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Geassocieerde Faculteit Toegepaste Taalkunde

From conversation to conversion
An explorative study on the adoption of social media and the application of sentiment analysis in Flemish media and web shops

Lana Eeckhout

Scriptie voorgedragen tot het bekomen van de graad van

Master in de meertalige communicatie

Masterproefbegeleider:
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1 INTRODUCTION

"*Voor het eerst in de geschiedenis van de mensheid komen interpersoonlijke communicatie, organisatiecommunicatie en massacommunicatie samen*".[1] – Prof. Dr. Jan Van Dijk, University of Twente.

The emergence of social media has accounted for a major shift in the communication landscape. Traditionally, every means of communication had a clearly defined purpose: letters were used for personal correspondence, leaflets and banners for publicity and television or radio spots to reach the general public. Since the beginning of the 21st century, however, social media have blurred these traditional boundaries and also privacy has been given a new meaning as we now share everything with everyone online, ranging from trivial daily activities to reviews and personal opinions.

This digitalisation has not only made a wide range of information available online, it has also changed our manner of communicating. The term 'multilingual communication' does no longer exclusively refer to an international component. Now, it also represents a new form of compact writing, a sort of language on its own, that is generally adopted by the current generation.

Researchers at the University College Ghent Faculty of Translation Studies are highly aware of this emergent digitalisation. The *Language and Translation Technology Team (LT^3)* has gained broad experience in the field of Natural Language Processing and part of its research focuses on end-user applications such as sentiment analysis. From May 1, 2012 until April 30, 2016, researchers of the LT^3 team are involved in the PARIS project. This project on personalised advertisements built from web sources aims at studying user-generated content, which is challenging due to its informal and ungrammatical form. This information will then be used to generate advertisements that are tailored to the needs of users online and conceptualized in novel forms of advertising.

The focus of this study is on sentiment analysis, which is in line with the PARIS project. While PARIS aims at integrating the so-called user-generated content with advertisements, we will focus on how online content is used and analysed in a corporate

[1] Translated quote: "*For the first time in the history of human kind, interpersonal communication converges with corporate and mass communication*." [30.04.2013]

context. Since companies depend more and more on their online reputation, social media and other web platforms are being more closely exploited and analysed. Companies no longer decide how their brand should be perceived but are guided by their consumers' opinions and thoughts. This requires a new marketing strategy.

Our main research objective is to find out to what extent companies are dependent on their online image and how they are trying to monitor it by means of sentiment analysis tools and applications.

In order to support this main research question various aspects need to be analysed. Since sentiment analysis is a relatively new research field, we first need to understand the current state-of-the-art in this field which requires a thorough literature study. Then we will discuss a number of tools and applications that are available to perform sentiment analysis. An explorative market study will eventually shed a light on whether this particular NLP-task has already been adopted in a business context. These aspects will allow us to conclude whether there is a lacuna between what companies expect of sentiment analysis, what kind of services the tools in the field currently offer and whether these tools are actually used.

For our market study, we decided to focus on various aspects in order to gain more insights in how companies adopt social media and whether they are acquainted with sentiment analysis.

This dissertation is structured as follows: in Chapter 2 we will summarize the status quaestionis in the domain of sentiment analysis (SA) by means of a thorough literature study. We will discuss both SA and social media as the approaches to perform opinion mining. Chapter 3 presents a number of tools to analyse online content. In Chapter 4 and 5, we will proceed with our market study of Flemish media channels and web shops and discuss its results. Finally, we present a resume of the results and formulate a conclusion to our main research question (Chapter 6).

2 LITERATURE STUDY

2.1 Sentiment analysis in general

Defining the main object of study is essential if we are to shed a light on its practical applications and challenges. In his seminal work on sentiment analysis (SA), Liu (2012:7) defines this segment in language technology as the field of study that analyses people's subjective utterances towards entities, such as organizations and their products and services (i.e. topics), and their attributes. Kumar and Sebastian (2012) define opinion mining as a computational study of opinions and emotions expressed in texts and describe its goal as the detection of polarity in various sources that determine the mind-set of an author. From these two definitions we can already deduce that various synonyms are used interchangeably to address this field of study. These are opinion mining, opinion extraction, subjectivity analysis, review mining and appraisal extraction. These terms represent slightly different tasks, but can be gathered under the umbrella term of SA (Liu, 2012:7).

2.1.1 Two major tasks

Kumar and Sebastian (2012) distinguish two major tasks in SA: subjectivity classification (2.1.1.1) and sentiment classification (2.1.1.2), which have to be tackled incrementally. First, we will try to clarify the terminological difference between these two tasks by defining *subjectivity* and *sentiment*. The challenges that arise will be discussed and illustrated in section 2.1.2.

Although subjectivity and sentiment are closely related to each other, their actual meaning differs to some extent. Subjectivity refers to the expression of "personal evaluations, opinions [...] and speculations" (Wiebe et al., 1999) in contrast with objectivity, or the expression of facts . Sentiment, on the other hand, reflects a positive or negative evaluation of an entity. It sometimes overlaps with the concept of emotion that reflects our inner state of mind, e.g. joy, anger, sadness. Liu (2012) distinguishes two types of evaluations, i.e. rational and emotional ones. The former results from rational reasoning, whereas the latter is an emotional reflection of the state of mind. We will illustrate the terminology in the following examples:

- Subjectivity: *I think the quality of Starbucks coffee is overrated*. *Think* expresses the personal view of the author. In this case, the utterance also expresses a negative sentiment towards the entity, *Starbucks coffee*. Subjective sentences do not always express sentiment, however, e.g. *I think his car broke down*.
- Objectivity: *Starbucks launches initiatives to decrease the environmental impact of disposable cups*[2]. This sentence states factual information, without expressing a personal opinion.
- Sentiment: *Your audio system is terrific*. In this example, the target *audio system* is positively evaluated (*terrific*) by the author of the utterance.
- Rational evaluation: *This car is worth the price*. The evaluation is tangible and can be verified, and hence results from rational reasoning.
- Emotional evaluation: *Chanel n°5 is the best perfume ever*. This utterance cannot be generalized as it is a reflection of the inner state of mind of the author. The evaluation might not be shared by others.

2.1.1.1 SUBJECTIVITY CLASSIFICATION

Subjectivity classification consists of classifying objective and subjective sentences. Subjective sentences express personal opinions, although not all of them indicate an emotional value. This means that a sentence can be subjective without specifically expressing a positive or negative sentiment or emotion, e.g. *Your new perfume smells like roses.* In contrast, objective sentences can imply opinions as well, e.g. *After taking the drug there is no more pain.*

The concept of subjectivity is strongly related to the appraisals interlocutors make of events. These appraisals or evaluations cause subjective reactions that vary with each person. This concept is also known as Appraisal Theory, which states that emotions are often a result of a previous appraisal (“Appraisal theory”, 2013). Appraisal theory summarizes the systems in a language that determine how interlocutors behave towards each other and how they express themselves with regard to their specific interlocutor. These mutual relationships are constantly negotiated during the conversation(http://repository.usu.ac.id/bitstream/123456789/28099/4/Chapter%20II.pdf.[25.04.2

[2] Example from: http://www.starbucks.com/responsibility/environment/recycling

013]). For example, a person will choose only the words that match the other person's knowledge (this is of course only an assumption made by the interlocutor).

This theory is part of a broader theory, i.e. Systemic Functional Linguistics (SFL). This meaning-based linguistics theory formulates how language can convey meaning. Instead of looking at the semantic and syntactic level of language, SFL researches into the participants, circumstances and actions of a conversation (ibid., 2013). The theory discerns three meta-functions that convey meaning, i.e. the ideational, textual and interpersonal meta-function. The latter meta-function refers to the Appraisal Theory we discussed above.

On the basis of this theory, Wiebe and Riloff (2005) created a set of guidelines to distinguish subjective from objective sentences. The authors used a training dataset to create classifiers that rely on unannotated data. These rule-based classifiers look for clues to determine patterns in the entire sentence, which are eventually used to train a Naive Bayes classifier. In section 2.3.1.3 we will further elaborate on a number of specific classifiers.

Read, Hope and Carroll (2007) used the appraisal framework to annotate data (book reviews) that provide a training set for further appraisal analysis. After obtaining two annotation sets, the authors measured inter-annotator agreement. The main result of their experiment was that annotators often did not agree on a number of appraisal types (e.g. engagement, judgement, force) because they interpreted these types differently.

In Hatzivassiloglou and McKeown (1997) the wrong subjective expressions were filtered by applying the notion of *gradability.* More specifically, this method consists of finding gradable adjectives such as *a little, very, small,...* which are good indicators of subjectivity (Liu, 2012: 46).

2.1.1.2 SENTIMENT CLASSIFICATION

Sentiment classification can be seen as the next step in SA, where the polarity of a subjective sentence or piece of text is identified on different levels. Three text-related levels can be distinguished, viz. the document level, sentence level and entity and aspect level.

On the document level the whole document is screened for subjective utterances about a product or service. This approach, however, does not take into account that one document may consist of multiple opinions or of multiple products that are being compared. Kumar and Sebastian (2012), for example, remark that not all sentences contain opinion words and that not all words are directly subjective. Therefore, an analysis on the sentence level imposes itself.

On this level, sentences are screened separately from the whole document to determine their polarity, viz. neutral, positive or negative as the basic grades. Liu (2012:11) critically notes that polarity and hence subjectivity are not a synonym of sentiment as many objective sentences can imply opinions as well (cf. infra). The basic assumption is that one sentence contains only one opinion, but example (1) shows that this premise is not always fulfilled.

(1) *The restaurant was outstanding: it served the best chocolate ice cream ever.*

This sentence contains an opinionated utterance on *the restaurant* and on *ice cream*.

This brings us to the third level, the entity and aspect level, which Kumar and Sebastian term “the feature-based level”. This involves looking at the opinion itself by analysing attributes to a particular target or topic. We will illustrate this with example (2).

(2) *Campbell’s soup tastes too salty.*

In this sentence *Campbell’s soup* is the target entity and *too salty* is its attribute.

This type of aspect-based analysis is more fine-grained compared to an analysis at the document or sentence level. It consists of some basic subtasks: identifying the target entity that has been commented and its attributes (a), determining the polarity of these attributes (b) and finding feature synonyms (c). At this intricate stage, however, researchers are still facing many challenges and problems which will be discussed in the next section.

2.1.2 Problems and challenges

Sentiment analysis (SA) is a challenging task, especially because sentiment is an abstract concept and natural language text is often unstructured. In this section we will try to enumerate the major challenges and problems that occur in this research field and clarify them by giving an example. Some of these problems have already been solved by analysis at a more detailed level of the text, for example at the feature level, whereas other challenges are still work in progress.

1. The polarity of a word can alternate, i.e. a positive word can also have a negative meaning and vice versa.

   (3) *This mp-3 player sucks.* versus (4) *This vacuum cleaner really sucks*.

   In (3) the verb *sucks* has a negative connotation as it is not normally a feature of the target entity i.e. *this mp-3 player*. In (4), however, this implies a positive evaluation as a *vacuum cleaner* is supposed to *suck*.

2. A sentence containing opinion words does not always express sentiment.

   (5) *Can you tell me where I can buy a cute dress*?

   This sentence contains no sentiment whatsoever as there are no target entity or attribute(s) that are directly evaluated.

3. An objective sentence may contain an implicit opinion.

(6) *This bottle of wine contains lees*.

Example (6) is also called a polar fact expression (cf. 2.3.1.1) From this sentence we can deduce that *contains lees* has a negative effect on the target entity *this bottle of wine*. The resulting situation is 'This wine is not drinkable'.

4. Negation words can change the polarity of a sentence. Verbs that have a negative meaning, such as '*avoid*', may reverse polarity as well. A combination of two negatively connoted words, however, can again shift polarity. Example (9) illustrates this.

(7) *I like Pearl Jam*. versus (8) *I don't like Pearl Jam*.

In example (8) the positive opinion that was expressed in (7) shifts towards a negative opinion due to the modifier of negation *not* (*don't*). It affects the polar expression *like* that is expressed towards the target entity *Pearl Jam*.

(9) *The local authorities declared that the crash caused only a few casualties.*

Few and *casualties* are words that are negatively connoted. In this sentence, however, their polarity is shifted as they appear together in a phrase.

Councill et al. (2010) emphasize that the automatic detection of negation is a critical need for text analysis applications. Detecting the negation scope can improve sentiment prediction by 29,5% and 11,4% for positive and negative polarity predictions, respectively.

5. Sarcasm is hard to detect for SA tools.

(10) *I love the fact that Twitter doesn't show Instagram pictures anymore. Good job Twitter*![3]

[3] Example from: Mr Sarcasm Guy, January 10, 2013 (https://twitter.com/MoreSarcasm/status/289405800810700800)

We might detect sarcasm in this sentence. Given some world knowledge, the target entity *Twitter* is supposed to *show Instagram pictures* (this would be considered a standard attribute, thus positive). The modifier of negation *not,* however, implies that this is no longer the case and shifts the polarity towards a negative evaluation of *Twitter*. The final sentence, i.e. the sarcastic utterance, can only be correctly identified with contextual knowledge. From the first sentence it appears that the target entity is negatively evaluated, so the polarity of *good job* should be reversed. The exclamation mark works as a modifier of increase to emphasize this sarcastic utterance.

6. Fake reviews may deliberately express an opinion to mislead readers and to influence the reputation of the target entity. Many review sites provide a feedback tool to recognize and delete fake reviews.

7. Sentiment is domain-specific, e.g. '*unpredictable*' has a different meaning when reviewing a car and a movie plot, i.e. a negative attribute to the target entity *car* and a positive attribute to the target *movie plot*.

We illustrated the major problems and challenges in the state-of-the-art of SA, without this list being exhaustive. In section 2.4.1 we will discuss the problems and challenges imposed by social media platforms in particular in greater detail.

In the following section we will discuss the major data sources in research on SA. Traditional Web 2.0 sources such as blogs, reviews and forums have recently lost their popularity to social networks and micro-blogging services which contain an even vaster volume of opinionated data. Both traditional and social network platforms will be discussed in closer detail.

2.2 Social media

Most research on sentiment analysis (SA) has been conducted on review sites and blogs. With the emergence of a rapidly progressing digital era, however, social networks and micro-blogging sites have provided a different dimension to the data sources used in SA research. We will start by discussing the more traditional Web 2.0 applications, such as review sites, blogs and forums, after which we will briefly describe the main social networks and the trend of micro-blogging.

2.2.1 Traditional Web 2.0 applications

Kumar and Sebastian (2012) define a review site as “a website which allows users to post reviews that give a critical opinion about people, businesses, products or services”. Since a review mostly contains only a single topic, it is easier for researchers and companies to grasp the main features shared by web users. Most research has been done on movie and product reviews as they provide a clear display of topic and attributes. Dinu and Iuga (2012), for example, explained how Naive Bayes works in SA applications based on a dataset of movie reviews. They used the most frequent words as their feature set to develop an application on *the Internet Movie Database (IMDb[4])* which calculates subjective comments regardless of the star-rating. Product reviews were used as dataset in Khan et al. (2011). On the basis of lexicons, they identified the polarity of a review or blog by analyzing it at the sentence level and extracting contextual information. The authors achieved an average accuracy of 86% for customer reviews and 83% for blog comments.

