the feasibility of bridging this gap and thus facilitate computing marketing metrics through the analysis of SM content. This will enable for the first time measuring customer-based brand equity by using SM content. The benefits of using SM content to measure customer-based brand equity include the ability to use huge amounts of input in a highly economic manner and obatin results in near real-time. To the best of our knowledge this is the first attempt in the literature towards this direction.

Our exploratory study capitalises on Twitter as it is one of the most popular SM services, its data are public by default, and the short nature of its messages (aka tweets) facilitate opinion extraction. We initially collect and study tweets that mention two brands, namely IKEA and Gatorade. We, thereafter, design an algorithm that classifies tweets into categories derived from brand equity theory, such as satisfaction and image. This classification enables computing marketing metrics, e.g. by counting the amount of tweets per category and calculating ratios such as the number of tweets in one category to the total number of tweets.

We anticipate that this article will motivate further research and practice in widely adopting marketing theories in the development of applications that monitor and manage brand reputation through SM content.

The rest of the paper is structured as follows. [Section 2] outlines the methodology adopted in this paper. [Section 3] presents a literature review on SM and marketing metrics. In [Section 4] we manually classify tweets based on brand equity theory. In [Section 5] we construct the classification algorithm which is then implemented into a statistical model in [Section 6]. We evaluate our classification algorithm in [Section 7] and [Section 8] discusses the results. Finally, [Section 9] concludes this research and provides future work suggestions.

2 Approach

The research work we present in this paper is exploratory [Bhattacherjee 2012] as we aim at analysing the feasibility of computing marketing metrics directly through SM content. In general, exploratory research is conducted for problems not clearly defined. It often occurs before we know enough to make conceptual distinctions or posit an explanatory relationship [Shields and Rangarajan 2013].

As exploratory, our approach draws upon the following steps:

Step 1 Identification and definition of SM and marketing metrics for the quantification of brand-related consumer opinion. For this purpose, we conduct a literature review in the two areas. This step results in the selection of three marketing metrics for further investigation, namely brand satisfaction, brand image and purchase intention.

Step 2 Manual classification of tweets based on brand equity theory. For this purpose, we initially collect tweets concerning two well-known brands from the domains of retail and beverages, namely IKEA and Gatorade respectively. We compute SM metrics, such as volume and sentiment. In order to compute volume we just count the number of tweets. In order to compute sentiment, we study the text of each tweet and classify it into one of the following sentiment categories:

- Positive. This category includes tweets showing positive feelings about a brand. These tweets are used to compute positive sentiment.
- Negative. This category includes tweets showing negative feelings about a brand. These tweets are used to compute negative sentiment.
- Neutral. This category includes tweets that do not show feelings about a brand.

In order to compute marketing metrics we use a similar method with the one used for computing sentiment. Indeed, we study the text of each tweet and classify it into one of the following categories:

- Satisfaction. This category includes tweets showing satisfaction or dissatisfaction about a brand. The tweets of this category are used to compute brand satisfaction metric.
- Image. This category includes tweets showing (positive or negative) perception of a brand. These tweets are used to compute brand image metric.
- Intention. This category includes tweets showing intention to purchase a brand. These tweets are used to compute purchase intention metric.
- None. This category includes the rest of the tweets that refer to a brand but do not belong to any of the three other categories.

In this paper we refer to the above-mentioned categories as Brand Equity Theory (BET) categories, as they facilitate the computation of metrics proposed in brand equity theory.

The manual classification of tweets in sentiment and BET categories is performed by two authors of the paper. In case of disagreement, the tweet is classified in the None category. The manual analysis suggests that a significant amount of tweets is related to brand image, brand satisfaction and purchase intention.

Step 3 Design of an algorithm for the classification of tweets based on brand equity theory. The algorithm enables the automatic classification of tweets in BET categories hence alleviates the significant burden of manual classification.

Step 4 Implementation of the classification algorithm. In this step, we develop a statistical model that implements the classification algorithm of the previous step. Particularly, we employ a supervised machine learning text classifier in each of the decision nodes of the algorithm. We validate the statistical model by computing average recall and accuracy using 10-fold cross validation.

Step 5 Evaluation of the classification algorithm against a baseline model. Our baseline model is actually the text classifier alone that categorises tweets into BET categories in one only step, i.e. without following the decision nodes of our algorithm. We validate the baseline statistical model by computing average recall and accuracy using 10-fold cross validation. We, finally, compare average accuracy and recall of our model with the baseline model.

3 Quantifying the opinion of consumers: A literature review

3.1 Quantifying the opinion of consumers using Social Media metrics

Scientific studies employ the *volume* and *sentiment* of brand-related posts as metrics for the quantification of consumer opinion. The metrics are used, for example, to understand the effect of SM consumer opinion on a company's economic outcomes [Ghose and Ipeirotis 2011] and decision making [Chamlertwat et al. 2012, Smith et al. 2012, Abrahams et al. 2012, Salas-Zárate et al. 2014], to examine its influence on consumers attitude [Mostafa 2013], to investigate the word-of-mouth effect on microblogging [Jansen et al. 2009], to predict the attention of brand-related posts [Lakkaraju and Ajmera 2011], to predict the behaviour of financial markets [Salas-Zárate et al. 2016] and to forecast box-office revenues [Asur and Huberman 2010, Liu et al. 2010, Habernal et al. 2013].

The estimation of volume from brand-related posts is a straightforward process. For example, relevant methods include the counting of the number of relative reviews (e.g. [Ghose and Ipeirotis 2011, Liu et al. 2010]) or tweets (e.g. [Chamlertwat et al. 2012, Jansen et al. 2009, Mostafa 2013, Habernal et al. 2013, Asur and Huberman 2010]) regarding a brand or product.

On the other hand, sentiment analysis (or opinion mining) usually requires additional effort. In the simplest case opinion is expressed through rating of products and sentiment is expressed by computing the average rating (e.g. [Ghose and Ipeirotis 2011]). In the case however of textual content sentiment is computed using Natural Language Processing (NLP) methods. The most common NLP approaches are lexicon-based and machine learning, with the latter however inducing more accurate results in SM than the former [Bermingham and Smeaton 2010, Kalampokis et al., 2013]. Lexicon-based approach uses a lexicon with, usually, domain-dependant sentiment terms in order to evaluate text as positive or negative [Turney 2002]. Relevant scientific studies (e.g. [Liu et al. 2010, Chamlertwat et al. 2012, Lakkaraju and Ajmera 2011, Abrahams et al. 2012]) use lexicon-based classifiers such as SentiWordNet [Esuli 2006, Peñalver-Martinez et al. 2014] and OpinionFinder [Wilson et al., 2005] or employ a manually/semi-automatically generated sentiment lexicon (e.g. [Turney 2002, Mostafa 2013]). Machine learning approaches utilise textual features coupled with statistical algorithms to perform text classification [Pang et al. 2002]. Researchers here utilise semantic features by incorporating sentiment lexicon terms (e.g. [Ghiassi et al. 2013]), syntactic measures including n-grams and part of speech (POS) tags (e.g. [Go et al. 2009, Asur and Huberman 2010, Ghiassi et al. 2013, Habernal et al. 2013]), features that capture expressions of writing style and micro-blogging features such as emoticons (e.g. [Ghiassi et al. 2013, Habernal et al. 2013]). Relevant studies also uses machine learning algorithms including naive bayes (e.g. [Go et al. 2009]), support-vector machines (e.g. [Go et al. 2009, Ghiassi et al. 2013, Habernal et al. 2013]), dynamic language model (e.g. [Asur and Huberman 2010]), maximum entropy (e.g. [Go et al. 2009, Habernal et al. 2013]) and neural networks (e.g. [Ghiassi et al. 2013]).