Blogs are frequently used as data source in SA because they are one of the most popular means to express personal opinions (Vinodhini and Chandrasekaran, 2012). Each user can create a webpage with paragraphs in which opinions, personal diary entries or information in general are displayed. Kumar and Sebastian (2012) specify that interactions are faster and more real-time than reviews since bloggers post at a fixed and continual basis. A close analysis of blogs is more challenging though, because its content is not clearly structured around and confined to a single target entity. A forum, on the other hand, is a public platform that allows its members to interact with each other on a particular subject. Forums are generally limited to one topic, which allows analysts to focus on one domain.

[4] http://www.imdb.com/

2.2.2 Social networks and Micro-blogging sites

Social networking sites are a platform to share ideas, activities and events with other people in the same community who often share a common interest (Kumar and Sebastian, 2012). The basic premise of these social services is that users subscribe in order to have access to their personal page on which they can share posts, videos and photos with their '*friends*'. The most well-known social networks are Facebook, Twitter, LinkedIn and Google+. These social networks were included in our market study to analyse the presence and activities of companies on these networks. Figure[5] 1 illustrates the number of users worldwide (left bar chart) and in Belgium more specifically (right bar chart).

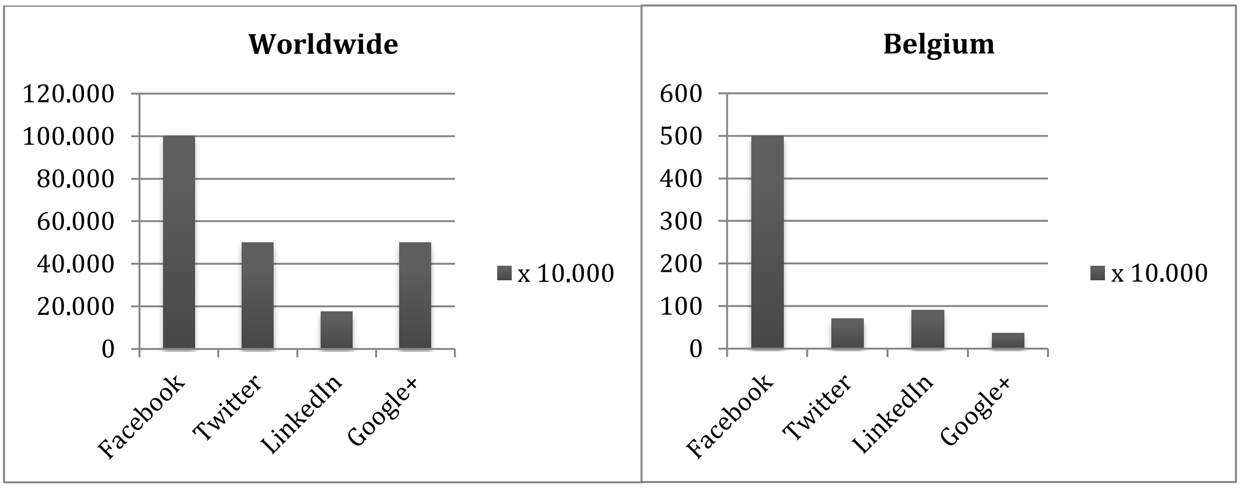

Figure 1: Users on social network sites worldwide and in Belgium.

A majority of the literature consulted on SA uses Twitter data. Since this network is somewhat different from the traditional social networking sites, we will give a brief account of its fundamentals.

Twitter is ranked in the list of social networks although its structure is more closely linked to that of a micro-blogging site. The service, launched in 2006, differs from Facebook and other social media in its public default setting, i.e. users can see content without registering or giving mutual permission (Jansen et al., 2009). This allows

[5] Bastijns,L. and Briesen, K. (2012). *Solliciteren via social media*. [PowerPoint slides]. Retrieved from https://chamilo.hogent.be/index.php?application=weblcms&course=9622&tool=document&go=course_viewer&publication_category=80043&browser=table&tool_action=browser

analysts to collect a significant amount of freely available data. These data consist of short messages limited to 140 characters, commonly known as *tweets*, which express opinions about various topics pertaining to the daily lives of their publishers (Lai, 2012). An explanation as to why Twitter data is so popular in sentiment analysis can be found in Pak and Paroubek (2012). Users from various countries and different social and interest groups post tweets, which allows for a wide variation of Twitter data.

2.3 Approaches to SA

One of the main reference works used to conduct this literature study on the practical aspect of SA, i.e. its main tasks and approaches, was Kumar and Sebastian's paper (2012) on the past, present and future of the state-of-the-art. They consider sentiment analysis to be the answer to the herculean task that resides in analyzing and comprehending user-generated content. They enlist the major tasks of this process and present an overview of the most prominent approaches to extract useful information from Web 2.0 content. Liu's seminal work (2012) served as a guideline during the elaboration of this segment in language technology. In what follows, we will briefly go into the fundamentals of the main approaches.

SA lies at the crossroads of Natural Language Processing techniques and Information Extraction. Following Vinodhini and Chandrasekaran (2012), we will now describe and explain the two main techniques to perform sentiment analysis, viz. machine learning (2.3.1) and semantic orientation (2.3.2).

Both approaches can be applied to the three major levels: document level, sentence level and feature level with the document level being the least fine-grained. The majority of literature consulted points out that analyses at the document and the sentence level can be useful but they are often inadequate to conceive opinions on a particular topic or target entity. It is therefore necessary to proceed to the aspect-based level where targets and their attributes are being analysed.

2.3.1 Machine Learning

This approach is called supervised learning, which means that a training and a test dataset are used to classify opinionated messages. The collected datasets are screened to select features that will train a sentiment classifier. More specifically, a determined set of features will facilitate classifying the polarity of a document or sentence. The training data are screened for particular features and are then labelled, i.e. they are assigned a positive, negative or neutral label. Based on these labelled data, a classifier is trained to determine the sentiment of an unlabelled test set.

Supervised learning is in that way dependent both on training data and on an effective set of features. In the next section, we will describe how training data can be made. This requires sentiment annotation of a particular dataset.

2.3.1.1 GOLD-STANDARD DATASET

Sentiment annotation is one of the first tasks, before proceeding onto a statistical analysis. This is mostly done by human annotators. As mentioned supra, this stage consists of labelling documents, sentences or features as positive, negative or neutral. It is first of all important to distinguish objective from subjective utterances and to identify the type of utterance.

Van de Kauter and Desmet (2012) propose a refined scheme of annotation guidelines that takes into account both subjective utterances as well as sentiment-laden factual sentences, covered by the umbrella term of *polar expressions*. They distinguish three types of expressions in their annotation scheme.

- Private state expressions: an explicit mention of one's opinion towards a target entity.

(11) *James believes that U2 is one of the biggest bands in the world today.*

Believes refers to the personal conviction of *James*. In this case it tells us that he holds a positive attitude towards the band as it is said to be *one of the biggest bands in the world today*.

- Polar fact expressions: a factual sentence with a sentiment-laden content towards a target entity. These expressions can generally be verified.

(12) *Heineken's turnover rose by 7% in 2012*[6].

From *turnover rose by 7%* we deduce a positive attitude towards the target entity, *Heineken*.

- Polar resultative causatives: one entity has a positive or negative effect on another entity, the target entity.

(13) *Drinking green tea reduces belly fat*.

Reduces indicates that the cause *drinking green tea* has a positive effect on the target entity *belly fat*. The resulting situation 'belly fat is reduced' is a polar expression about the target entity and expresses a positive evaluation.

After detecting the polar expression and, preferably, assigning it to one of the three types mentioned above, the core task is to mark several elements. These elements comprise: the target entity, the source or the author, the source expression or the attribute(s), the modifiers that shift polarity and the cause (only present in polar resultative causatives). When these elements are identified, the next step is to determine the polarity and intensity of the sentiment expressed (Van de Kauter and Desmet, 2012). It is, however, important to perform this task at different levels since one polar expression can be embedded in another one. Van de Kauter and Desmet note that annotation should be performed from the lowest level up to the highest level of the expression that is being annotated. The authors give guidelines as to how the annotation scheme should be used correctly and specify each element in greater detail.

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[6] Example from: http://www.nrc.nl/nieuws/2013/02/13/heineken-boekt-meer-winst-en-omzet-in-2012/

2.3.1.2 FEATURES

As soon as a gold-standard dataset is framed, one can start to determine features, or characteristics, to automatically perform SA. These features will function as a sort of predictor to determine to which class a new item belongs. The main idea is to train a machine learning program or tool by 'teaching' it to assign an item (for example the phrase: *you are ugly*) from a training dataset to a particular class (*negative*) by screening its features (for example*: adjectives*).

The list below is based on Pang and Lee (2008) and specifies the types of features that can be distinguished without being exhaustive.

- Words and their frequencies: these words can be unigrams, bigrams or n-grams along with their frequency or presence in the dataset.

  An n-gram can be any combination of letters, varying from phonemes, to syllables and even to words. The n refers to an indeterminate size of sequence, ranging from a unigram, bigram, trigram, and so on. In Table 1 we illustrate the meaning of a unigram and a bigram.

Sample sequence	Unigram	Bigram
...to_be_or_not_to_be...	...t,o,_,b,e,_,o,r,_,n,o,t,_,t,o,_,b,e,...	...,to,o_,_b,be,e_,_o,or,r_,_n,no,ot,t_,_t,to,o_,_b,be,e_,...

Table 1: Example[7] of a unigram and bigram.

- Part of Speech (POS): a sentence can be tagged into several syntactic parts. Each part is assigned a label that facilitates the task of identifying polarity.
- Opinion words and phrases: apart from individual opinion words, e.g. *ugly*, *delicious*,… some phrases can also convey a specific sentiment, e.g. *on cloud nine*.
- Negation words and sentiment shifters: these words, verbs or other textual elements need to be identified as they change the polarity of an opinion.
- Syntax: some patterns, such as collocations, can be used to discern subjectivity patterns.

[7] N-gram(Figure 1). (s.d.). In *Wikipedia*. Retrieved 11 March, 2013 from http://en.wikipedia.org/wiki/N-gram

2.3.1.3 CLASSIFIERS

As soon as both training data and features are available, machine learning techniques can be applied. Classification basically amounts to labelling a document or piece of text, depending on the level of analysis. In machine learning, this particular task consists of identifying the category to which a new written document belongs based on the predetermined features it contains. The identification of this new document is based on a training set that had already been labelled (cf. supra). Depending on the type of classification, a written document can be screened for both its subjectivity (subjectivity classification) and the sentiment polarity it expresses (sentiment classification).

The unsupervised method of classification is called clustering. This involves grouping data that are quite similar to each other into one category, a cluster. Popular clusters are, for example, based on the distance between data included in the cluster. This principle assumes that data or objects are more related to nearby objects than to objects that appear further away in the document or sentence.

The majority of literature consulted for this study refers to three major classifying algorithms to automatically label a dataset, viz. Naive Bayes, Maximum Entropy and Support Vector Machines which will now be discussed in closer detail.

Naive Bayes

Naive Bayes is one of the base-classifiers in SA, often outperforming other classifiers (Go et al., 2009; Pang et al., 2002).

Naive Bayes estimates the probability of a new object, word or piece of text by measuring the joint probabilities of other words and categories. All words or objects are naively assumed to be independent, i.e. each feature contributes to labelling a document, regardless of the other features that are present (Vinodhini and Chandrasekaran, 2012). According to Dinu and Iuga (2012) a Bayes classifier “assigns the most likely class to a given example described by its feature vectors”. Figures (2a and b) (Hill and Lewicki, 2007) illustrate these theoretical definitions on the basis of a scatter plot, but can be extended to the calculations the classifier makes in a machine learning context.

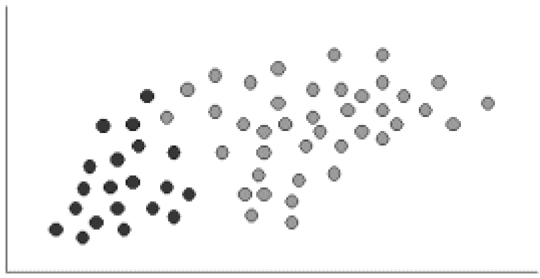

Figure 2a: Graph illustrating Naive Bayes.

This plot shows that there are twice as many grey dots as black ones. The task of the Naive Bayes classifier is to assign, when presented with a new case, one of these two labels. Based on the previous experience, the new case is more likely to be assigned a grey label. This prediction is known as prior probability, which is calculated for each label by dividing the number of dots in the grey and the black set, respectively, by the total amount of dots in the same colour set. The prior probability in this case is 40/60 for grey and 20/60 for black.

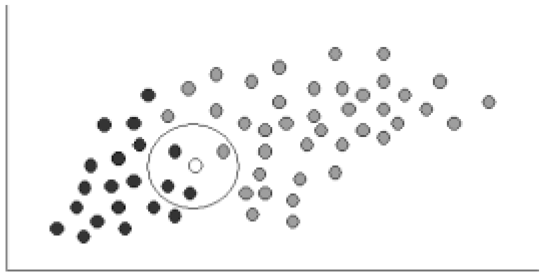

Figure 2b: Graph illustrating Naive Bayes.

At the next level, a new case will be classified, viz. the white dot. Since the coloured dots are well clustered, we can assume that the white dot will belong to the colour that appears most in its vicinity, also known as the likelihood. Therefore, a circle is drawn around a number of dots, irrespective of their colour, to calculate the number of different labels in the circle. The likelihood of a particular colour is determined by dividing the number of grey dots, for example, in the vicinity of the white dot by the total amount of grey dots. This results in a likelihood of the white dot, X, given grey being 1/40 and given black being 3/20.

In a final stage, the Bayes classifier combines these two sources of information to determine the posterior probability, i.e. the definite class label. Therefore, it multiplies the prior probability and the likelihood of each existing class. In this example, the posterior probability is 1/60 and 1/20 for grey and black, respectively. We can thus conclude that the white dot receives a black label.

Maximum Entropy

An alternative to the Naive Bayes classifier is the maximum entropy classifier, which does not assume that words are independent of each other. The basic assumption here is uncertainty or ignorance, since entropy can be defined as the average unpredictability of a random variable ("Entropy", "Expected value", 2013). On the basis of probability distributions, the maximum entropy classifier discovers the probability of a new word or object that has the highest value of uncertainty in a set of tested or labelled data (words or objects, for example).

Berger et al. (1996) illustrate the concept of uncertainty in a maximum entropy model that is adopted to the field of translation studies. Via maximum entropy, they wish to extract a set of facts about the decisions that are made in the translation process. More specifically, a model concerning the translation of the English word 'in' into French.

Berger et al. refine their model p based on a set of constraints that are added along the process. The first constraint imposes that only five French words or phrases are regularly chosen to translate the English preposition 'in'. This assumption is illustrated in the formula below:

p(*dans*) + p(*en*) + p(*à*) + p(*au cours de*) + p(*pendant*) = 1

The maximum entropy model will then assign an estimated probability to each French translation, without assuming anything about unknown data. In this case the probability of each phrase is 1/5. The process of adapting the model can be influenced by the context, and hence can be subject to several additional constraints. For example, when looking at the other words in the English sentence, the translator might choose a specific phrase more often to translate ‘in’. This again imposes a constraint on the model and changes the probability of each phrase, until a maximum probability is assigned to one of the French variables.

Support Vector Machines (SVM)

An SVM is a discriminative classifier that separates training data into two classes. It screens a set of data and predicts for each object in the dataset to which class it belongs. Based on these marked data, it builds a model that assigns new objects into one of these two classes. This model is called a hyperplane, i.e. a representation of the objects as dots that are separated into two classes by a clear gap. New objects are represented in that hyperplane and are assigned a class depending on which side of the gap they fall on (“Support Vector Machine”, 2013), or what Vinodhini and Chandrasekaran (2012) describe as “the class corresponding to the most similar vector”.

Figure 3 illustrates the notion of a hyperplane and clarifies what support vectors are.

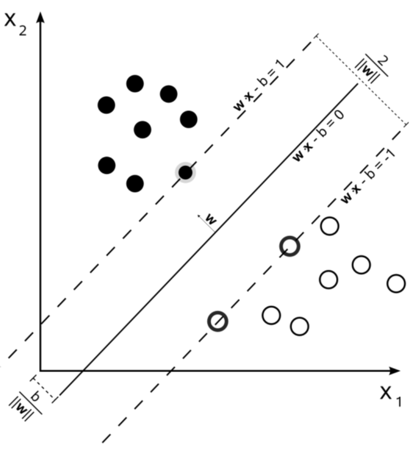

Figure 3: Support Vector Machine.

The black and white dots represent two different classes. The solid line represents the maximum separating hyperplane, i.e. the widest gap between the two classes. The dotted lines represent the margins. The dots that are situated on these lines are called support vectors.

2.3.2 Semantic Orientation

In contrast with the machine learning technique, this approach is known as unsupervised learning. The main difference is that this concept does not require prior training to perform opinion mining, but that it uses lexical relations to determine polarity (Vinodhini and Chandrasekaran, 2012), also known as the lexicon-based approach. While machine learning is hard to adopt in various domains, this unsupervised technique sometimes lends itself to a larger number of domains, although there are still a number of drawbacks.

Two frequently used methods to build lexicons are the dictionary- and corpus-based method. From the work of Kumar and Sebastian (2012) it is clear that in the former case, a list of opinion terms with their polarity is created and then compared to a document of unseen words. Their polarity is determined by calculating the relative distance of the unseen words from the seed list. In the latter case, a corpus with analysed words is built to measure the co-occurrence of new words by means of syntactical or statistical techniques.

2.3.2.1 DICTIONARY-BASED LEXICONS

This is a simple technique to determine the sentiment words in a text, since online dictionaries automatically list synonyms and antonyms for each entry. First, a small seed list of sentiment words with their determined polarity is collected manually. In the next step, an algorithm browses WordNet[8] or other online dictionaries for synonyms and antonyms of the seed words to extend the seed list. This process is being repeated until no more new words can be found (Liu, 2012:91)

Another technique is the distance-based one which determines the polarity of an adjective by calculating its distance from two seed adjectives, for example *good* and *bad*.

[8] http://wordnet.princeton.edu/

Another statistical method determines the polarity of a word by calculating its association with a set of positive and negative words. More specifically, the word's strength of its association with a negative set of words is subtracted with the strength of its association with a set of positive words. The statistical calculations are computed by means of supervised techniques, viz. classifiers such as Naive Bayes, graphs, vectors, etc. (Liu, ibid.)

As mentioned above, this approach allows to rapidly collect a large set of sentiment words with their polarity. Overlap or errors in the seed list can be manually cleaned up, taking into account the time-consuming aspect. There is, however, one major drawback to this approach, viz. the words in the seed list are domain-specific since many sentiment words are context dependent. The corpus-based approach offers a solution to this problem.

2.3.2.2 CORPUS-BASED LEXICONS

Liu distinguishes two techniques, viz. expanding a seed list with sentiment words from a domain corpus, and adapting a general sentiment lexicon to a new domain by using a domain corpus. It is, however, a complicated task to build a domain-specific lexicon since a positive word can become negative in a particular context as in example (14):

> (14) *An unpredictable car* versus *an unpredictable movie plot*.
> In the first phrase *unpredictable* is used in a negative sense, whereas it has a positive meaning in the second phrase, depending on the target entity that is evaluated.

The first technique can be refined by exploiting linguistic rules or conventions to identify more sentiment words from the corpus, in addition to the seed list. Hatzivassiloglou and McKeown (1997), for example, defined a set of rules to determine patterns based on conjunctions, e.g. adjectives linked by *and* are assumed to have the same polarity. A supervised learning technique verified if this assumption was indeed true.

As previously mentioned, it does not suffice to build a domain-specific lexicon. Therefore, an extra step in the process imposes itself, i.e. finding context-specific opinions by identifying the aspects modified by sentiment words (Liu, 2012:97). Example (15) illustrates this:

(15) *The car is very quiet* versus *The audio system in the car is very quiet*.

By determining the aspect that is modified by *very quiet*, it becomes clear that in the first sentence *very quiet* is a positive attribute given the target entity *car*. In the second sentence, however, *very quiet* is a negative attribute given the target *audio system*.

2.4 SA on social media platforms

In our market study (cf. Chapter 4) we will try to gain insights into the application of SA in a business context. Our main point of interest is whether companies or marketers use tools to monitor their online image and whether they adapt their marketing strategy in accordance with the online buzz. It is therefore first necessary to elucidate on SA studies in a more specific context, i.e. social media platforms.

As mentioned above, we used Kumar and Sebastian's paper as a guideline to point out the two major approaches in the state-of-the-art. Their overview, however, mainly focused on research done on product reviews, which are "documents that have a definite topic" (Kumar and Sebastian, 2012). We, however, focus on sentiment analysis in a Web 2.0 context which can be defined as "an evolution from passive viewing of information to interactive creation of user-generated data"(ibid, 2012).

Pak and Paroubek (2010) applied the general framework in sentiment analysis to a Twitter corpus. As in Go et al. (2009), Twitter was queried for emoticons to collect positive and negative sentiments. Pak and Paroubek set up rules to determine the polarity of a particular tweet. In their hypotheses, n-grams should capture patterns of subjective expressions, whereas unigrams should provide a good coverage of the data. They built a sentiment classifier based on Naive Bayes to extract features, in particular n-grams and part-of-speech distribution information, from the collected corpora. Bigrams and an increased dataset yielded the best results. It is important to take into account, however, that their approach was applied on English data only. For the results to be representative in an international context, a multilingual corpus needs to be collected and compared.

In line with Pak and Paroubek's research, Barbosa and Feng (2010) proposed a two-step approach by classifying tweets with regard to their polarity and by distinguishing subjective tweets as positive or negative. Barbosa and Feng vitiated the strength of Pak and Paroubek's study by claiming that using n-grams as features for Twitter is a main limitation since tweets are so short, viz. 140 characters. They also used meta-features identified by a part-of-speech tagger and combined these with characteristics of the writing style instead of n-grams to develop "an abstract representation of tweets". Sources of noisy data were leveraged as training data, viz. *Twendz*, *TwitterSentiment* and *TweetFeel.* The authors concluded that combining these data sources was more efficient than using one isolated dataset. We feel it is important to expound on the authors' choice to use commercial search-based tools as data source. These tools mostly aim at providing information about specific events, products or famous people but may not be sufficiently efficient when more complex sentences or abstract data are taken into consideration. Maynard et al. (2012) argued that these tools tend to analyse data fairly rudimentary and provide no proof as to how accurate their results really are.

In their paper, Maynard et al. (2012) summed up the challenges social media impose on Natural Language Processing systems for sentiment detection. They posited that micro-posts such as Twitter messages are the most challenging type for text mining tools since their content is dynamic, implicit and not linked to a typical conversation thread. In this view, the authors wanted to adapt the standard machine learning techniques to new domains and text types. They summed up general disadvantages of the existing work on machine learning techniques and a plethora of commercial tools for performing sentiment analysis, such as *Twitter Sentiment.* Deviating from traditional text mining systems, they introduced an entity-centric approach based on entity and event recognition which is claimed to lend itself better to non-standard text. Event recognition can be defined as "the recognition of entities and the relations between them in order to find domain-specific events" (ibid, 2012). In their study, satisfying results were achieved with SVM and Naive Bayes.

Vinodhini and Chandrasekaran (2012) share the conclusion of Maynard et al. in their paper on machine learning techniques and semantic orientation. In the authors' view, the semantic orientation approach is slightly less accurate but is more efficient to use in real-time applications. They considered both the Naive Bayes classifier and SVM to be the best classification algorithms, with SVM outperforming the Naive Bayes classifier. It must be objected that sentiment classifiers are dependent on particular domains or topics, so the conclusion reached in this paper should not be generalized.

In this section we summarized the literature concerning the application of sentiment analysis in a social network context. Subsequent to the general challenges in the field of SA enumerated in section 2.1.2, we will now point out the more specific challenges imposed by social media in this particular segment of language technology.

2.4.1 Problems and challenges

1. Not every comment on a public page is relevant, this in contrast to reviews that do not often stray from their original topic. Maynard et al. (2012) propose two attempts to deal with this issue, viz. filtering relevant tweets or clustering tweets that belong to the same topic.
2. The topic of the retrieved sentiment is not always the topic that is opinionated, e.g. a tweet may express sadness about a person (i.e. a negative sentiment), whereas this does not mean that the negative sentiment is directed against this person. The entity-centric approach of Maynard et al. (2012) allows making linguistic relations to associate target and attribute.
3. Tweets and social media messages depend to a great extent on contextual knowledge and contain more often sarcastic utterances that are hard to retrieve automatically. Research on sarcasm is actually still in its infancy.
4. Twitter messages are strongly time-bound, which means that opinions are volatile. It is therefore useful to time-stamp each message and to store it in an updated knowledge base (Maynard et al, 2012).

5. Micro-posts exhibit more language variation than formal messages. They tend to be less grammatical and frequently contain swear words, emoticons, abbreviations and hashtags[9]. Text normalisation can often be of interest when solving this issue.

Now that we have a clear view of the scientific state-of-the-art we can continue by presenting the practical application of SA by means of tools in the next chapter.

3 TOOLS

Communication has shifted from traditional sources such as newspapers, brochures and television spots to online platforms such as social networking sites where consumers can openly discuss and comment new trends or products emerging on the market. It is no longer the companies that determine how their product or brand is perceived. Instead, consumers are the main source of publicity as they constantly influence each other by online evaluations. This openness has obliged marketers to adapt their marketing strategy so as to respond immediately to the needs of these consumers. From a marketers' point of view, digital marketing has thus shifted from *talking* to *listening*.

In order to adapt their marketing strategy, companies first need to fully understand what is being said about them on those online platforms. This is where sentiment analysis and other machine learning techniques are useful services. The theoretical aspects of this NLP-field, as described in Chapter 2, have been implemented in several practical tools and applications that translate user-generated content into a clear structure.

In this section we present an overview of some existing tools that are widely used. Based on an online prospection of various web agencies such as InSights Consulting[10], Indie Group[11], The Reference[12], and our market research (cf. infra) we decided to discuss three types of services: actual sentiment miners (3.1), APIs[13] (3.2)

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[9] A hashtag categorizes tweets for other users. It can be defined as the theme of a tweet and provides a link to similar tweets ("Hashtag", 2013).
[10] http://www.insites-consulting.com/
[11] http://www.indiegroup.be/
[12] http://www.reference.be/en/
[13] An API is an interface that allows web technologies to communicate with each other. For more information, see section 3.2.

and hybrid tools (3.3). For each service we perform a SWOT-analysis of one tool or application that is clearly and sufficiently documented on the techniques used for sentiment analysis (SA). We will also describe two tools that were mentioned in our market study.

3.1 Sentiment miners

The changing online environment has caused a stream of user-generated content that might be a valuable source of information for companies who want to monitor their online image. A wide range of programs and tools allows to screen this content for opinions, issues and general comments with respect to a brand or product.

The majority of these tools offers a full-service package, which consists of general monitoring applications to measure the number of fans or count the number of likes, but also provides a more detailed analysis to gauge, for example, sentiment. This information is then often displayed in charts and tables so that companies receive an immediate overview of their current online reputation. Most of these tools come with a cost, but free tools are available as well. Their quality and accuracy is, however, not always guaranteed.

The first tool we will discuss, Engagor[14], is created by Belgian developers and presents itself as “an all-in-one social media management tool for marketing and customer service”. The relevance of this tool in digital marketing is shown by the companies’ customer portfolio: Microsoft, Ikea, McDonalds, Belfius, VRT, Atos, Ernst & Young, and many others.

The platform comprises a number of sub-tools for social media monitoring, analytics and customer engagement. Our focus is on the services Engagor provides for social media management and SA.

[14] http://engagor.com/

3.1.1 Concepts of Engagor

The tool comprises two main sections: Inbox and Insights.

The Inbox can be compared to an e-mail inbox containing all mentions on social network sites (such as Twitter and Facebook) and other sources (such as news sites, blogs, forums). By inserting filters, marketers can select information relevant to their company. In addition, the tool allows to combine several of these platforms and profiles so that they can be managed from within one tool.

As far as interaction is concerned, this section allows companies to react directly to online mentions or to publish one message onto several profiles at the same time. Similar to traditional mailboxes, users can add labels or notes to the conversations so as to preserve an overview. This type of interaction between companies and consumers allows companies to monitor their online image in detail. An example of the Inbox section is presented in Figure 4.

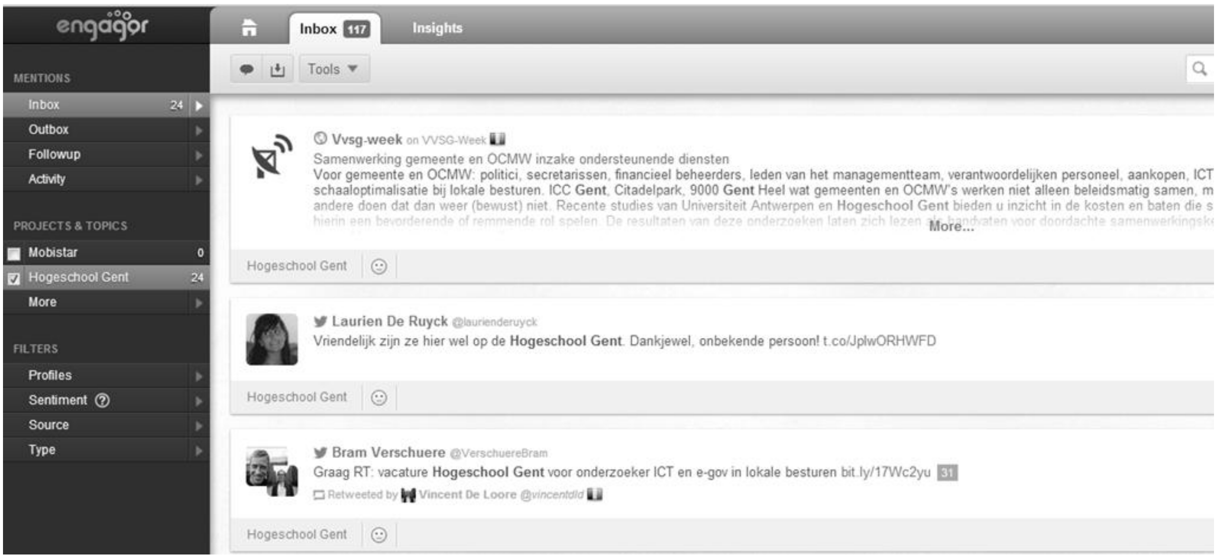


Figure 4: Screenshot of the Engagor Inbox with query 'Hogeschool Gent'.