3.2 Quantifying the opinion of consumers using marketing metrics

Brand equity is the marketing term to delineate the impact of a well-known brand name on companies and products and is able to grow up an enduring relationship between brands and consumers [Keller 1993]. The quantification of brand equity has been examined from three perspectives: financial brand equity, customer-based brand equity and a combination of the two previous perspectives [Kotler and Keller 2006]. The first perspective treats brand equity from the side of the company whilst the second one from the side of the customer. Combined brand equity is an integration of the other two perspectives. In this paper, we focus on the customer-based perspective of brand equity. For simplicity, we refer onwards to customer-based brand equity with the term brand equity.

Keller defines brand equity as the *"differential effect of brand knowledge on consumer response to the marketing of the brand"* [Keller 1993, p. 51]. In this definition, brand knowledge refers to the existing links of the consumers (e.g. perceptions, feelings and images) to a brand [Keller 2009], while consumer response is actually the purchase of a brand or the intention of a consumer to purchase a brand. Positive (or negative) brand equity occurs when consumers hold strong (or weak) and positive (or negative) associations with a brand. The quantification of brand equity is the subject of several conceptual models (e.g. [Aaker 1991, Keller 1993, Agarwal and Rao 1996, Kapferer 1994, Krishnan 1996, Maio Mackay 2001]). In our study, we follow Keller's knowledge-based model [Keller 1993]. This emphasises that brand equity can be quantified by measuring brand knowledge, i.e. brand awareness and brand image.

Brand awareness refers to the strength that a brand has in the memory of consumers and is reflected by the ability of the consumer to identify a brand under different conditions [Rossiter and Percy 1987, Keller 1993], i.e. how easy is for the consumers to recognise and recall a brand. Relative scientific studies employ and measure consumers brand awareness to examine its influence on brand equity [Atilgan et al. 2005, Bauer et al. 2005], on consumers selection of a brand [Hoyer and Brown 1990] and on the financial performance of companies [Kim et al. 2003], to investigate consumers behavioural intention towards a brand [Oh 2000] and to analyse its influence by SM activities [Hutter et al. 2013] and by external factors such as the country of origin of a brand [Pappu et al. 2006] or data relative to the family of the consumers [Bravo et al. 2007].

Brand image is described as the *"perceptions about a brand as reflected by the brand associations held in consumer memory"* [Keller 1993, p. 3]. Brand image is also defined as the thoughts and feelings that consumers hold about a brand [Roy and Banerjee 2008] and often used as liking of the brand [Lau and Lee 1999] or as the attitude of the consumers towards the brand [Liu et al. 2010, Ahmed et al. 2002, Oliver 1980]. Relative studies examine the dimensions of brand image (e.g. [Belén del Río et al. 2001]), its impact on the satisfaction of consumers [Dennis et al. 2007], on the loyalty of consumers [Tu et al. 2012, Creatu and Brodie 2007], on the intention of consumers to purchase a brand [Yu et al. 2013] and on the financial performance of a company (e.g. [Kim et al. 2003]).

While Keller's model focuses on brand knowledge perspectives of brand equity, a more recent research [Esch 2006] demonstrates that brand knowledge

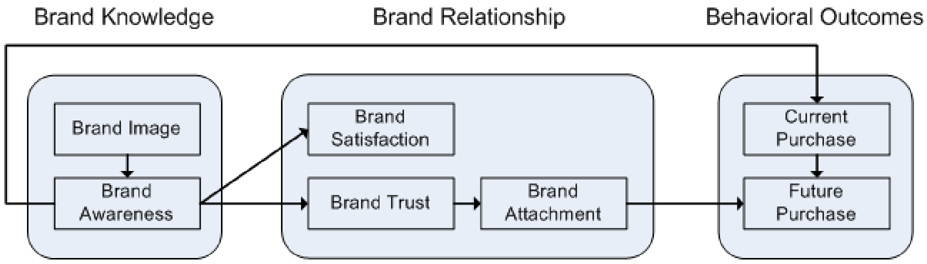

Figure 1: Esch et al.'s [Esch 2006] model for Brand Equity

stand-alone is insufficient for building brand equity. More specifically, [Esch 2006] outlines that brand knowledge is actually affecting consumer response via brand relationship dimensions. Brand relationship argues that consumers build relationships with brands in the same manner they build relationships with each other. Brand relationship metrics include *brand satisfaction*, *brand trust* and *brand attachment*. Esch et al.'s proposed model is illustrated in Figure 1.

Brand satisfaction refers to the evaluation of consumers of whether the exchange relationship with a brand is rewarding [Esch 2006]. Brand satisfaction is also called consumer satisfaction and, inversely, dissatisfaction (e.g. [Richins 1983, LaBarbera and Mazursky 1983]). Relative studies examine the impact of brand satisfaction on the loyalty of consumers to a brand [Tu et al. 2012, Sahin et al. 2011, Mittal and Lassar 1998, Lau and Lee 1999, Caruana 2002, Delgado-Ballester and Luis Munuera-Alemán 2001, Newman and Werbel 1973, Selnes 1993], its antecedents and consequences [Anderson and Sullivan 1993, Oliver 1980], its relationship with service quality and purchase intention [Cronin Jr and Taylor 1992, LaBarbera and Mazursky 1983] and its affection by brand image [Dennis et al. 2007] and complaint behaviour [Shemwell et al. 1998].

At the same time, *brand trust* regards the outcome of the communal relationship with the brand [Esch 2006] and is defined as the security feeling of consumers that a brand will be in line with its promises and consumption expectations [Delgado-Ballester and Luis Munuera-Alemán 2001]. Literature also perceives brand trust as guarantee of quality [Belén del Río et al. 2001] or as the risk perceived by consumers [Kwun and Oh 2004]. Researchers employ brand trust to provide empirical evidence about its impact on the loyalty of consumers to a brand [Sahin et al. 2011, Lau and Lee 1999, Delgado-Ballester and Luis Munuera-Alemán 2001] and on repurchase intentions [Zboja and Voorhees 2006, Hongyoun Hahn et al. 2009].

Brand attachment is the emotional bond between brands and consumers [Park et al. 2006]. In order to measure brand attachment the intensity of the emotional attachment of consumers to the brand should be measured [Thomson et al. 2005]. Brand attachment is employed by empirical studies to investigate its relationship with the quality of service of a brand [Thach and Olsen 2006], the loyalty of consumers to a brand [Patwardhan and Balasubramanian 2011] and the actual and ideal self-congruence of consumers [Malär et al. 2011].

Finally, current and future purchase refers to the current and future behaviour of the consumer regarding the purchase of the brand. Empirical studies usually mention these metrics as *purchase intention* (either current or future) or behavioural intention (e.g. [Kwun and Oh 2004]). Purchase intention has been used by researchers in order, for example, to examine its influence by brand image [Yu et al. 2013], by brand trust [Zboja and Voorhees 2006], by the satisfaction of consumers [Oliver 1980, Cronin Jr and Taylor 1992], by the store, name, brand name and product price [Grewal et al. 1998], by the country of origin of the brand or service [Ahmed et al. 2002], or by the brand, product price, and risk [Kwun and Oh 2004]. In addition, literature has also investigated how purchase intention is influenced by SM activities [Hutter et al. 2013].

In this article, we focus on three marketing metrics, namely brand image, brand satisfaction and purchase intention. There are three reasons behind this selection: (a) we want to include one metric from each of the components of Esch et al.'s model (i.e. brand knowledge, brand relationship and behavioural outcomes), (b) we want metrics that are not directly related in the same model and (c) we want metrics that, in our understanding, will be easily computed from tweets. For example, a tweet is more likely to be related to one of the selected metrics that to brand trust.

4 A manual classification of tweets based on brand equity theory

In this section we present our work on manually classifying tweets in BET and sentiment categories in order to compute marketing metrics and SM metrics respectively. The work starts by classifying tweets in BET categories. Thereafter, we measure brand satisfaction, brand image and purchase intention by computing the ratio of the number of tweets that fall into the relative BET category to the total number of tweets. Moreover, after classifying tweets in sentiment categories, we measure positive, negative and neutral sentiment by counting the ratio of the number of tweets that fall into Positive, Negative and Neutral categories respectively to the total number of tweets.