Once relevant conversations have been selected, the Insights section provides additional services to analyse these mentions in real-time. This is where the concept of sentiment mining is introduced. Two categories can be distinguished to perform a fine-grained analysis. An analysis on the project level (a) enables the user to compare and analyse several topics, whereas an analysis on the topic level (b) visualizes individual topics.

As discussed in our literature study (Chapter 2), SA of Web 2.0 messages is more intricate compared to regular newspaper articles. Since Engagor supposedly collects conversations from various sources, the SA techniques used should be able to perform well in both informal and formal text types.

The Insights section comprises a variety of categories to screen a conversation, e.g. by topic or by sentiment. This information is displayed in charts so that marketers get a clear overview of their online image. It provides a deeper insight into trending topics, the number and evolution of specific mentions, demographics of the authors, the top influencers on social media sites, and so on. This information can be exported into several formats such as Microsoft Office Excel or PDF. An example can be found below.

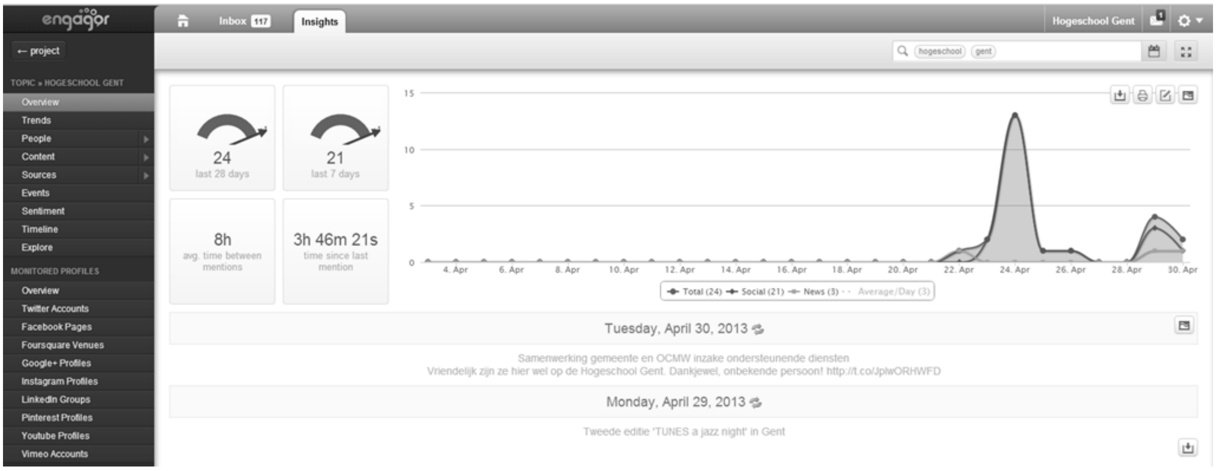


Figure 5: Screenshot of the general insights for query 'Hogeschool Gent'. The number of mentions on various platforms, the average time between mentions and the time since the last mention was displayed.

3.1.2 SA approach

The SA application allows to identify the sentiment of mentions either in total, individually or on a day to day basis. In this way, marketers can keep their marketing strategy up to date. Although Engagor presents itself as a polyglot, the service is currently only supported for English, Dutch and Greek. From a source it was clear, however, that the service will soon be drastically improved and sentiment analysis should become available for French, German, Spanish and Arab (J. De Beule, personal communication, March 27, 2013).

Within Engagor sentiment is itemized in four categories: positive, negative, neutral and unknown polarity. When the sentiment has been identified as unknown, the users can manually label a particular mention, and also the labels assigned to other mentions can be checked and adjusted. An example of this is presented in Figure 6.

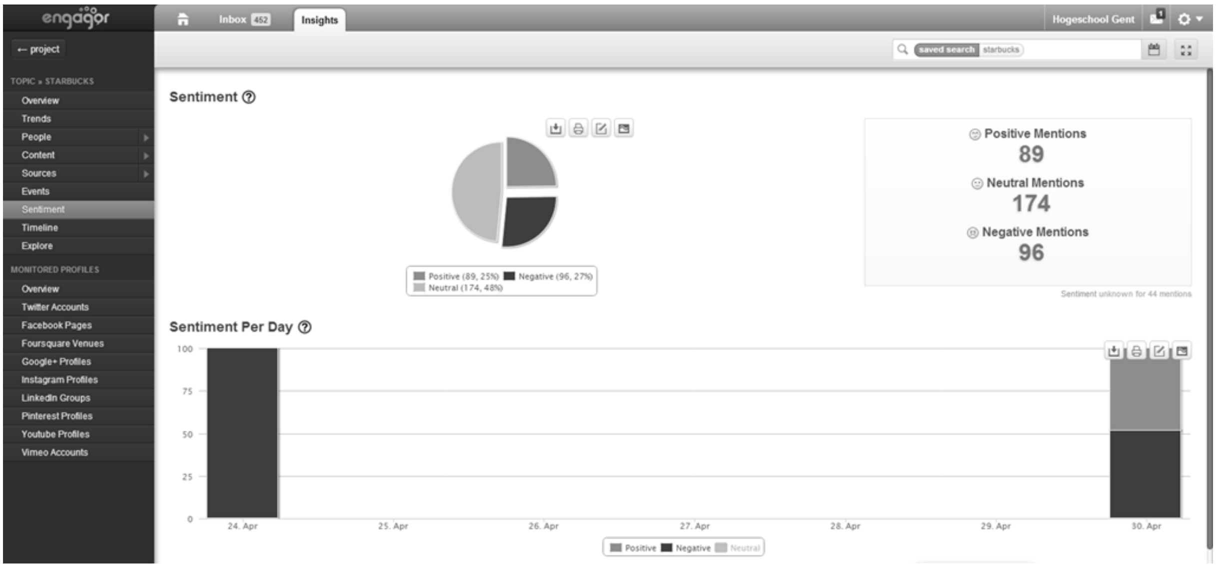


Figure 6: Screenshot of the SA results. Since the query 'Hogeschool Gent' contained only neutral mentions, we searched the query 'Starbucks' to show a more detailed example of this Insights option.

Engagor uses keywords to determine the sentiment of a particular mention. These keywords are run against a set of heuristics and a manually annotated corpus. The approach followed can thus be summarized as a lexicon-based technique. As a guideline, Engagor uses the paper of Rennie et al. (2013) which tackles the problem of some assumptions Naive Bayes classifiers make. In our literature study, we mentioned that this classifier assumes that words appear independently of each other which might in some cases affect the accuracy. The authors proposed a classifier that normalizes the weights assigned to the classes. More specifically, they introduced a Weight-normalized Complement Naive Bayes classifier (WCNB) which was found to perform better than the standard Naive Bayes.

An adapted version of this classifier is used in Engagor's approach to sentiment analysis. After an elaborate analysis of various strategies, the developers found that WCNB and Maximum Entropy yielded the most accurate results, i.e. accuracy of 80%. This is claimed to correspond with the accuracy of human sentiment analysis (J. De Beule, personal information, March 27, 2013). However, since users still need to add or correct sentiment labels, this assumption lacks significant evidence.

3.1.3 Strengths and weaknesses

Strengths

- A large array of tasks can be managed from within one tool at the same time.
- The tool encourages an interactive approach between companies and consumers.
- Several filters allow to retrieve only relevant information.
- Real-time data is visually displayed and charts can be exported to external software.
- Engagor grants a 14-day free trial and provides a clear manual for its customers.
- Mentions in nearly all languages are translated automatically.

Weaknesses

- When the free trial is expired, the tool is fairly expensive. The price varies from €250 per month to €1750, depending on the type of plan: basic, standard, professional or enterprise.
- Automatic sentiment analysis is only available in Dutch, English and Arab, but should soon be updated to other languages.

3.2 APIs

Using open APIs, application programming interfaces, has become an increasing trend in the Web 2.0 context. It allows websites to interact with each other via several web technologies ("Open API", 2013). More specifically, an API integrates systems so that one service provider can collaborate with another provider and outsource a particular service. OpenAmplify[15], for example, provides a SA service to *Salesforce Marketing Cloud*[16], another social media monitoring platform. APIs might be interesting tools for smaller companies which often do not have enough employees that specialize in social media management and can take on this task.

[15] http://www.openamplify.com/
[16] http://www.salesforcemarketingcloud.com/

OpenAmplify presents itself as "a leader in large scale, commercial Text Analysis and Natural Language Processing solutions". The API translates natural language into meaningful data in various structures such as XML and JSON.

3.2.1 Concepts of OpenAmplify

OpenAmplify can be divided into three main sub-APIs: Insights, Reactions and SocialView. Insights identifies the relevant information in online messages (websites, social networks, video content) so that marketers can implement them in their strategy. A number of 'signals', or labels, represent specific types of information and can be selected with respect to the level of analysis required (cf. Figure 7). These include:

- Topics and entities that are discussed online
- Domains, categories and classifications comprising these topics
- Sentiment analysis at topic- and document–level

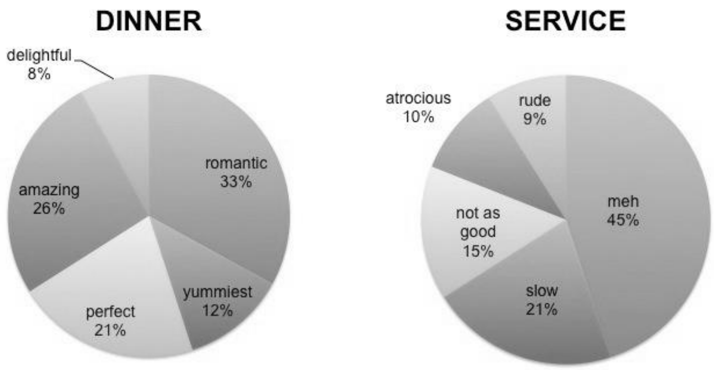


Figure 7: Topic Description Insights allows to get an overview of what customers are saying about a particular topic (Source: http://www.openamplify.com/node/6588).

Sentiment can be gauged by means of the Polarity signal that combines a number of linguistic features and calculates the mean polarity score. First, the single polarity of a particular topic is represented on a scale of -1.0, very negative, to +1.0, very positive. Then these individual scores are added to calculate the mean score.

In addition, OpenAmplify is said to be a pioneer in linking multiple sentences via pronouns, e.g. 'it'. An updated 3.0 version of their API provides major enhancements on the analysis-level and the speed of processing, but is also claimed to link the pronoun 'it' to the correct topic (Jo, 2013). We will discuss the specific approach followed in section 3.2.2.

The Reactions API can be compared to Engagor*'s Inbox*: it tracks the engagement that a companies' brand generates by screening how users link and comment on a specific web link or entity. This information can then be further analysed by means of the Insights API. Concretely, the API screens a wide range of platforms such as social networks, videos, blogs, campaign sites, and so on. When the relevant information is gathered, Reactions allows to segment the audience into specific groups, e.g. fans, critics, influencers and intenders.

The final section in OpenAmplify is SocialView, a web service built by *Visual Intelligence*[17]. This service displays the information gathered via Insights and Reactions in tables and charts, see Figure 8 for an example. This suggest that APIs can be of use as well when integrating Web 2.0 content in a business strategy.

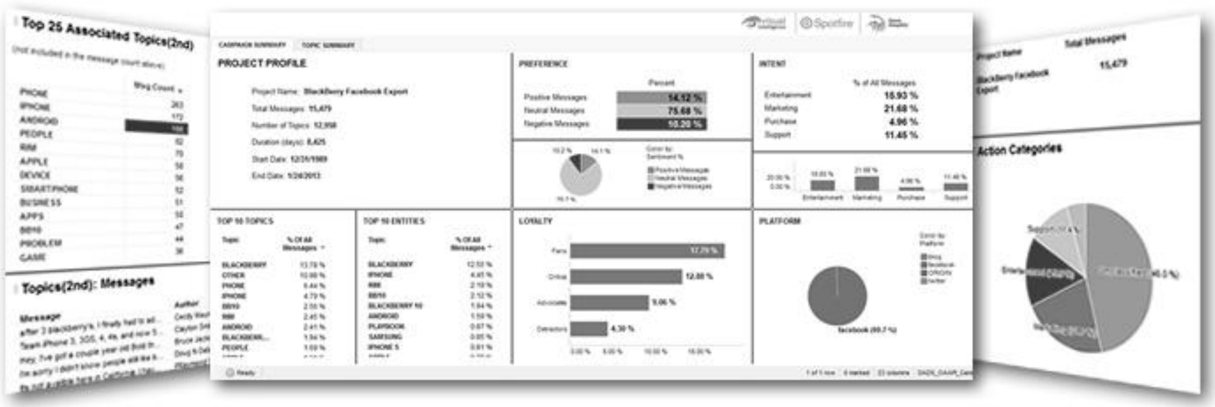


Figure 8: General overview of a number of OpenAmplify charts (Source: http://www.openamplify.com/socialview).

3.2.2 SA approach

OpenAmplify claims to perform a semantic analysis of web content by means of Natural Language Processing techniques. As we did not gain insights into the more specific

[17] http://www.vis-intel.com/

methods used, we will sketch the developers' approach as it is described on the OpenAmplify website[18].

The developers compare sentiment analysis with the process of language acquisition. During the first stage, a young child acquires some basic vocabulary to make clear what it wants. Later on, a grammar takes form and syntactic roles develop. In a final stage, the child fully interacts in its first language. Observation and judgement will then allow to discern subtleties such as sarcasm or irony. OpenAmplify tries to mimic this process in computer code.

This approach can thus be summarized as a rule-based technique in which the developers create vocabulary lists in order to deduct some simplistic rules to gauge sentiment. As mentioned in our literature study (cf. section 2.3.2.2), lexicons are often domain-specific and hence one lexicon does not lend itself to a wider range of text types. Since OpenAmplify screens a wide range of platforms, we doubt whether this approach is sufficiently qualitative for detailed sentiment analysis. The company can thus not present significant proof for their allegedly accurate method.

3.2.3 Strengths and weaknesses

<u>Strengths</u>

- OpenAmplify has 14 patents and hence presents itself as a qualitative tool. Nevertheless, the documentation on the website provides no evidence to confirm this proposition.
- Online content is displayed in various formats such as XML or graphs.
- Several types of analysis are possible on different text-levels.
- The API is widely used by other developers, e.g. *Radian6*[19], *Precise.*[20] and *Wunderman*[21].
- There is no practical limit to the amount of data input the service can handle.

[18] http://www.openamplify.com/
[19] http://www.salesforcemarketingcloud.com/
[20] http://www.precise.co.uk/
[21] http://wunderman.com/

- The API can freely be used up to 1.000 transactions per day. When this limit is exceeded, though, OpenAmplify demands a fee. A *Radian6* package with an OpenAmplify API starts at $60 per month.