Towards this end, we collect a corpus of 12122 tweets using the Twitter's REST API[1] and the keywords *"IKEA"* and *"Gatorade"*. We ignore non-English tweets, retweets, spam tweets and advertisements and we preprocess tweets to:

[1] https://dev.twitter.com/rest/public

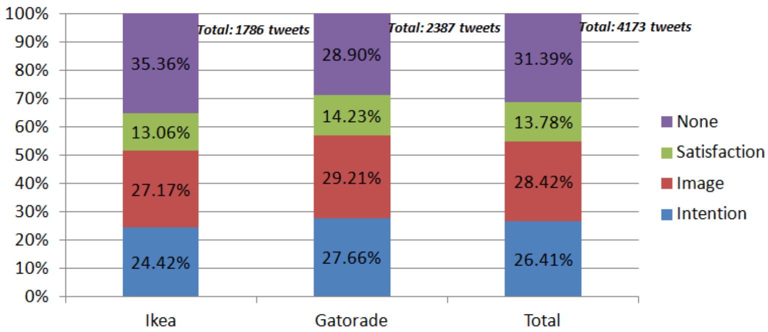

Figure 2: Marketing metrics in tweets

– remove URLs and references to Twitter users
– remove English stop words, such as "a", "the", "at", "on" etc.
– convert all letters in lower-case

The preprocessing of tweets results in our *gold standard* dataset comprising 4173 tweets, that is 34.44% of the initial dataset. The manually annotated gold standard dataset can be found online.[2]

The results of the manual classification are shown in Figure 2. More than half of the tweets (56.3% of our gold standard) are classified in one of the Satisfaction, Image and Intention categories while the rest (43.7%) of tweets are classified in the None category. This suggests that there is a significant number of tweets that refer to brand satisfaction, brand image and purchase intention. Moreover, we isolate each brand's tweets to examine whether the brand affects the relative number of tweets that fall into one of the BET categories. Figure 2 shows that there is a small difference between the percentage of each BET category in the two brands. In particular, the relative ratios of all BET categories are 1-3% increased in Gatorade tweets compared to IKEA tweets. Moreover, the relative ratios of the BET categories of the two brands have on average ±1.5% difference vis-à-vis the relative categories of total tweets (Figure 2). Hence, according to the data we examine, we do not find evidence that the brand significantly affects marketing metrics computed from tweets.

To measure the volume of the tweets we count the number of tweets that mention a brand. We result with 1786 tweets for IKEA and 2387 tweets for Gatorade.

Figure 3 shows the occurrence of positive, negative and neutral sentiment in tweets. In the total amount of tweets, the positive ones (52.94%) significantly outnumber the negative ones (7.57%). There is also a noticeable presence of neutral tweets (39.49%). Moreover, the ratio of neutral Gatorade tweets is lower

[2] `http://195.251.218.39:8181/tweets/classified_tweets.csv`

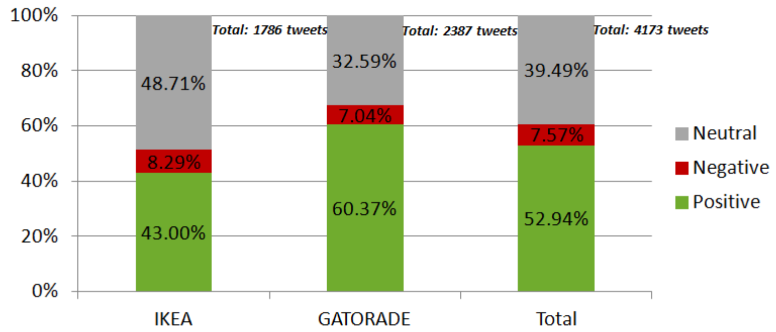

Figure 3: Sentiment in tweets

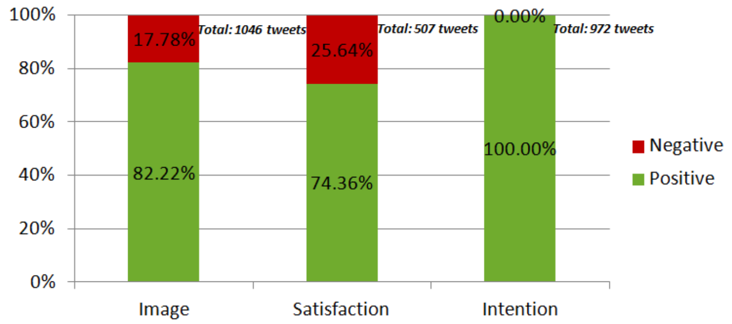

Figure 4: Marketing metrics & sentiment in the total of tweets

than the neutral IKEA and total tweets while the ratio of IKEA positive tweets is lower than the positive Gatorade and total tweets.

In addition, we concurrently compute marketing metrics and sentiment in tweets. As illustrated in Figure 4, tweets showing brand image and brand satisfaction are mostly positive with percentages 82.22% and 74.36% respectively. Moreover, all purchase intention tweets imply positive sentiment. Figures 5 and 6 show the relationship between each of the marketing metrics and the sentiment ratio computed from each brand's tweets. The charts show insignificant differences in the percentages when compared both with each other as well as with the chart in Figure 4.

5 An algorithm for classifying tweets based on brand equity theory

In this section, we design an algorithm that enables the automatic classification of tweets in the BET categories.

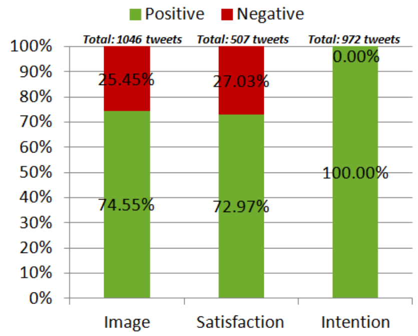

Figure 5: Marketing metrics & sentiment in IKEA tweets

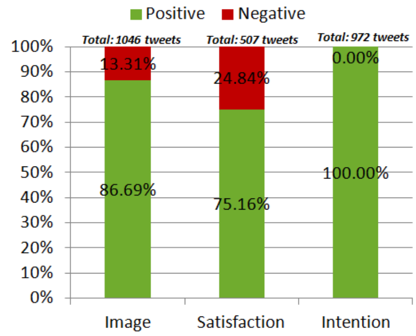

Figure 6: Marketing metrics & sentiment in GATORADE tweets

The manual classification of the previous section and the definitions of marketing metrics presented in [Section 3.2], lead us to the following observations:

1. A tweet that refers to a brand has a subject. The subject may actually be the author of the tweet or the person (or thing) that the tweet states that is related to the brand. For example, the subject in the tweet "I love Gatorade" is the author of the tweet, while the subject in the tweet "My dad loves Gatorade" is "dad". Nevertheless, some tweets do not have a specific subject such as the tweet "Calling Gatorade by the colour not the flavour". We consider "Someone" as the subject of these tweets. The classification of a tweet in BET categories is directly related to the relationship between the subject and the brand as it is expressed in the tweet.
2. A tweet that expresses satisfaction shows that the brand has been recently consumed/used or is being consumed/used at the time of its posting. For instance, consuming Gatorade actually implies buying or drinking Gatorade while consuming IKEA implies visiting IKEA to buy something, buying an object from IKEA or eating a meal at IKEA. Once this consuming criterion is satisfied, a tweet can be classified in the Satisfaction category only if the subject was satisfied (or dissatisfied) with his/her consuming experience regarding the brand. In the sixth example of Table 1 the subject is the author of the tweet. If there was not the phrase "@IKEA" we could not for sure conclude that the author has recently visited or is now at IKEA. However, the parenthesis satisfies the consumption criterion for this tweet, showing that the author is now at IKEA which he/she considers as his/her worst nightmare. We should, thus, classify this tweet in the Satisfaction category. Hence, tweets are related to brand satisfaction when they state that the

subject has consumed a product or service related to a brand.

3. Brand image in tweets shows the general stance of the subject about the brand, a stance that has been formed over time. Being also in line with the definition of brand image in brand equity theory, tweets are classified in the Image category when they show how the subject perceives and feels about the brand over time. The perception of the brand could imply positive (e.g. "I love going to IKEA") or negative (e.g. "I hate going to IKEA") feelings of the subject about the brand (the sentiment of the tweet). The tweets expressing brand image do not always denote consumption or use of the brand. These tweets may also compare a specific brand with other relative brands (e.g. "Gatorade is better that Powerade") or express a subject's suggestion of the brand to someone else (e.g. "You should drink Gatorade every morning"). The latest claim is derived by the logical claim that if someone suggests a brand, he/she has a positive perception of it. Hence, brand image in tweets does not conclusively suggest that the subject has consumed or intents to consume a product or service related to a brand. Instead, it shows that the subject has a general stance towards the brand over time or compares the brand with other brands or suggests the brand to others.
4. Purchase intention is related to tweets that clearly state that the subject intends to consume or use the brand in the near future.
5. Some tweets are not related to marketing metrics. An example is the tweet "I go to ikea just to people watch..".

Table 1 shows examples of tweets, their subject, whether they imply consumption and their BET category.

Based on the manual classification of tweets and the derived observations, we design the classification algorithm. The pseudocode for the algorithm is presented in Figure 7. Figure 8 also shows the algorithm as a decision tree with the "if conditions" presented as questions. According to the algorithm, in order to classify a tweet into one of the BET categories, one should initially check if the text of the tweet implies consumption of the brand. In case it does, if the text expresses satisfaction or dissatisfaction about the brand the tweet is classified in the Satisfaction category, otherwise in the None category. If the tweet does not imply consumption and expresses intention to buy it is classified in the Intention category. Otherwise, if the tweet implies brand image it is classified in the Image category. Otherwise the tweet is classified in the None category.

6 Implementation of the algorithm

In this section we present the statistical model that implements the algorithm of the previous step. The model automatically classifies a tweet into one of the BET

Tweet Text	Subject	Consumption	BET category
My dad doesnt like gatorade	Dad	Not clear	Image (-)
My cat really likes Gatorade	Cat	Not clear	Image (+)
i drink gatorade all day everyday	Author	Yes	Image (+)
This fruit punch gatorade taste weird	Author	Yes	Satisfaction (-)
Had like 5 ikea ice creams yum	Author	Yes	Satisfaction (+)
Ikea ... this is my worst nightmare (@IKEA)	Author	Yes	Satisfaction (-)
I fancy lunch at IKEA meatballs & chips.	Author	No	Intention
Ikea will be the death of my visa card	Author	No	Intention
I am so thirsty my throat is burning I want purple gatorade nao.	Author	No	Intention
Make yourself useful and go get me a Gatorade	Author	No	Intention
Calling Gatorade by the color not the flavor.	Someone	No	None

Table 1: Examples of manually classified tweets into marketing metrics

categories. Towards this end, we train our model using the manually annotated gold standard dataset.

In particular, we employ the Lingpipe DynamicLMClassifier which is based on a character-based N-gram language model. We use two parameters to construct the classifier: the categories of the classification and a language model. The categories of the classification are the classes that the classifier is trained to predict and are described below. The language model we use is a character n-gram model with $N = 9$. We also use 10-fold cross validation as it is suitable for limited size datasets. This means that our gold standard dataset is initially divided into 10 roughly equal parts (aka folds). In each of the 10 rounds of the cross validation, each fold in turn was used as validation data and the rest 9 folds as training data. We train the classifier to predict three of the BET categories: Satisfaction, Image, and Intention. We exclude tweets classified in None category from our gold standard.

Being in line with our classification algorithm, our model performs two stages of classification, one for each decision node of the algorithm. Hence:

- the first stage classifies tweets based on whether their text expresses consumption of the brand or not (first decision node). As we exclude tweets classified in None category, tweets showing consumption are actually tweets that should be classified in the Satisfaction category.

```
Input tweet
if tweet implies consumption then
        if tweet implies satisfaction/dissatisfaction then
                tweet.label = SATISFACTION
        else
                tweet.label = NONE
else
        if tweet implies intention to buy then
                tweet.label = INTENTION
        else
                if tweet implies image then
                        tweet.label = IMAGE
                else tweet.label = NONE
```

Figure 7: The classification algorithm

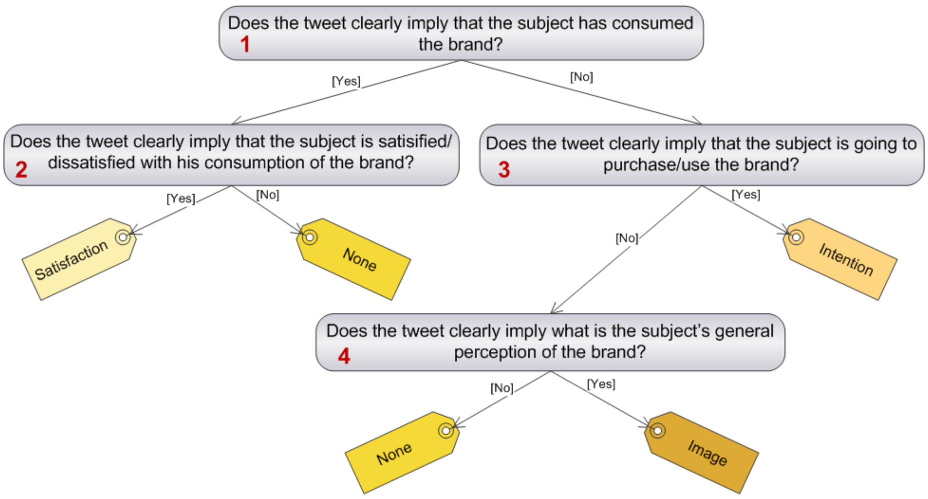

Figure 8: Visualisation of the algorithm

– the second stage classifies tweets classified from the first stage as not denoting consumption based on whether they indicate intention to buy/use the brand (second decision node). As we exclude tweets classified in None category from the classification, tweets classified as not expressing intention are actually tweets that should be classified in Image category.

In order to validate the statistical model, we calculate accuracy and average recall. Because we use cross validation, the value of each measure derives from

#Fold	Total Accuracy	Confidence 95%	Avg Recall
0	0,79	±0,07	0,5
1	0,83	±0,06	0,5
2	0,82	±0,06	0,5
3	0,82	±0,06	0,5
4	0,8	±0,07	0,5
5	0,77	±0,07	0,5
6	0,79	±0,07	0,5
7	0,81	±0,06	0,5
8	0,74	±0,07	0,5
9	0,8	±0,07	0,5
Avg	0,798		0,5

Table 2: 1st Stage: Accuracy and average recall for each fold

the average values of each of the 10-folds. For example, accuracy is the average of each fold's estimated accuracy. In particular, accuracy is defined as:

$$Accuracy = \frac{TotalCorrectClassifications}{TotalNumberofClassifications} \tag{1}$$

Recall measures the true positive rate for a class and is defined as:

$$Recall_A = \frac{tp_A}{tp_A + fn_A}, \tag{2}$$

where tp_A is the number of true positive predictions for class A and fn_A is the number of false negative predictions for class A. Average recall is calculated as the average recall per class. Average recall, hence, is defined as:

$$AvgRecall_A = \frac{\Sigma_i Recall_i}{TotalNumberofClasses} \tag{3}$$

Table 2 describes the values of accuracy and recall for each fold of the first stage of the classification along with the 95% confidence intervals for accuracy. We can see from the Table that the average accuracy of the first stage is 79,8% while the average recall is 50%.