Weaknesses

- The API processes English conversations only which is a drawback compared with other APIs in the field. These APIs may not reach a similar level of advancement, but provide services in a wider range of languages which is more interesting for international companies.
- OpenAmplify does not present a transparent scientific basis.

3.3 Hybrid tools

Hybrid tools offer both a regular sentiment mining service and an API. In most cases, the tool can be used freely, whereas the API requires payment. The range of services in hybrid tools is often less extensive than in sentiment miners only, e.g. the focus will be on one aspect of social media monitoring, mostly sentiment analysis. The API then allows to integrate the sentiment technology in other web platforms. Hybrid tools are interesting for companies that perform only a basic social content analysis or for those who want to test a tool before buying an API. The hybrid tool discussed in this section lends itself to regular web users as well that want to gain insights into trending topics.

Sentiment 140[22] was formerly known as Twitter Sentiment and is uniquely designed to analyse mentions on Twitter.

3.3.1 Concepts of Sentiment 140

While Engagor and OpenAmplify provide a wider range of services, Sentiment 140 solely focuses on sentiment analysis. The number of data fields analysed is thus limited, i.e. queries, text and polarity. Contrary to the previous tools, Sentiment 140 does not focus

[22] http://www.sentiment140.com/

on the commercial aspect and the advantages the tool might generate in a business context. Instead, it presents itself as a service to "discover the sentiment of a brand, product, or topic on Twitter".

Sentiment 140 was developed by Go et al. (2009). They made both a tool and an API based on machine learning algorithms to discover the sentiment of a particular brand, product or topic on Twitter. The polarity of each mention is reflected by means of colours and numbers, viz. red or 0 is negative, white or 2 is neutral and green or 4 is positive. Depending on the type of API that is selected, responses are generated in bulk, i.e. 10,000 tweets per call, or per individual tweet. A license for the API costs about $200 to classify one million tweets per day. An example of the information displayed after SA is presented on the next page in figure 9.

3.3.2 SA approach

Go et al. (2009) used a distant supervision approach to train their tweet-classifier. They collected a dataset of tweets with emoticons in them which determine the polarity of the mention. This distant supervision approach is less time-consuming than manual training since a large number of topics is discussed on Twitter. The training set, collected via the Twitter API (https://dev.twitter.com/), was then run against a test set of tweets, regardless of the emoticons they contain.

Different machine learning classifiers and feature extractors were tested, viz. Naive Bayes, Maximum Entropy and SVM. Unigrams, bigrams, a combination of both and POS-tags were used as feature extractors. To test the classifiers on a new dataset, the emoticons were stripped out of the training data since they would negatively influence the accuracy of some algorithms. The emoticons were hence used as noisy labels as they often fail in determining the correct polarity.

After collecting a test dataset via the Twitter API, the polarity of tweets was manually marked, regardless of the emoticons they contain. This test set was used to train the classifiers by extracting features. The unigram feature extractor appeared to be the simplest method to retrieve features from a tweet. A combination of both unigram and bigrams, though, generated better results. In this case, the accuracy for both Naive

Bayes and Maximum Entropy improved. There was, however, a decline in the accuracy of SVM (Go et al., 2009). In general, Go et al.'s approach generated accuracy above 80%.

Figure 9: Sentiment analysis for query 'Ghent'.

3.3.3 Strengths and weaknesses

<u>Strengths</u>

- The project issued by Stanford University, is scientifically elaborated on in a paper and is based on a solid machine learning approach.
- The developers are continually updating their approach. They may, for example, extend to other platforms such as Facebook, MySpace and YouTube ("Sentiment 140-Site Functionality", 2013).

<u>Weaknesses</u>

- The service is currently only available in English and Spanish.
- The API does not automatically create reports or graphical statistics. An Embed Code, however, allows to display a small graph onto a website to visualize the

polarity of a query ("Sentiment 140-Embed Code", 2013). Neutral mentions are not displayed in these charts.

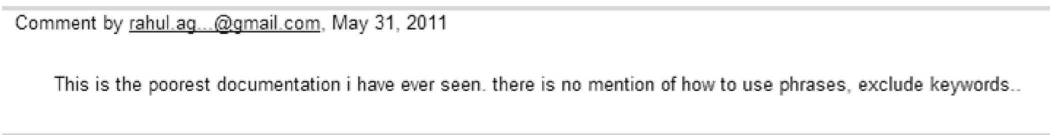
- The classifier only determines polarity and hence does not distinguish subjectivity and objectivity.
- Comparisons are not analysed profoundly. A sentence such as *Stanford is better than Berkeley* would be considered positive for both *Stanford* and *Berkeley*. The classifier does not take into account that the comparative relation expressed by *better than* negatively connotes *Berkeley*.
- The Stanford Parser used in this tool is trained on a formal dataset and does not handle informal language very well.

As mentioned in the introductory part of the this section, we will also describe two hybrid tools that were mentioned in our market study.

3.3.4 SocialMention

SocialMention[23] is defined as "a social media search and analysis platform that aggregates user-generated content from across the universe into a single stream of information". The hybrid tool outputs information in several formats and identifies the original source, a language code, the type of utterance, and so on (cf. Figure 10). A licensed API allows to determine sentiment and enumerates the most popular keywords and hashtags.

The approaches used are, however, not supported by scientific evidence. The website is poorly documented and from user comments it appears that the service leaves much to be desired. We enlist some of these comments[24] below:


Comment by rahul.ag...@gmail.com, May 31, 2011

This is the poorest documentation i have ever seen. there is no mention of how to use phrases, exclude keywords..

[23] http://socialmention.com/
[24] All the comments were retrieved from https://code.google.com/p/socialmention-api/wiki/APIDocumentation [08.04.2013]

Comment by neeraj.d...@gmail.com, Aug 9, 2011

How to get Social mention API? I am not able to locate it.

Please help anyone!!!

Comment by max.shar...@impactdata.com.au, May 22, 2012

This is the worst documentation for a paid API service I have ever seen.

Please list the options available for src parameter.

Since there are hardly any strengths that can be attributed to this tool, we consider it irrelevant to draw up a SWOT-analysis. Furthermore, we find it peculiar that this tool should be used for sentiment analysis in a business context. An explanation for this might be the fact that the tool itself is freely available.

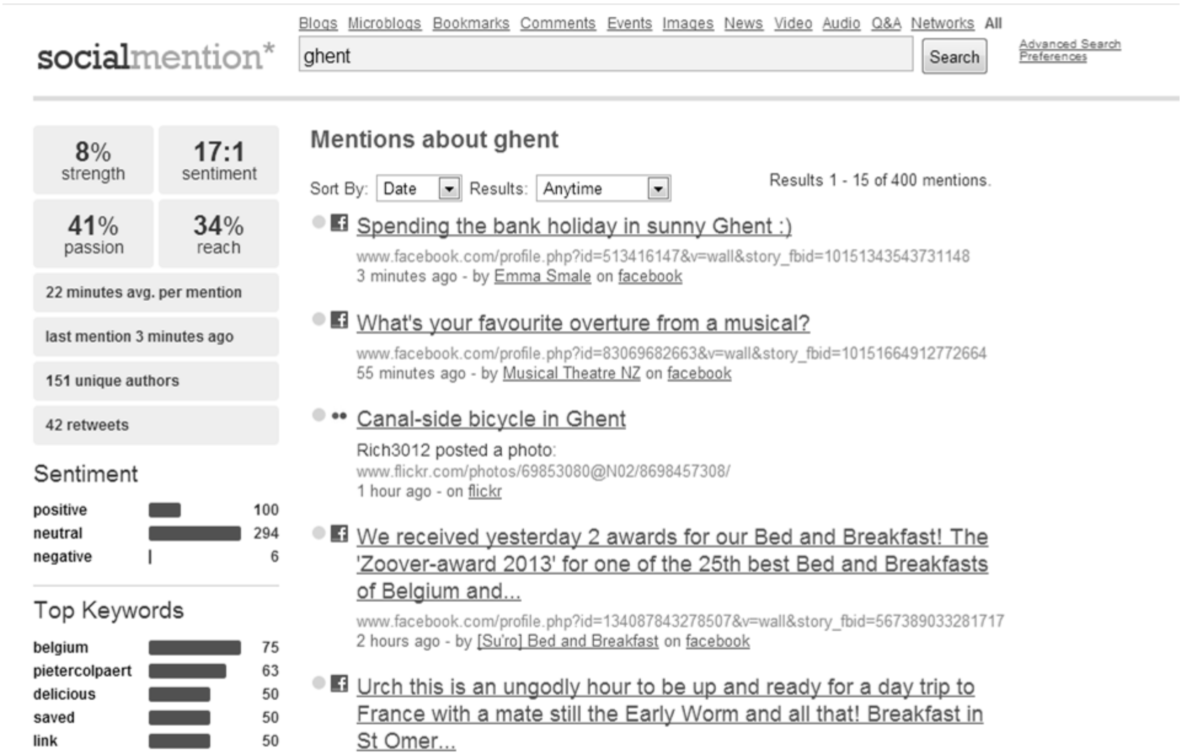


Figure 10: Screenshot of the results for query 'Ghent'.

3.3.5 Facebook Insights

"Facebook Insights[25] provides Facebook Platform developers and Facebook Page owners with metrics around their content". The Insights Dashboard allows to screen data on Facebook and to export it into Microsoft Office Excel or a CSV-file. The information gathered is presented in charts so that marketers can tailor their marketing strategy in accordance with their online profile (cf. Figure 11 and 12). The Dashboard on the top of the page allows to get an immediate overview of the engagement a particular profile yields. An API is available as well so that the service can be integrated into other programs or websites.

Figure 11: Overview of the number of likes, fans and friends, the general engagement and the weekly total reach in a certain time span (Source: https://www.facebook.com/help/336893449723054/).

[25] https://www.facebook.com/help/search/?q=insights

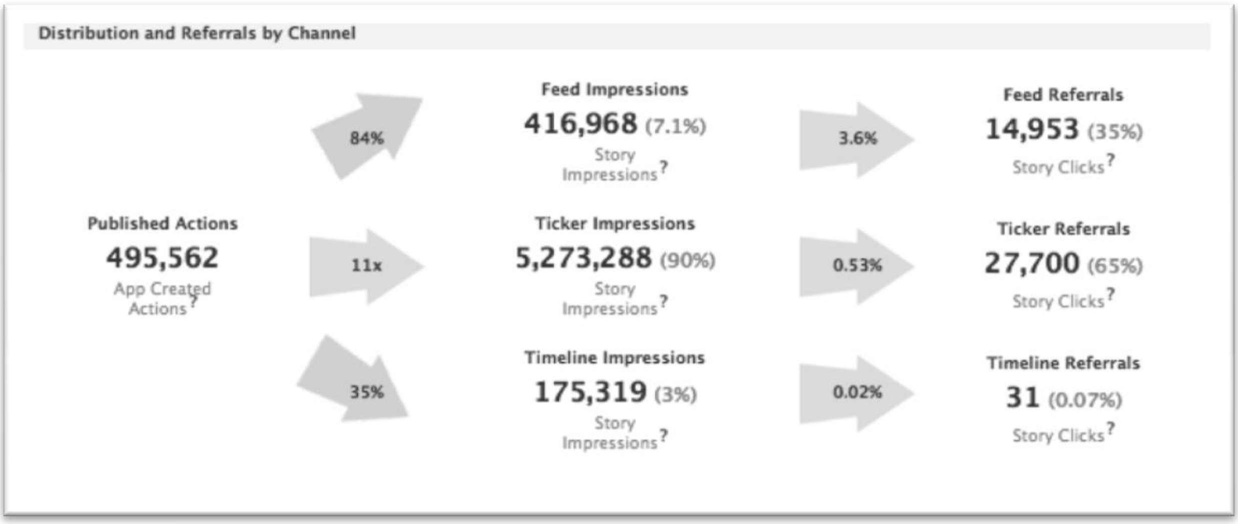


Figure 12: The chart allows to gauge how each Facebook channel is performing (Source: https://developers.facebook.com/docs/opengraph/guides/insights/#site-engagement).

3.3.5.1 CONCEPTS OF FACEBOOK INSIGHTS

There are two types of Insights, viz. User Insights and Interactions Insights. The former one allows to track the daily number of active users and likes, and displays, for example, demographics. The latter one shows the daily page activity, the number of mentions and so on. Insights data can be reviewed on Page level, i.e. on all aggregated data on the Facebook page, or on Post level, i.e. on posts individually. The tool allows, for example, to screen to what extent a specific company post generated buzz with the general audience.

There are, however, some limitations to the service, i.e. Facebook Page Insights is only available for pages that are liked by at least 30 users (“Facebook Developers-FAQs”, 2013). In addition, only page administrators can view data for the pages they own.

3.3.5.2 STRENGTHS AND WEAKNESSES

Strengths

- A clear manual helps marketers stepwise to engage their audience.

- All information is displayed in charts so that marketers get an immediate overview.
- The tool is freely available.
- The service offers a wide variety of information that can be screened, which allows marketers to adapt their marketing strategy accordingly.

Weaknesses

- The tool is fairly new (a new version has been introduced in 2011) which means that small issues still frequently occur.
- Since Facebook is a private social network, i.e. users first need to register and data is less easily available, data will only be displayed for pages that are liked by minimum 30 users in order to protect user privacy.
- We have not encountered information on the scientific technique Facebook uses to perform social media analyses. We hence cannot confirm the accuracy of the tool.

In appendix 8.1 we present an overview of the assets of each tool and API we discussed. This overview suggests that Engagor is by far the best tool to perform sentiment analysis, and social media monitoring in general, in a business context. Now that we have discussed both the theoretical and the practical aspect of SA, we will continue with our market study.

4 MARKET STUDY

With nearly five million Facebook users in Belgium (http://www.socialbakers.com/facebook-statistics/belgium) and 175 million tweets sent per day (http://infographiclabs.com/news/twitter-2012/) the world wide web comprises a vast amount of user-generated data. This digital tendency somewhat obliges marketers to screen social media content if they want to stay up to date with trending topics, but most of all if they want to know what is being said online about their brand or products.

This major shift in the communication landscape has lead to companies resorting to specialized e-CRM[26] software and social media monitoring agencies to develop a customized strategy to translate the large amount of user-generated content into a well-structured overview. A European pioneer and the first web agency in Belgium, The Reference[27] offers such a full service to companies that want to monitor their online image. They conducted two market studies, one in 2011 (http://www.referencedata.be/nl/investeringen-digitale-marketing) and another in 2012 (http://www.reference.be/Media/pdf/details-e-crm-surveyNL) to grasp the current state of affairs in the field of social media integration, i.e. the extent to which social media content is implemented in the marketing strategy.

The results of their 2011-study show that the budget for social media measurement in Belgian companies accounts for more than half of the budget to keep their website up to date. This proves that they are steadily adopting a digital marketing strategy. In 2011, the general level of social media adoption, however, was still in a premature phase. In 2012, marketers are thoroughly aware that e-CRM provides added value and they recognize the importance of social media integration. Still, the adoption of adjusted and optimal approaches remains in a very early stage.