In terms of the second stage we also train the same text classifier to predict Intention and Image as categories in "no consumption" tweets. At this stage, hence, the training as well as the testing data consist only of tweets that do not state consumption of the brand. As we omit None tweets, according to the algorithm, "no consumption" tweets express either purchase intention or brand image. As we can see in Table 3, the total average accuracy of the second stage is 70,7% while the average recall is 70,4%.

#Fold	Total Accuracy	Confidence 95%	Avg Recall
0	0,68	±0,09	0,68
1	0,74	±0,08	0,74
2	0,7	±0,08	0,7
3	0,73	±0,08	0,72
4	0,7	±0,08	0,7
5	0,7	±0,08	0,69
6	0,69	±0,09	0,69
7	0,72	±0,08	0,72
8	0,69	±0,09	0,69
9	0,72	±0,08	0,71
Avg	0,707		0,704

Table 3: 2nd Stage: Accuracy and average recall for each fold

As we deal with two independent classifications, the final accuracy of the classifications can be calculated as their average accuracy i.e. 75,25% and the final recall as their average recall i.e. 60,2%.

Moreover, Table 4 presents average recall but this time for each BET category. We observe that 69,3% of the tweets that show intention to purchase are correctly classified in the Intention category. In addition, 71,6% of the tweets that show image are correctly classified in the Image category and 49,76% of the tweets that show satisfaction are correctly classified in the Satisfaction category.

	Intention	Image	Satisfaction
Avg Recall	0,693	0,716	0,4976

Table 4: Average recall in BET categories

7 Evaluation of the algorithm

We evaluate our algorithm against a text classifier. We perform the classification of the previous step again, but this time we use the text classifier one single time in order to classify tweets into the BET categories at once.

Towards this end, we construct a baseline model using only the text classifier, without the classification algorithm. We use again the Lingpipe's DynamicLM-Classifier text classifier. The classifier is trained using again the gold standard. This time we train the classifier to predict in one step the three categories:

#Fold	Total Accuracy	Confidence 99%	Avg Recall
0	0,56	±0,08	0,53
1	0,64	±0,08	0,59
2	0,54	±0,08	0,5
3	0,57	±0,08	0,54
4	0,64	±0,08	0,59
5	0,62	±0,08	0,55
6	0,57	±0,08	0,53
7	0,57	±0,08	0,52
8	0,58	±0,08	0,54
9	0,52	±0,08	0,49
Avg	0,581		0,538

Table 5: Baseline of the evaluation: Performance measures for each fold

	Intention	Image	Satisfaction	*Avg*
Avg Recall	0,648	0,66	0,2994	0,538

Table 6: Baseline model - Average recall in BET categories

Satisfaction, Intention and Image. We again exclude tweets classified in None category from our gold standard.

The baseline model is validated by computing average recall and average accuracy using 10-fold cross validation. The computed values for each fold are shown in Table 5. The classification ends up with an average accuracy of 58,1% and an average recall 53,8%.

Table 6 also presents average recall, this time for each BET category of the baseline model. We can see that 64,8% of the tweets that show intention to purchase are correctly classified in the Intention category. Moreover, 66% of the tweets that show image are correctly classified in the Image category and 29,94% of the tweets that show satisfaction are correctly classified in the Satisfaction category.in

We then compare average accuracy and recall of our model that implements the algorithm with the ones of the baseline model (Table 7). The comparison shows that our algorithm improves the accuracy of classification by 75,25 - 58,1 = 17,15 units and average recall by 60,2 - 53,8 = 6,4 units.

Moreover, we compare the recall of each BET category calculated from our model with the corresponding recalls of the baseline model's BET categories. As we can see in Table 8 our algorithm improves the recall of Intention category by 69,3 - 64,8 = 4,5 units, the recall of Image category by 71,6 - 66 = 5,6 units and the recall of Satisfaction category by 49,76 - 29,94 = 19,82 units.

	Algorithm-based model	Baseline model (text only)	Improvement
Avg Accuracy	75,25%	58,1%	17,15
Avg Recall	60,2%	53,8%	6,4

Table 7: Comparison of accuracy and average recall of the algorithm-based model with the baseline model

	Algorithm-based model	Baseline model (text only)	Improvement
Intention	69,3%	64,8%	4,5
Image	71,6%	66%	5,6
Satisfaction	49,76%	29,94%	19,82

Table 8: Comparison of average recall (BET categories) of the algorithm-based model with the baseline model

8 Discussion

In this section, we discuss the approach along with the results of our study aiming at exploring the use of brand equity theory for enabling understanding the opinion of consumers in SM.

The second step of our approach requires the manual classification of a large number of tweets. Similar works in literature (e.g. [Asur and Huberman 2010]) usually crowdsource manual classification to the Amazon Mechanical Turk. However, Amazon Mechanical Turk services are not supported out of the USA. As a result, we employed 300 university students to perform the classification. However, as we did not obtain high quality results from the students' effort, we had to perform the manual classification of the tweets by ourselves. The lessons learned from the manual classification of tweets is that classifying tweets into BET categories is not as easy and straightforward as classifying them in positive and negative sentiment. As a result, we believe that only domain experts can induce the desired quality of results in the classification. This is a significant problem that needs to be addressed in the future. Moreover, another problem we have to address is the limited number of tweets. In this work, we overcome this issue using 10-fold cross validation.

Moreover, we suppose that each tweet is classified exclusively only in one BET category. However, in reality this is not always accurate. As an example, consider the following tweet: "I had a fantastic day at IKEA today. I'm visiting again tomorrow". This tweet could be classified in both Satisfaction and Intention categories, as it shows that the subject (a) is satisfied with his visit to IKEA (i.e. he visited IKEA and is now satisfied) and, at the same time, (b) intends to visit IKEA tomorrow. In our study we ignore these tweets to simplify the implementation of the algorithm.

Literature uses different SM metrics to quantify the opinion of consumers. SM metrics are computed from the analysis of SM content and can be differently measured depending on the context and type of SM used. For example, in relevant studies volume is measured with the number of blog posts [Chen et al. 2011], the number of product ratings [Moe and Trusov 2011], the number of Facebook likes [De Vries et al. 2012], the number of threads [Netzer et al. 2012] or the difference in number of reviews [Tirunillai and Tellins 2012]. In the same way, sentiment has been measured in literature with the average rating or the (positive or negative) valence of the product reviews in order to estimate the sales of a product [Adjei et al. 2010, Godes and Silva 2012]. Moreover, sentiment has also been measured with the bullishness index to forecast stock price from micro blog posts [Oh and Sheng 2011]. The bullishness index is calculated as the ratio of total bullish (positive) postings to the total bearish (negative) postings.

From the above it follows that, although different studies measure sentiment in various ways, at last they all classify SM content in the same two categories of sentiment i.e. positive and negative. One of the major contributions of our research is that we go one step further and introduce three categories derived from brand equity theory, i.e. brand satisfaction, brand image and purchase intention. According to our understanding, these are subcategories of sentiment. In this context, brand satisfaction expresses the positive or negative feelings of someone that has consumed a product or service related to a brand, brand image the positive or negative stance of someone towards a brand over time while purchase intention the positive only feeling of someone that aims to consume or use the brand in the near future.

Our manual classification of tweets suggests that a significant amount of tweets is related to brand image, brand satisfaction and purchase intention. This classification of SM content allows the computation of the actual marketing metrics. In this work we measure marketing metrics by computing the ratio of the number of tweets that fall into the relative BET category to the total number of tweets. For example, we count the number of tweets classified in Satisfaction category and we compute the ratio of this number to the total amount of tweets that mention the brand. However, a number of alternative ways of computing marketing metrics can be used. For example we can also measure brand satisfaction by computing the ratio of the number of tweets in the Satisfaction category to the sum of all categories' tweets except None. In addition, we can count the number of tweets that express satisfaction in different time periods so as to observe how brand satisfaction changes over time, how it changes in relation to other marketing metrics or how it changes in relation to the stages of the life cycle of a product.

The simplest approach to explore whether marketing metrics can be automatically and accurately computed from SM content would be to use a text classifier and create a model that classifies tweets at once into Satisfaction, Image and Intention categories. The implementation of this approach induces an average accuracy of 58,1%, which is close to chance-level accuracy. The implementation, however, of our algorithm improves the accuracy of the classification to 75,25%. This suggests that our classifier enables computing marketing metrics from SM content. This is a significant contribution of this paper as it gives a first sign that the opinion of consumers can be automatically computed out of SM content, at least in the case of tweets.

We believe our work is important for both academia and businesses. Specifically, our findings contribute to academia that investigates the exploitation of SM content towards strengthening the relationship between consumers and companies. Moreover, our research can be used by businesses to design and develop a new era of relative algorithms and software applications that will compute marketing metrics to understand the opinion of consumers in SM and monitor and manage brand reputation.

9 Conclusion

The potential of understanding the opinion of consumers expressed in SM about brands, products and services is huge. To this end, a number of studies in the scientific literature quantify the opinion of consumers by computing SM related metrics such as the volume and sentiment of SM content. At the same time, brand equity theory quantifies the opinion of consumers using marketing metrics such as brand image, consumer satisfaction and purchase intention.

In this article we explore the feasibility of bridging the gap between SM and marketing metrics through the direct analysis of SM content. To this end, we study the text of 4173 tweets that refer to two brands of the retail and beverages domains (namely IKEA and Gatorade) and manually classify them in BET and sentiment categories. We also design an algorithm for the classification of tweets into BET categories to enable the computation of marketing metrics. We then create a statistical model that implements the algorithm using a machine learning text classifier. We evaluate the algorithm against a baseline which is a simple text classifier.

Our work revealed the following results:

– A significant amount of tweets is related to brand image, brand satisfaction and purchase intention. Particularly, 68,61% of tweets is classfied to one of the BET categories. Moreover, tweets mostly denote brand image (28,42%), then purchase intention (26,41%) and finally customer satisfaction (13,78%). We also found that 60,51% of tweets express sentiment. Interestingly, most of the tweets (52,95%) show positive sentiment, which agrees with the previous work of [Jansen et al. 2009].

– Regarding the content of tweets, we observe that: (i) tweets have a subject, (ii) tweets are related to brand satisfaction when they state that subject has consumed a product or service related to a brand, (iii) purchase intention is related to tweets that clearly state that the subject intends to consume or use the brand in the near future, and (iv) brand image in tweets does not conclusively show that the subject has consumed or intents to consume a product or service related to a brand; however, it shows that the subject has a general stance towards the brand over time or compares the brand with other brands or suggests the brand.

– Marketing metrics can be accurately and automatically computed from tweets using statistical learning approaches. Particularly, we show that the implementation of our classification algorithm outperformed the accuracy of a simple text classifier.

In the future we envision to enhance the work done in this paper in the following ways in order to bridge significant gaps and limitations:

– Enrich the gold standard. Our research described in this paper uses a limited number of tweets. Once we found that the implementation of our algorithm induces promising results, we aim to collect a larger corpus of tweets and re-implement the algorithm so as to obtain more accurate results.

– Include more brands. Our current work focuses on two brands, namely IKEA and Gatorade. Future research will include tweets regarding more brands.

– Involve more domains. Our current work also focuses on two domains, namely retail and beverages. However, we plan to apply our method and evaluate its accuracy in other domains in future endeavours.

– Involve additional marketing metrics. We currently use only three marketing metrics i.e. brand image, brand satisfaction and purchase intention. Future work could extend the algorithm so as to accommodate additional marketing metrics such as brand trust and brand awareness. This could be a challenging task as some marketing metrics influence others according to Esch's model described in [Section 3.2].

– Use different machine learning algorithms to implement the classification algorithm. Examples of algorithms used in the literature to compute sentiment include support vector machines (e.g. in [Go et al. 2009]) and maximum entropy (e.g. in [Habernal et al. 2013]).

We believe that the results of the current study and its enhancements in future work, will reveal the potential of computing marketing metrics for enabling the understanding of the opinion of consumers in SM.

Acknowledgements

The authors would like to acknowledge that the work presented in this paper has been partially carried out in the course of the Linked2Media project, which was funded by the European Commission within the 7th Framework Programme under grand agreement No. 286714.

References

[Aaker 1991] Aaker, D.: "Measuring brand equity"; (1991) p. 206

[Abrahams et al. 2012] Abrahams, A., Jiao, J., Wang, G., Fan, W.: "Vehicle defect discovery from social media"; *Decision Support Systems*, **54**(1) (2012), 87–97.

[Adjei et al. 2010] Adjei, M. T., Noble, S. M., Noble, C. H.: "The influence of C2C communications in online brand communities on customer purchase behavior"; *Journal of the Academy of Marketing Science*, **38**(5) (2010), 634–653.

[Agarwal and Rao 1996] Agarwal, M., Rao, V.: "An empirical comparison of consumer-based measures of brand equity"; *Marketing letters*, **7**(3) (1996), 237–247.

[Ahmed et al. 2002] Ahmed, Z., Johnson, J., Pei Ling, C., Wai Fang, T., Kah Hui, A.: "Country-of-origin and brand effects on consumers' evaluations of cruise lines"; *International Marketing Review*, **19**(3) (2002), 279–302.

[Anderson and Sullivan 1993] Anderson, E., Sullivan, M.: "The antecedents and consequences of customer satisfaction for firms"; *Marketing science*, **12**(2) (1993), 125–143.

[Asur and Huberman 2010] Asur, S., Huberman, B.: "Predicting the future with social media"; Proc. *Web Intelligence and Intelligent Agent Technology, (WI-IAT), 2010 IEEE/WIC/ACM International Conference on, vol. 1, IEEE* (2010), 492–499.

[Atilgan et al. 2005] Atilgan, E., Aksoy, S., Akinci, S.: "Determinants of the brand equity: A verification approach in the beverage industry in turkey"; *Marketing intelligence & planning*, **23**(3) (2005), 237–248.

[Bambauer-Sachse and Mangold 2011] Bambauer-Sachse, S., Mangold, S.: "Brand equity dilution through negative online word of-mouth communication"; *Journal of Retailing and Consumer Services*, **18**(1) (2011), 38–45.

[Bhattacherjee 2012] Bhattacherjee, A.: "Social science research: principles, methods, and practices"; (2012)

[Bauer et al. 2005] Bauer, H., Sauer, N., Schmitt, P.: "Customer-based brand equity in the team sport industry: Operationalization and impact on the economic success of sport teams"; *European Journal of Marketing*, **39**(5/6) (2005), 496–513.

[Belén del Río et al. 2001] Belén del Río, A., Vazquez, R., Iglesias, V.: "The effects of brand associations on consumer response"; *Journal of consumer marketing*, **18**(5) (2001), 410–425.

[Bermingham and Smeaton 2010] Bermingham, A., Smeaton, A.: "Classifying sentiment in microblogs: is brevity an advantage?"; Proc. *Proceedings of the 19th ACM international conference on Information and knowledge management,ACM* (2010), 1833–1836.

[Bravo et al. 2007] Bravo Gil, R., Fraj Andres, E., Martinez Salinas, E.: "Family as a source of consumer-based brand equity."; *Journal of Product & Brand Management*, **16**(3) (2007), 188–199.

[Caruana 2002] Caruana, A.: "Service loyalty: The effects of service quality and the mediating role of customer satisfaction"; *European journal of marketing*, **36**(7/8) (2002), 811–828.

[Chamlertwat et al. 2012] Chamlertwat, W., Bhattarakosol, P., Rungkasiri, T., Haruechaiyasak, C.: "Discovering consumer insight from twitter via sentiment analysis"; *J. UCS (Journal for Universal Computer Science)*, **18**(8) (2012), 973–992.