A marketing research agency in Belgium, Insights Consulting[28] conducts surveys to help global brands become locally relevant and wants to gain insights into customer behaviour and the integration of this behaviour in a corporate strategy. A survey conducted in 2011 demonstrated to what extent companies in the USA and the UK have integrated social media content in their business strategy. The results reveal that the telecom, technology and media sectors are much more active on social media networks, i.e. 80 to 90%, than other sectors such as finance and healthcare. The study also demonstrates that more than 40% of the companies in these sectors have integrated social media to a large extent and that about 24% of them are fully integrated, i.e. using online content as a strategic resource in an optimal way (Van Belleghem, 2011).

By performing a market analysis we want to explore the current situation on the Flemish market: are Flemish companies integrated at the same level and can we draw

[26] e-CRM stands for electronic customer relationship management which focuses on optimizing customer relations by combining marketing, sales, customer service and technical support. (Source: http://en.wikipedia.org/wiki/Customer_relationship_management [01.05.2013])
[27] http://www.reference.be/en/
[28] http://www.insites-consulting.com/

parallels with the above mentioned studies? Our main point of interest is to what extent media chains and web shops try to monitor their online image using sentiment analysis. We will discuss whether they are active on social networks and which digital marketing strategy they adopt. The answers to these questions will allow us to conclude if there is a gap between the theoretical aspect discussed in our literature study (Chapter 2) and the practical application of tools and APIs that exist in the field (Chapter 3).

4.1 Methodology

The market study in this dissertation comprises an explorative analysis of both Flemish media respondents and a number of web shops. By means of a qualitative and quantitative data analysis we will try to get an overview of both the integration of social media and the application of sentiment analysis (SA) in a Belgian business context.

4.1.1 The Target market

4.1.1.1 MEDIA

Following the scheme of media concentration[29] (cf. Figure 13) in Flanders, we randomly contacted 29 respondents in the media sector to participate in our market study. We addressed several sources of media, i.e. newspapers, magazines, television chains, radio stations and media chains in general, in order to achieve a varied and hence more representative reflection of the media landscape. The following media conglomerates participated (in)directly in our market study:

- Roularta: comprises mostly specialised magazines, e.g. Knack, Nest, Grande, and media channels.
- Sanoma Magazines: mainly offers a wide range of women's magazines, for example Feeling, Flair, Marie-Claire, Libelle.
- VRT: comprises three media channels (Eén, Canvas/Sporza and Ketnet/Op12) and a number of radio stations, such as Radio 1, Studio Brussel and Klara.

[29] Vlaamse Regulator voor de Media. (2012). *Mediaconcentratie in Vlaanderen* (D/2012/3241/327). Brussels, Belgium: Vlaamse Regulator voor de Media.

- Vmma: consists of a variety of commercial media channels, e.g. 2BE and VTM, and two radio stations: Q-music and Joe FM.
- De Persgroep: is the main group which possesses the majority of Flemish newspapers and a number of magazines, and also encloses Vmma.

For a complete overview of the contact respondents please see Appendix 8.2.

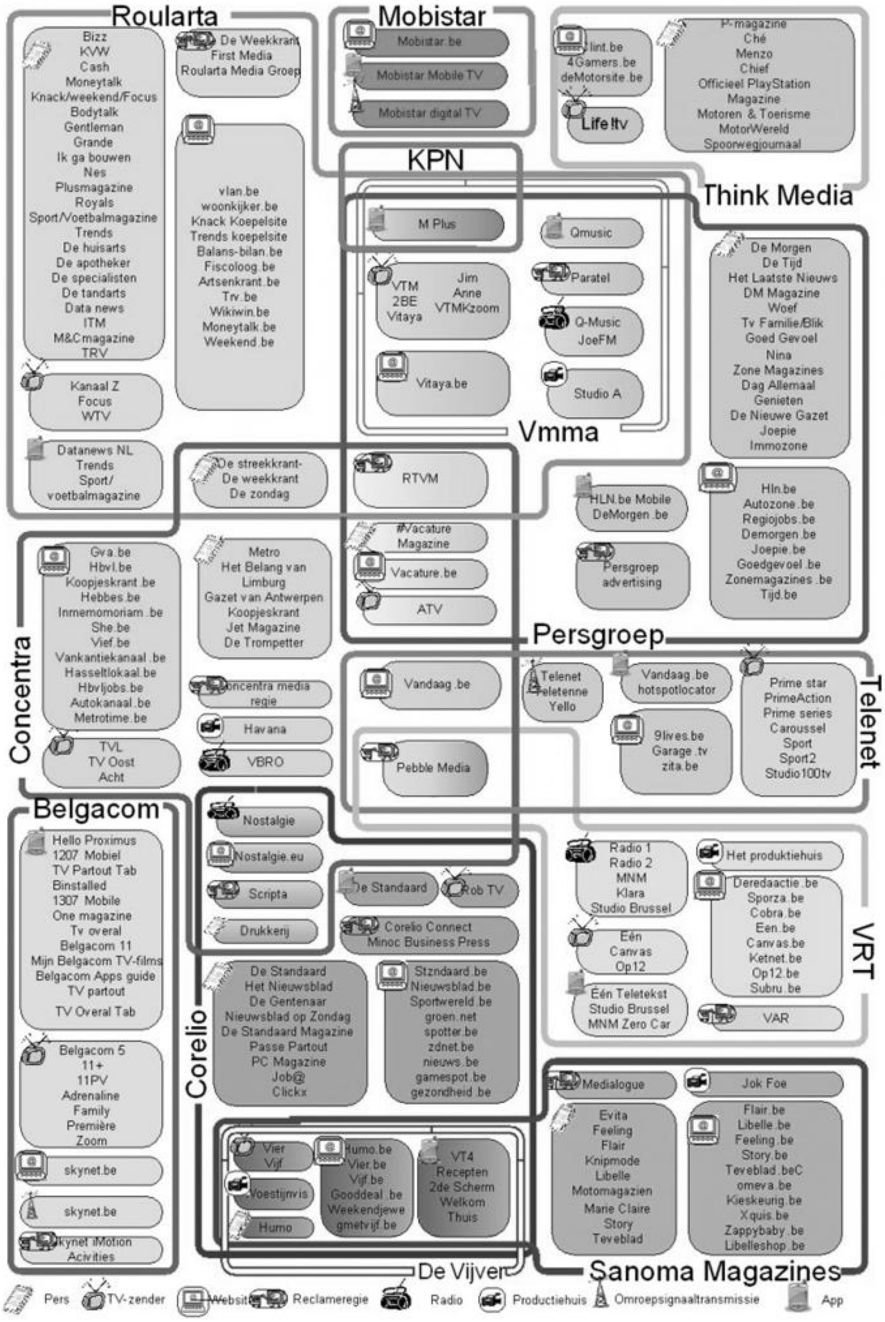


Figure 13: Scheme of media concentration in Flanders, 2012.

4.1.1.2 WEB SHOPS

We wanted to compare the Flemish media with another sector to gain a broader insight into the integration of social media and the application of SA in a business context.

We therefore selected a number of web shops as the FMCG (fast moving consumer goods) sector is significantly different from the media sector but still retains a link with it. More specifically, both sectors want to inform consumers, but web shops focus more on selling and advertising than media do. Furthermore, it would be interesting as well to discover to what extent web shops have integrated Web 2.0 content in their marketing strategy.

From a reliable source at Indie Group it was clear that the web shops in their client portfolio were considering adopting a Web 2.0 content management strategy (K. Hillewaere, personal information, 2013). We thus randomly selected 29 web shops (see Appendix 8.2) on the basis of the client portfolios of Indie Group[30] and InSights Consulting[31]. We tried to mirror the variation of web shops in the sector, but due to a lack of respondents this group is less representative than the media respondents. The web shops that participated in our survey are enlisted below according to which industry they belong:

- Food/Beverages
    - Duvel-Moortgat
- Clothing
    - Bel&Bo
    - Bonprix
    - e5 mode
    - Vente Exclusive
- Electronics
    - Free Record Shop
- Furnishing
    - Axeswar Design

[30] http://www.indiegroup.be/portfolio
[31] http://www.insites-consulting.com/working-for/

- Other
    - confidential

4.1.2 Data collection

In order to perform a qualitative and quantitative analysis, a survey with 13 multiple choice and open questions has been created with *Qualtrics Survey Software*[32]. An example of this document is included in Appendix 8.3 (survey A). As soon as this questionnaire was drafted, our first respondent group, i.e. Flemish media, was contacted via e-mail and the survey was activated. This first questionnaire ran from December 26, 2012 until February 13, 2013.

Since we were informed that web shops in the portfolio of Indie Group were considering adopting a Web 2.0 content management strategy, we decided to draft a second survey (cf. Appendix 8.3: survey B) that included five additional questions on sentiment analysis. While the media respondents were solely questioned on their acquaintance with the concept of SA and their use of specific tools, web shops were questioned in more detail on the problems they encountered when using tools and on their expectations with respect to SA.

An overview of the target groups, the time span of the survey and the reminders are presented in the next table.

Respondents	Time span and reminders	Survey
Flemish media	December 26, 2012 - February 13, 2013 Reminder 1: after ten days, reminder 2: after six days.	13 questions (cf. survey A)
Web shops	February 25, 2013 - March 25, 2013 No reminders necessary.	18 questions (cf. survey B)

Table 2: Overview of surveys.

[32] http://www.qualtrics.com/

In the next chapter, we will present our results in three main sections, hence representing what we discussed in our literature study. More specifically, the collected responses will be divided into three themes, i.e. social media (5.1), digital strategy (5.2) and sentiment analysis (5.3).

In the social media section we will first focus on the general adoption of social media sites in companies and how they manage their online profile(s). We will then take a closer look at the advantages these networks generate. The digital strategy section will indicate how companies interact with customers and how social media content is integrated into their marketing strategy. The final section will provide insights into acquaintance with sentiment analysis and the application of tools. This is where the number of questions differs in our two surveys. The final question of each survey consisted in specifying the company name.

5 DISCUSSION

5.1 Social media

In this section we will compare both the adoption of social media, how our respondents manage their profiles and the advantages these networks entail. Since the surveys were conducted in Dutch, we translated the responses into English. In order to improve readability, we will provide each section with an example of the survey questions relating to that particular section.

5.1.1 Adoption of social networks

1	Is your company active on social media? ☐ *Yes* ☐ *No*
2	On which social media networks is your company active? (multiple choice) ☐ *Twitter* ☐ *Facebook*

	☐ *LinkedIn* ☐ *Google+* ☐ *Other (specify)*

Tables 3 and 4 indicate that our respondents have all adopted at least one social media profile.

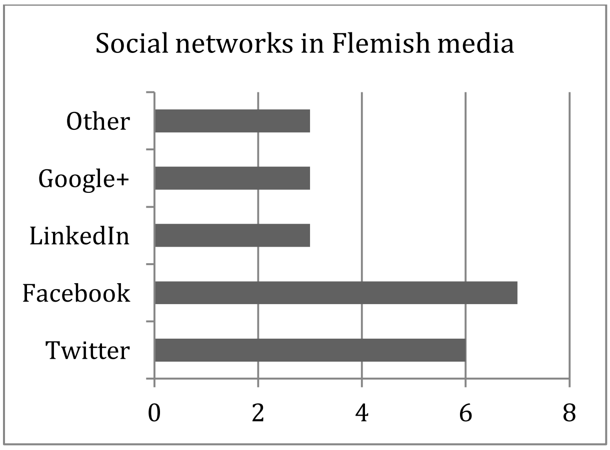
#	Answer		Response	%
1	Yes		7	100%
2	No		0	0%
	Total		7	100%

Table 3: Adoption of social media in Flemish media.

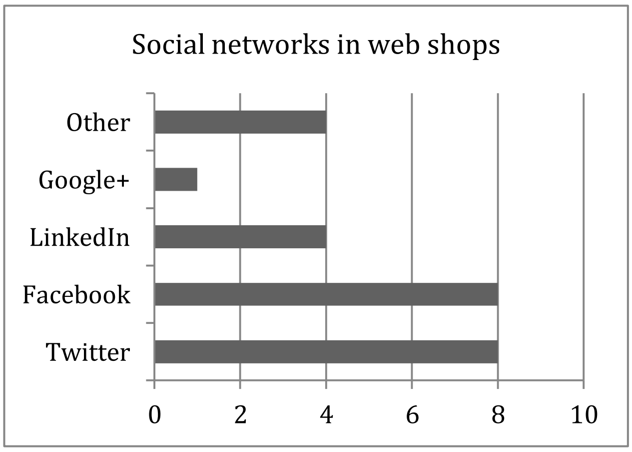
#	Answer		Response	%
1	Yes		8	100%
2	No		0	0%
	Total		8	100%

Table 4: Adoption of social media in web shops.

Bar charts 1 and 2 illustrate on which social networks they are active.



Bar chart 1: Social networks in Flemish media.



Bar chart 2: Social networks in web shops.

The charts show that both Facebook and Twitter are the most commonly adopted social network sites. This corresponds with statistics from the Social Media Report 2012 by Nielsen (2012). The report indicates that Facebook is the most popular social media platform and that Twitter is ranked in the top 3.

On a global scale, Google+ is making headway to surpass the number of Twitter users, but in Belgium the majority of users is still somewhat unfamiliar with the platform. Nevertheless, Google+ is expanding rapidly as the number of Belgian users has exceeded the 350.000 barrier. The charts suggest that there is a clear difference in the adoption of Google+ in a business context. About 43% of the Flemish media channels participating in our study have created a Google+ profile, while only 14% of the web shops (i.e. 1 in 7 respondents) is active on this social network. A possible explanation might be that Google designed Google+ explicitly "to simplify sharing with select private groups" (as cited in Winter, 2012). Since the engagement on Google+ is also fairly low, it might not be an interesting data source for web shops.

The option 'Other', generally comprised Pinterest, Instagram, Polyvore, YouTube and blogs. Pinterest is adopted by 67% of the media channels that indicated 'Other' and by 75% of the web shops that did so. Instagram is both used by one respondent in the media and the web shop sector, while Polyvore was encountered once in the media statistics only. Interestingly, YouTube was mentioned only once.

5.1.2 Management

3	How often do you manage your social profile or personal account? ☐ *Once a week* ☐ *Twice a week* ☐ *Every day* ☐ *Other (specify)*
4	For which activities is your corporate page used? ☐ *Giving information about the company* ☐ *Advertising* ☐ *Organize games*

	☐ *Publish vacancies* ☐ *Measure number of fans* ☐ *Other*

In chart 3 we compare how often media channels and web shops manage their online profile. The participants had to indicate their overall frequency, instead of specifying this for each social platform individually.