[Chen et al. 2011] Chen, Y., Fay, S., Wang, Q.: "The role of marketing in social media: How online consumer reviews evolve"; *Journal of Interactive Marketing*, **25**(2) (2011), 85–94.

[Creatu and Brodie 2007] Cretu, A., Brodie, R.: "The influence of brand image and company reputation where manufacturers market to small firms: A customer value perspective"; *Industrial Marketing Management*, **36**(2) (2007), 230–240.

[Cronin Jr and Taylor 1992] Cronin Jr, J., Taylor, S.: "Measuring service quality: a reexamination and extension"; *The journal of marketing* (1992), 55–68.

[Delgado-Ballester and Luis Munuera-Alemán 2001] Delgado-Ballester, E., Luis Munuera-Alemán, J.: "Brand trust in the context of consumer loyalty"; *European Journal of marketing*, **35**(11/12) (2001), 1238–1258.

[Dennis et al. 2007] Dennis, C., King, T., Martenson, R.: "Corporate brand image, satisfaction and store loyalty: A study of the store as a brand, store brands and manufacturer brands"; *International Journal of Retail & Distribution Management*, **35**(7) (2007), 544–555.

[Esch 2006] Esch, F., Langner, T., Schmitt, B.H., Geus, P.: "Are brands forever? How brand knowledge and relationships affect current and future purchases"; *Journal of Product & Brand Management*, **15**(2) (2006), 98–105.

[Esuli 2006] Esuli, A., Sebastiani, F.: "Sentiwordnet: A publicly available lexical resource for opinion mining"; In *Proceedings of LREC, vol. 6, Citeseer* (2006), 417–422.

[Facebook 2016] Facebook: Company info (2016) `http://newsroom.fb.com/company-info`

[Ghiassi et al. 2013] Ghiassi, M., Skinner, J., Zimbra, D.: "Twitter brand sentiment analysis: A hybrid system using n-gram analysis and dynamic artificial neural network"; *Expert Systems with applications*, **40**(16) (2013), 6266–6282.

[Ghose and Ipeirotis 2011] Ghose, A., Ipeirotis, P.: "Estimating the helpfulness and economic impact of product reviews: Mining text and reviewer characteristics"; *Knowledge and Data Engineering, IEEE Transactions on*, **23**(10) (2011), 1498–1512.

[Go et al. 2009] Go, A., Bhayani, R., Huang, L.: "Twitter sentiment classification using distant supervision"; *CS224N Project Report, Stanford* (2009), 1–12.

[Godes and Silva 2012] Godes, D., Silva, J. C.: "Sequential and temporal dynamics of online opinion"; *Marketing Science*, **31**(3) (2012), 448–473.

[Grewal et al. 1998] Grewal, D., Krishnan, R., Baker, J., Borin, N.: "The effect of store name, brand name and price discounts on consumers' evaluations and purchase intentions"; *Journal of retailing*, **74**(3) (1998), 331–352.

[Habernal et al. 2013] Habernal, I., Ptácek, T., Steinberger, J.: "Sentiment analysis in czech social media using supervised machine learning"; Proc. *Proceedings of the 4th workshop on computational approaches to subjectivity, sentiment and social media analysis* (2013), 65–74.

[Hanna et al. 2011] Hanna, R., Rohm, A., Crittenden, V. L.: "We are all connected: The power of the social media ecosystem"; *Business horizons*, **54**(3) (2011), 265–273.

[Hoffman and Fodor 2010] Hoffman, D. L., Fodor, M.: "Can you measure the ROI of your social media marketing?"; MIT Sloan Management Review, **52**(1) (2010), 41.

[Hongyoun Hahn et al. 2009] Hongyoun Hahn, K., Kim, J.: "The effect of offline brand trust and perceived internet confidence on online shopping intention in the integrated multi-channel context"; *International Journal of Retail & Distribution Management*, **37**(2) (2009), 126–141.

[Hoyer and Brown 1990] Hoyer, W., Brown, S.: "Effects of brand awareness on choice for a common, repeat-purchase product"; *Journal of consumer research* (1990), 141–148.

[Hutter et al. 2013] Hutter, K., Hautz, J., Dennhardt, S., Füller, J.: "The impact of user interactions in social media on brand awareness and purchase intention: the case of mini on facebook"; *Journal of Product & Brand Management*, **22**(5/6) (2013), 342–351.

[Jansen et al. 2009] Jansen, B., Zhang, M., Sobel, K., Chowdury, A.: "Twitter power: Tweets as electronic word of mouth"; *Journal of the American society for information science and technology*, **60**(11) (2009), 2169–2188.

[Kalampokis et al., 2013] Kalampokis, E., Tambouris, E., Tarabanis, K.: "Understanding the predictive power of social media"; *Internet Research*, **23**(5) (2013), 544–559.

[Kapferer 1994] Kapferer, J.: "Strategic brand management: New approaches to creating and evaluating brand equity"; *New York: Free Press* (1994)

[Keller 1993] Keller, K.: "Conceptualizing, measuring, and managing customer-based brand equity"; *The Journal of Marketing* (1993), 1–22.

[Keller 2009] Keller, K.L.: "Building strong brands in a modern marketing communications environment"; *Journal of marketing communications*, **15**(2-3) (2009), 139–155.

[Kim et al. 2003] Kim, H., Gon Kim, W., An, J.: "The effect of consumer-based brand equity on firms' financial performance"; *Journal of consumer marketing*, **20**(4) (2003), 335–351.

[Kotler and Keller 2006] Kotler, P., Keller, K.L.: "Marketing management"; *Prentice Hall,New Jersey* (2006)

[Krishnan 1996] Krishnan, H.: "Characteristics of memory associations: A consumer-based brand equity perspective"; *International Journal of research in Marketing*, **13**(4) (1996), 389–405.

[Kwun and Oh 2004] Kwun, J., Oh, H.: "Effects of brand, price, and risk on customers' value perceptions and behavioral intentions in the restaurant industry"; *Journal of Hospitality & Leisure Marketing*, **11**(1) (2004), 31–49.

[LaBarbera and Mazursky 1983] LaBarbera, P., Mazursky, D.: "A longitudinal assessment of consumer satisfaction/dissatisfaction: the dynamic aspect of the cognitive process"; *Journal of marketing research* (1983), 393–404.

[Lakkaraju and Ajmera 2011] Lakkaraju, H., Ajmera, J.: "Attention prediction on social media brand pages"; Proc. *Proceedings of the 20th ACM international conference on Information and knowledge management, ACM* (2011), 2157–2160.

[Laroche et al. 2013] Laroche, M., Habibi, M.R., Richard, M.: "To be or not to be in social media: How brand loyalty is affected by social media?"; *International Journal of Information Management*, **33**(1) (2013), 76–82.

[Lau and Lee 1999] Lau, G., Lee, S.: "Consumers' trust in a brand and the link to brand loyalty"; *Journal of Market-Focused Management*, **4** (4) (1999), 341–370.

[Liu et al. 2010] Liu, Y., Chen, Y., Lusch, R., Chen, H., Zimbra, D., Zeng, S.: "User-generated content on social media: Predicting market success with online word-of-mouth"; (2010)

[Mangold 2009] angold, W. G., Faulds, D. J.: "Social media: The new hybrid element of the promotion mix"; *Business horizons*, **52**(4) (2009), 357-365.

[Maio Mackay 2001] Maio Mackay, M.: "Evaluation of brand equity measures: further empirical results"; *Journal of product & brand management*, **10**(1) (2001), 38–51.

[Malär et al. 2011] Malär, L., Krohmer, H., Hoyer, W., Nyffenegger, B.: "Emotional brand attachment and brand personality: The relative importance of the actual and the ideal self"; *Journal of Marketing*, **75**(4) (2011), 35–52.

[Mangold and Faulds 2009] Mangold, W., Faulds, D.: "Social media: The new hybrid element of the promotion mix"; *Business Horizons*, **10**(1) (2009), 38–51.

[Mittal and Lassar 1998] Mittal, B., Lassar, W.: "Why do customers switch? The dynamics of satisfaction versus loyalty"; *Journal of services marketing*, **12**(3) (1998), 177–194.

[Moe and Trusov 2011] Moe, W. W., Trusov, M.: "The value of social dynamics in online product ratings forums"; *Journal of Marketing Research*, **48**(3) (2011), 444–456.

[Mostafa 2013] Mostafa, M.: "More than words: Social networks' text mining for consumer brand sentiments"; *Expert Systems with Applications*, **40**(10) (2013), 4241–4251.

[Netzer et al. 2012] Netzer, O., Feldman, R., Goldenberg, J., Fresko, M.: "Mine your own business: Market-structure surveillance through text mining"; *Marketing Science*, **31**(3) (2012), 521–543.

[Newman and Werbel 1973] Newman, J., Werbel, R.: "Multivariate analysis of brand loyalty for major household appliances"; *Journal of marketing research* (1973), 404–409.

[Oh 2000] Oh, H.: "The effect of brand class, brand awareness, and price on customer value and behavioral intentions"; *Journal of Hospitality & Tourism Research*, **24**(2) (2000), 136–162.

[Oh and Sheng 2011] Oh, C., Sheng, O.: "Investigating predictive power of stock micro blog sentiment in forecasting future stock price directional movement"; *, in 32nd International Conference on Information Systems, AIS* (2011), 17.

[Oliver 1980] Oliver, R.: "A cognitive model of the antecedents and consequences of satisfaction decisions"; *Journal of marketing research* (1980), 460–469.

[Pang et al. 2002] Pang, B., Lee, L., Vaithyanathan, S.: "Thumbs up?: sentiment classification using machine learning techniques"; Proc. *Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10, Association for Computational Linguistics* (2002), 79–86.

[Pappu et al. 2006] Pappu, R., Quester, P., Cooksey, R.: "Consumer-based brand equity and country-of-origin relationships: some empirical evidence"; *European Journal of Marketing*, **40**(5/6) (2006), 696–717.

[Park et al. 2006] Park, C., MacInnis, D., Priester, J.: "Beyond attitudes: Attachment and consumer behavior"; *Seoul National Journal*, **12**(2) (2006), 3–36.

[Patwardhan and Balasubramanian 2011] Patwardhan, H., Balasubramanian, S.: "Brand romance: a complementary approach to explain emotional attachment toward brands"; *Journal of Product & Brand Management*, **20**(4) (2011), 297–308.

[Peñalver-Martinez et al. 2014] Peñalver-Martinez, I., Garcia-Sanchez, F., Valencia-Garcia, R., Rodríguez-García, M. Á., Moreno, V., Fraga, A., Sánchez-Cervantes, J. L.: "Feature-based opinion mining through ontologies"; *Expert Systems with Applications*, **41**(13) (2014), 5995–6008.

[Peters et al. 2013] Peters, K., Chen, Y., Kaplan, A. M., Ognibeni, B., Pauwels, K.: "Social media metrics–A framework and guidelines for managing social media"; *Journal of Interactive Marketing*, **27**(4) (2013), 281-298.

[Richins 1983] Richins, M.: "Negative word-of-mouth by dissatisfied customers: a pilot study"; *V Journal of Marketing*, **47** (1983).

[Rossiter and Percy 1987] Rossiter, J., Percy, L.: "Advertising and promotion management"; McGraw-Hill Book Company (1987).

[Roy and Banerjee 2008] Roy, D., Banerjee, S.: "CARE-ing strategy for integration of brand identity with brand image"; *International Journal of Commerce and Management*, **17**(1/2) (2008), 140–148.

[Sahin et al. 2011] Sahin, A., Zehir, C., Kitapçı, H.: "The effects of brand experiences, trust and satisfaction on building brand loyalty; an empirical research on global brands"; *Procedia-Social and Behavioral Sciences*, **24** (2011), 1288–1301.

[Salas-Zárate et al. 2014] Salas-Zárate, M.P., López-López, E., Valencia-García, R., Aussenac-Gilles, N., Almela, Á., Alor-Hernández, G.: "A study on LIWC categories for opinion mining in Spanish reviews"; *Journal of Information Science*, **40**(6) 2014, 749–760.

[Salas-Zárate et al. 2016] Salas-Zárate, M.P., Valencia-García, R., Ruiz-Martínez, A., Colomo-Palacios, R.: "Feature-based opinion mining in financial news: An ontology-driven approach"; *Journal of Information Science* (2016).

[Selnes 1993] Selnes, F.: "An examination of the effect of product performance on brand reputation, satisfaction and loyalty"; *Journal of Product & Brand Management*, **2**(4) (1993), 45–60.

[Shemwell et al. 1998] Shemwell, D., Yavas, U., Bilgin, Z.: "Customer-service provider relationships: an empirical test of a model of service quality, satisfaction and relationship-oriented outcomes"; *International Journal of Service Industry Management*, **9**(2) (1998), 155–168.

[Shields and Rangarajan 2013] Shields, P., Rangarajan, N.: "A Playbook for Research Methods: Integrating Conceptual Frameworks and Project Management"; *New Forum Press Inc* (2013)

[Smith et al. 2012] Smith, A., Fischer, E., Yongjian, C.: "How does brand-related user-generated content differ across youtube, facebook, and twitter?"; *Journal of Interactive Marketing*, **26**(2) (2012), 102–113.

[Thach and Olsen 2006] Thach, E., Olsen, J.: "The role of service quality in influencing brand attachments at winery visitor centers"; *Journal of Quality Assurance in Hospitality & Tourism*, **7**(3) (2006), 59–77.

[Thomson et al. 2005] Thomson, M., MacInnis, D., Park, C.: "The ties that bind: Measuring the strength of consumers' emotional attachments to brands"; *Journal of consumer psychology*, **15**(1) (2005), 77–91.

[Tirunillai and Tellins 2012] Tirunillai, S., Tellis, G. J.: "Does chatter really matter? Dynamics of user-generated content and stock performance"; *Marketing Science*, **31**(2) (2012), 198-215.

[Tu et al. 2012] Tu, Y., Wang, C., Chang, H.: "Corporate brand image and customer satisfaction on loyalty: An empirical study of starbucks coffee in Taiwan"; *Journal of Social and Development Sciences*, **3**(1) (2012), 24–32.

[Turney 2002] Turney, P.: "Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews"; Proc. *Proceedings of the 40th annual meeting on association for computational linguistics, Association for Computational Linguistics* (2002), 417–424.

[Twitter 2015] Twitter: Company (2015) `https://about.twitter.com/company`

[De Vries et al. 2012] De Vries, L., Gensler, S., Leeflang, P. S. (2012): "Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing"; *Journal of Interactive Marketing*, **26**(2) (2012), 83-91.

[Wilson et al., 2005] Wilson, T., Hoffmann, P., Somasundaran, S., Kessler, J., Wiebe, J., Choi, Y., Cardie, C., Riloff, E., Patwardhan, S.: "Opinionfinder: A system for subjectivity analysis"; Proc. *Proceedings of hlt/emnlp on interactive demonstrations, Association for Computational Linguistics* (2005), 34–35.

[Yu et al. 2013] Yu, C., Lin, P., Chen, C.: "How brand image, country of origin, and self-congruity influence internet users' purchase intention"; *Social Behavior and Personality: an international journal*, **41**(4) (2013), 599–611.

[Zboja and Voorhees 2006] Zboja, J.J., Voorhees, C.: "The impact of brand trust and satisfaction on retailer repurchase intentions"; *Journal of Services Marketing*, **20**(6) (2006), 381–390.