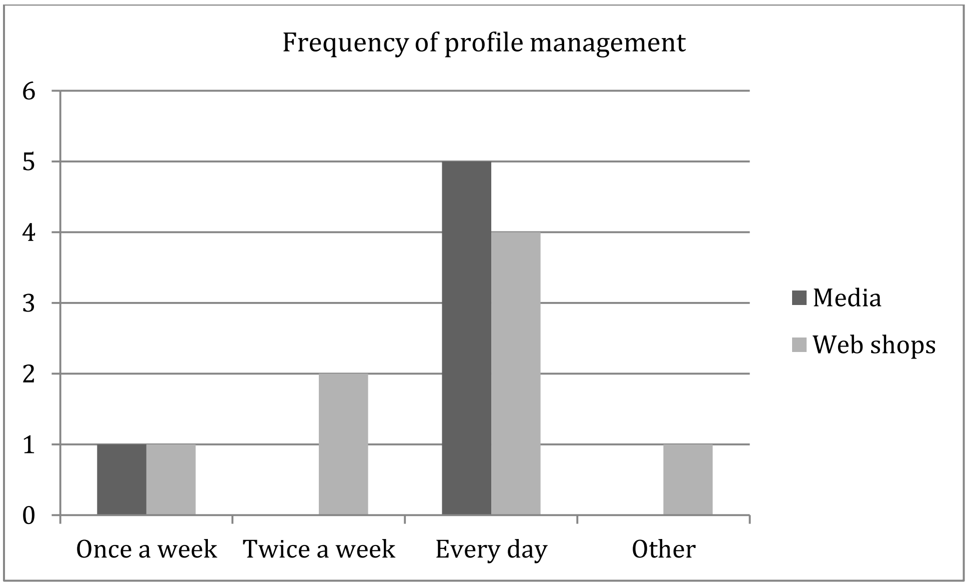


Chart 3: Frequency of profile management for media channels and web shops.

This chart suggests that 83% of the media respondents, i.e. 5 out of 6, (this question was skipped by one respondent) and 50% of the web shops manage their profile every day. A minority of the companies monitors its profile only once a week. One respondent specified that the companies' profile was managed several times per week, but not in a systematic manner. These statistics suggest that the majority of companies consider the management of their online profile(s) a daily task. Every respondent in both sectors specified that one of the company members was responsible for this task.

Furthermore, we inquired about the main activities that were performed on the respondents' social profiles which is visualized in chart 4.

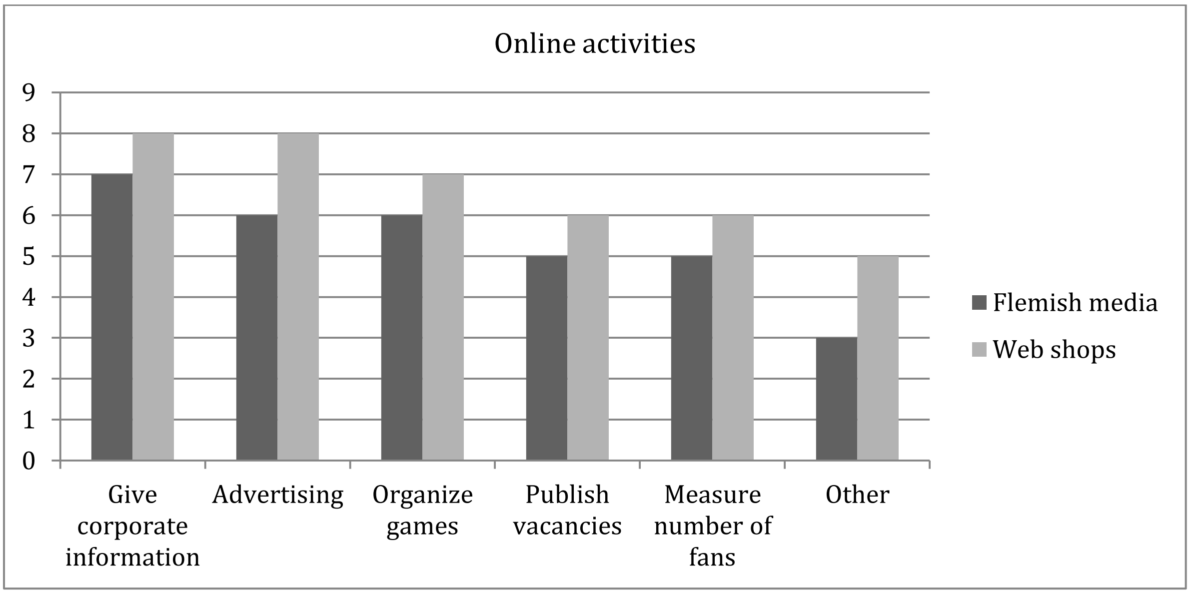


Chart 4: Online activities on Flemish media and web shop profiles.

The results suggest that giving information about the company on social media is the most general activity, i.e. performed by every respondent. In the Flemish media sector, 87% of the respondents ranked the importance of this activity above 60%, whereas this percentage was lower for web shops (82%). We already mentioned that both sectors retain a link, i.e. wanting to inform the public, but that they differ slightly in their main goals. This is illustrated by the 'Advertising' option. For web shops, this activity is among one of the main goals, whereas media channels consider informing consumers as the main activity. The results with regard to the performance of the other activities are identical in both sectors, although the importance accorded to these activities slightly differs.

5.1.3 Evaluation of advantages

This theme inquired about the level of advantage that is generated after creating a social media account.

5	To what extent does your presence on the following social networks generate advantages? ☐ *Facebook* ☐ *Twitter*

	☐ *LinkedIn* ☐ *Google+* ☐ *Other (specify)* Respondents could indicate: *no advantage at all / hardly any advantage / neutral / some advantage / a significant advantage.*

The results displayed in charts 5 and 6 indicate that the most popular platforms, i.e. Facebook and Twitter, generate a significant advantage. This might be due to the large number of users on these network sites that can be reached online, viz. approximately five million Facebook users and around 700,000 Twitter profiles in Belgium (Bastijns and Briesen, 2012). The numbers on the y-axis show the number of respondents that have indicated a particular level of advantage. These numbers do not refer to the general number of respondents in one of the sectors. The results for LinkedIn in chart 5, for example, should be interpreted as follows: one of the three respondents active on LinkedIn (see charts 1 and 2 for media and web shops respectively) thinks that this network entails some advantages, whereas the other two respondents checked the 'neutral' and the 'hardly any advantages' boxes.

In the media sector (cf. chart 5), Twitter generates the greatest level of advantage, i.e. 5 out of 7 respondents indicated that their presence on Twitter entails a significant advantage for the company. The real-time character of Twitter and the openness of the platform compared with, for example, Facebook allows users to directly post comments online on events or persons. This content can be of great interest for media channels when identifying trending topics. There have been various incidents, for example, with politicians tweeting inappropriate content, which resulted in a scoop for several media channels. Thanks to Twitter, they could easily track comments in response to the event.

For one and two of the three respondents that are active on LinkedIn and Google+ respectively, these platforms entail hardly any advantages. This might be because both networks have a more professional character compared with, for example, Facebook where the main activity is to share interests (Bastijns and Briesen, 2012).

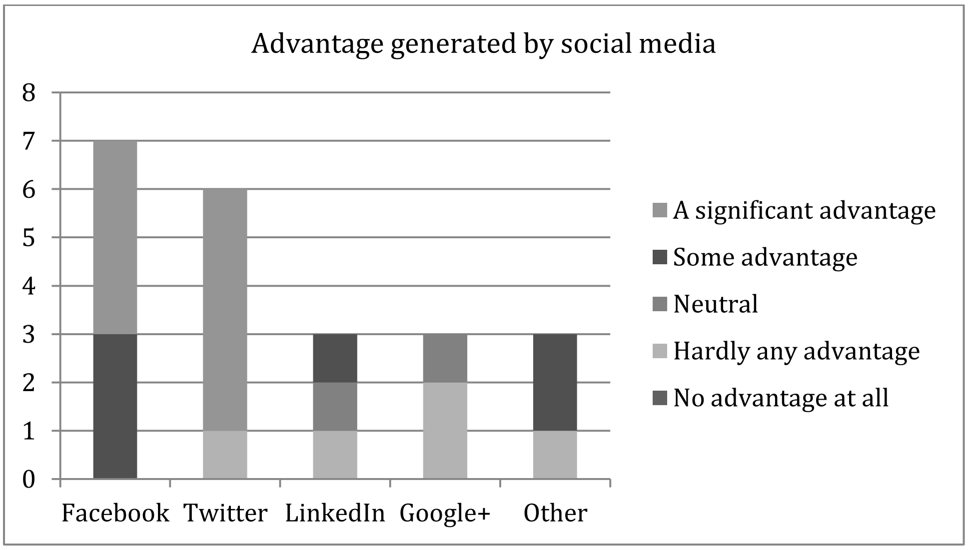


Chart 5: Advantage generated by social media for Flemish media.

Chart 6 illustrates that Facebook entails a significant advantage for web shops, while the media sector seems to prefer Twitter. Facebook lends itself more for advertising as advertisements are often displayed in the right bar of a Facebook page. Furthermore, the *Advertisement* function on this network allows marketers to create their personal advertising page which is of course interesting for web shops.

Google+ again yielded hardly any advantage. The label 'Other' refers to Instagram and Pinterest and a weblog. For web shop *Bel&Bo* this blog yields a significant advantage. We want to nuance this by noting that their weblog is probably read by regular customers, which makes it a less interesting tool to attract a broader audience.

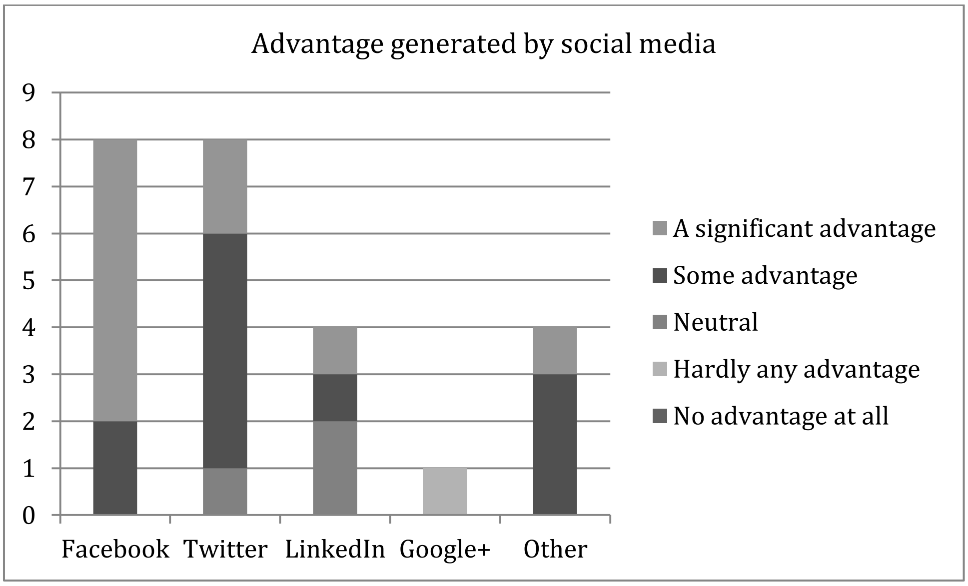


Chart 6: Advantage generated by social media for web shops.

5.2 Digital strategy

The balance of power in marketing has shifted from corporate advertising to buzz generated by consumers online. Customers choose when and where they voice their opinions, issues and complaints and share them with the rest of the world via social media (Nielsen, 2012). Brands therefore have to consider this evolution and adapt their marketing strategy accordingly.

We have researched into the general digital strategy of our respondents. More specifically, we screened if user-generated content was introduced in their marketing strategy and how this was realized concretely. We also inquired about the extent to which interaction was possible between brands and their customers and if companies screen social media in general to get an overview of the main trends.

6	Is the information on social networks implemented in the companies' marketing strategy? ☐ *Yes* ☐ *No*
7	Describe how this information is implemented. (open question)
8	Do you enter into dialogue with customers online? Can they, for example, use these social networks to mention issues and complaints with regard to your brand or products? ☐ *Yes* ☐ *No*
9	Does your company screen social media in general in order to get an overview of the current trending topics? ☐ *Yes* ☐ *No*

The charts on the next page display whether the participants in our survey have integrated Web 2.0 context into their marketing strategy. The left-bar chart suggests that only one respondent in the Flemish media group, i.e. *De Persgroep Advertising,* has not yet integrated this content into its marketing strategy. This might be because this sub-group of *De Persgroep* mainly focuses on B2B relations and is less interwoven with the marketing aspect towards regular customers. The right bar chart indicates that 1/8 of the web shops in our study does not use user-generated content in their strategy. This participant, *Free Record Shop*, is mainly active in a particular branch of online shopping, viz. Music and Film. It attracts a particular audience so this might clarify why the company does not feel the need to screen all the content displayed online and to integrate it in the broader marketing strategy.

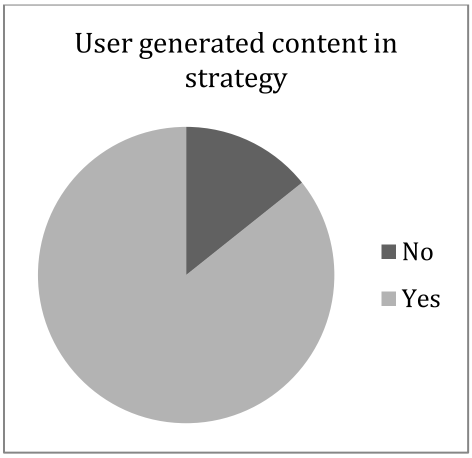


Chart 7: User-generated content used in strategy of Flemish media.

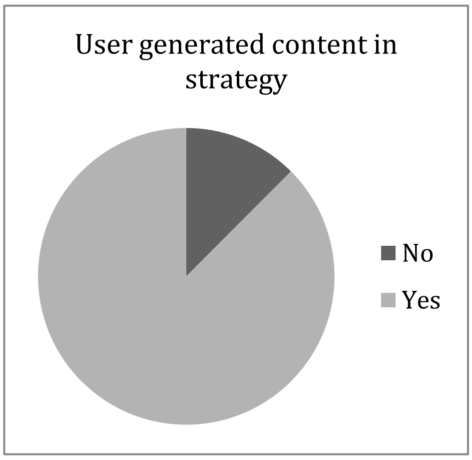


Chart 8: User-generated content used in strategy of web shops.

By means of an open question we tried to get an insight into how our respondents integrate online content into their marketing strategy. Not all participants answered this question, so we can only enlist a few strategies by means of example.

The Flemish magazine *Humo*, for example, screens user-generated content to determine its target groups. The marketers use this information to adapt their media messages to each specific target group. Furthermore, they use their website and social profiles for traffic building and link strategy. Link strategy means that they verify how often a link gets clicked on. A topic that is often selected by the readers will be elaborated on in a separate article, for example. Traffic building consists of increasing the number of readers passing through an online platform, such as a website, by means of promotional campaigns or special actions (“Traffic builder”, 2013). *Roularta Media Group* has adopted the same linking strategy as *Humo*.

Three respondents in the web shop group have expounded on how they implement online content, viz. *Axeswar Design*, *Vente Exclusive* and an anonymous respondent. *Axeswar Design*, a trend shop in Ghent, often campaigns on Facebook. The click-through rate[33], i.e. a method to measure the success of an online advertising campaign ("CTR", 2013), determines which products are listed as the most popular ones on the homepage. Facebook is also used as a platform to display photos from behind the scenes and to inquire about the opinion of customers. Twitter is used to provide incentives when new products or a new campaign are launched. *Vente Exlusive* is a web shops that organizes private sales of the most common clothing and lifestyle brands (http://www.vente-exclusive.com/nl-BE/About/Concept, 2013). It uses online platforms to ask for feedback when new applications or brands are introduced. It uses this information to prepare future campaigns and marketing actions.

Our anonymous respondent says to offer additional products on social platforms and to adapt products in accordance with the demands of customers. Via these social networks he or she allows the audience to participate in the selection of new campaign images.

Apart from screening social networks for customer evaluations or for brand management, companies also interact with their customers online. All of the respondents in both groups claim to enter into dialogue with consumers. Marketers respond, for example, to questions or issues, but they also take account of complaints. The line between marketing and consumer service is hence blurred (Nielsen, 2012).

Chart 9 illustrates how many Flemish media channels and web shops screen social media in general in order to get an overview of their competitors and trending topics.

The results suggest that both media channels and web shops are interested in the current tendencies on social media, with web shops showing a significantly high interest. By screening social networks, companies get an insight into what customers want and need, which allows them to position themselves amongst early movers on the market.

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[33] This is measured by dividing the number of clicks on an advertisement by the number of times the advertisement is shown, i.e. the impressions ("CTR", 2013).

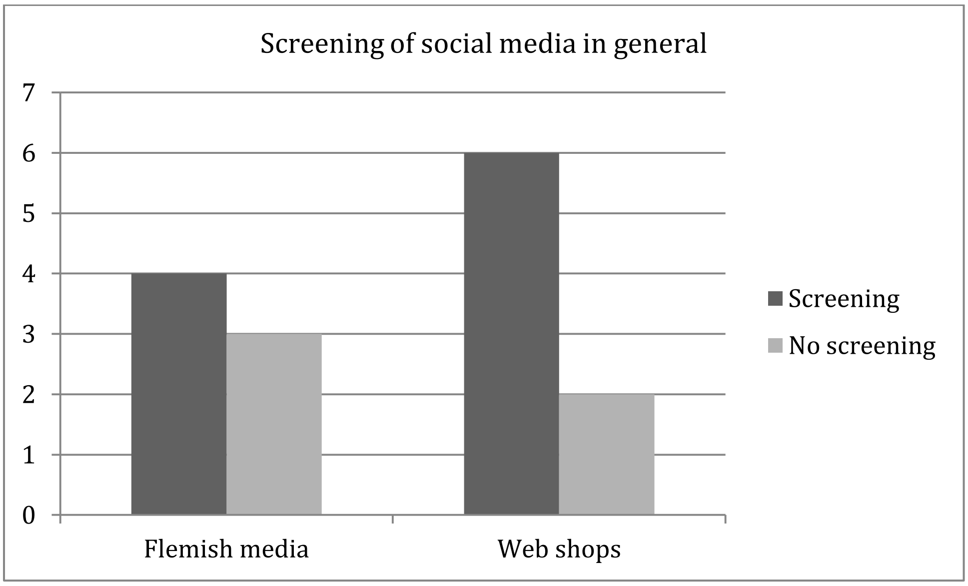

Chart 9: General screening of social media by Flemish media and web shops.

5.3 Sentiment analysis

Since sentiment analysis is the main point of interest in this study, we will take a detailed look at the state of affairs in both the media and web shop sectors. We will try to gain a deeper insight into whether our respondents are familiar with the concept and whether they use tools or applications to actively filter user-generated content for sentiment.

As mentioned in our methodology (cf. section 4.1), we added several extra questions on this subject since we understood that web shops are currently considering to adopt a digital marketing strategy in which sentiment analysis plays a prominent role. We will therefore analyse the web shops individually, instead of mentioning the results for the whole sector. Nevertheless, we will still make a comparison between both the media and the web shop sectors when they answered the same questions.

We first inquired about whether the companies are acquainted with the concept of sentiment analysis. We used a skip logic, so not all questions were displayed to the respondents. If they were acquainted with sentiment analysis, we asked whether they use tools to perform this particular NLP-task. For web shops, we asked if the task is performed by someone in the company or outsourced. When it is performed in the company itself, the respondents were asked to specify which tools they use and the problems they encounter. Finally, we inquired about the expectations of our web shop respondents with regard to sentiment analysis and which results this task has already yielded. These are the questions in our survey:

10	Are you acquainted with sentiment analysis (also: opinion mining, sentiment detection)? ☐ *Yes* ☐ *No*
11	Do you use tools to perform sentiment analysis? If yes, specify which tools. ☐ *Yes* ☐ *No*

These are the additional questions for web shop respondents:

10	Are you acquainted with sentiment analysis (also: opinion mining, sentiment detection)? ☐ *Yes* ☐ *No*
11	Is sentiment analysis performed by an employee in the company or is the task outsourced? ☐ *Performed in the company* ☐ *Outsourced*
12	Do you use tools to perform sentiment analysis? If yes, specify which tools. ☐ *Yes* ☐ *No*
13	Have you so far encountered problems when using these tools? If yes, specify. ☐ *Yes* ☐ *No*
14	What has your company realized by performing sentiment analysis? (open question)
15	What do you want to achieve by performing sentiment analysis and screening social media? Options are listed in *table 5: Expectations with regard to sentiment analysis.*

5.3.1 Acquaintance with the concept

Charts 10 and 11 illustrate that acquaintance with sentiment analysis significantly differs in both sectors. Chart 10 indicates that 71% of the media channels, i.e. 5 in 7, have heard of the concept. In the web shop sector, however, only one respondent is familiar with SA. This underscores what our contact person at Indie Group mentioned, i.e. web shops understand the need of a digital strategy but they have not yet adopted it and are thus not familiar with its key concepts.

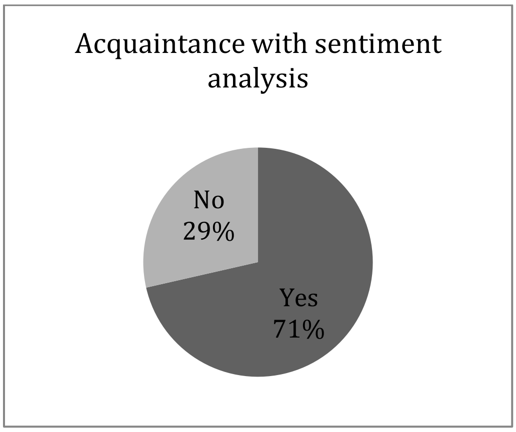

Chart 10: Percentage of Flemish media channels that are familiar with SA.

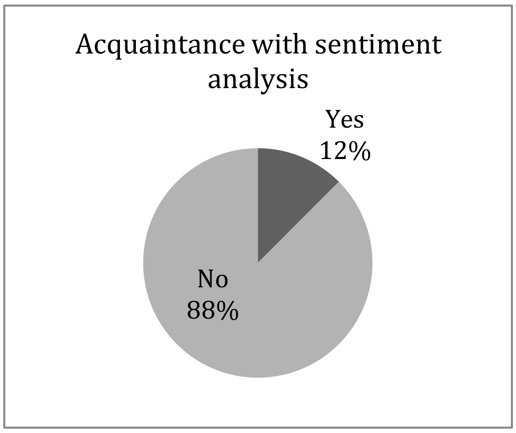

Chart 11: Percentage of web shops that are familiar with SA.

5.3.2 Application of tools

Those respondents that answered the previous question positively, were asked if they used tools and applications for SA. Interestingly, not one respondent in the Flemish media sector said to apply tools. This suggests that although media channels are familiar with the concept of SA, they do not use it in their marketing strategy. As for the web shops, only 1 respondent in 8 uses tools to perform sentiment analysis.

This corresponds with the findings of The Reference in their E-CRM Survey conducted in December 2012. They indicated that companies understand the importance of customer data integration but that this process is still in a very early stage and not yet implemented in the most optimal way. Technology is still perceived as a less important factor, which may explain why the integration of SA in Belgian companies is still in its infancy. The main obstacle, though, might be the lack of budget to implement these technologies in the marketing strategy.

Since there is only one respondent in our study that uses tools for sentiment analysis, we will analyse his or her responses to the additional questions in our survey. Unfortunately, this respondent desired to remain anonymous so we cannot address the company by its name.

As mentioned in Chapter 3, our respondent uses SocialMention and Facebook Insights as tools. SA is performed in the company itself, which allows us to find out which problems our respondent encountered, if at all. Interestingly, the anonymous participant had already encountered some difficulties when using SocialMention, viz. the tool that is freely available online does not always seem to work. This given corresponds with the evaluations that can be read on the SocialMention website, e.g. the service is claimed to be of poor quality. With regard to Facebook Insights, the respondent reported no problems or difficulties.

Apart from getting an insight into the technological and practical application of tools, we wanted to find out what our respondents have realized by means of sentiment analysis. Since there was only one respondent who was familiar with the application of SA, this question was displayed to him or her only. The anonymous participant mentioned that thanks to this segment in language technology, the customer service in the company was much more efficient. It was, for example, easier to respond to customer complaints and to analyse which products or services were less satisfying. At Engagor, Dimitri Callens (2012) refers to this as 'Marketing 2.0'. He points out that "customer service is becoming the foundation of marketing through social media". It allows marketers to better fit the needs of their customers and to ameliorate brands and products accordingly, which will strengthen the relationship between sellers and buyers.

5.3.3 Expectations

In section 6 we will resume what companies currently do with tools and which tasks they would like to be able to perform. We will hence formulate whether the current tools provide an answer to their needs. We therefore tried to get an insight into what marketers expect of sentiment analysis. By means of a multiple choice question our web shop respondents could indicate their expectations. Since we used a skip logic, only the respondents that were acquainted with sentiment analysis could answer this question.

Below we enlist the answers of our anonymous respondent.

#	Answer		Response	%
1	By means of sentiment analysis, I want to have an overview of what is being said online about my company.		1	100%
2	I want to respond to positive or negative comments (e.g. by adapting campaigns).		0	0%
3	I want to know how often my company is mentioned on a social network.		1	100%
4	I want to obtain a higher return on investment.		1	100%
5	I want to compare the position of our company with that of our competitors by analysing online content.		1	100%
6	Other (specify).		0	0%

Table 5: Expectations with regard to sentiment analysis.

The results suggest that this company wants both a general and more detailed overview of what is being spread by consumers on social networks. By measuring how often the companies' name is mentioned, the participant gets a general insight. However, he or she also wants to look at online content in detail to discover what is perceived to be positive or negative with regard to the company and its products. A finer-grained analysis also allows to compare the current position of the company with that of its competitors. By combining the results of these analyses, the company can obtain a higher return on investment.

6 DISCUSSION AND CONCLUSION

6.1 Resume of the results

In this section we will resume the current state of affairs in the adoption and management of social media. The main point of interest of this study, however, was to discover what companies currently do with tools, which tasks they would like to be able to perform and whether the current tools answer their needs. On the basis of this lacuna, if at all, between the theoretical and the practical aspect of sentiment analysis (SA), we will give some recommendations to devise the 'ideal' tool.

The results in the Social Media section of our market study indicate that all respondents have adopted at least one social media network and that Facebook and Twitter are the most popular social media platforms. As for the management of their social media profiles, 83% of the media channels and 50% of the web shops said to manage their profile every day, which indicates that social media have taken a prominent role in the daily business activities. For both media channels and web shops, Facebook and Twitter entail a significant advantage for the companies' strategy and reputation. Google+ is often mentioned as the platform that is the least advantageous. This might be because it encourages private sharing instead of public message posting, and is hence less interesting for our respondents who want to inform and persuade the general public.

From the results of the digital strategy analysis it is clear that 86% of the media channels and 87.5% of the web shops have integrated general Web 2.0 content in their business strategy. This content is used by most respondents to determine their target groups and to launch campaigns in accordance with the needs of their customers. These campaigns are set up for traffic building and to create a link strategy. This means that companies measure how often a specific link gets clicked on in order to get an overview of the public's interests. Apart from the promotional aspect, social network sites also function as a platform for feedback. This suggests that marketers actively want to involve their customers in the company and that they want to stimulate an interactive relationship. The notion of interaction is also displayed in the companies' integration of customer service in social media networks. Issues and complaints are replied to online so that marketers can immediately respond to the particular needs of their customers.

Finally, the Sentiment Analysis section brings us to the core question of this market study. We noticed that both sectors significantly differ in their acquaintance with the concept of SA, i.e. 71% of the media channels questioned were familiar with the concept compared to only 12% in the web shop sector. Although 5 out of 7 media channels were said to be familiar with SA, not one of these respondents used tools to perform this intricate task. This illustrates that although companies are aware of the emergent need of social media content in their strategy, they have not yet adopted the technology to implement this content in the most detailed and optimal way. Interestingly, the sole respondent in the web shop sector that was familiar with SA, also uses tools to perform this task.

On a more detailed level, we inquired about the tools themselves and the problems that arose when using these tools. SocialMention and Facebook Insights were reported as applications to analyse sentiment in online messages. Our respondent indicated that free tools such as SocialMention often deliver a poor service and do not seem to work properly. No other problems were encountered, but this might be because only one respondent could provide us with more detailed information on the application of tools. Our results are thus mainly indicative and should not be generalized. Finally, we inquired about what marketers have concretely realized by performing sentiment analysis. The answer to this question pointed out that the company's customer service could be improved thanks to the analysis of online content. This illustrates that several branches in a business context are becoming increasingly interwoven and that interaction is a key word when adopting a solid digital strategy.

In order to suggest recommendations on how to devise the 'ideal' tool we wanted to get an overview of the expectations marketers have with regard to sentiment analysis. Again, only one respondent could answer this question which entails that the answers are mainly indicative. The results suggest that companies first of all want to get a general overview of their online image. They are interested in how often their brand or products are mentioned on a social network in order to trace whether they generate a lot of buzz.

On a more detailed level, marketers want to find out what is being said about their company specifically and how they are positioned towards their competitors. A financial goal is to eventually obtain a higher return on investment.

6.2 Conclusion

Given the finding that social media take an increasingly prominent role in the communication landscape, language technology is at a turning point. This is illustrated by the large amount of scientific developments in the field and the emergence of new and improved tools to perform social media monitoring tasks. This study is thus an interesting guideline for companies who wish to adopt or refine an online marketing strategy and for developers of sentiment analysis tools to gain an overview of what marketers actually need.

From the results of our market study and previous market studies by The Reference and InSights Consulting we can deduce that companies are aware of a transformed marketing landscape in which social media play an increasingly prominent role. The adoption of social networks illustrates that marketers acknowledge that social media sites are a valuable source of information. Although 90% of the respondents use general social media content in their strategy, only 1 out of 15 respondents performs sentiment analysis to get a detailed image of what is being said online. This illustrates that companies do not integrate this marketing resource in the most optimal way. Compared with the UK and the USA (see results in section 4.1) Flemish media still lag behind in the application of SA and the integration of specific Web 2.0 content in their marketing strategy.

This gap between the adoption and the integration of social media in a business context, allows us to conclude that there is a high need for easy-to-use opinion mining tools that facilitate the processing of online data. What seemed to be most important for the companies we questioned, was that tools give a clear overview of how popular the brand or products are, e.g. by means of measuring the number of mentions. In addition, the tool needs to represent the results of a more detailed analysis in a clear way, so that marketers can easily measure the return on investment their social media activities have generated. We therefore recommend that future tools focus on representing analytical statistics in a graphic visualization so that companies can filter the most relevant information easily.

The majority of tools we have selected provide a large array of multilingual services. We feel that this is a less important aspect for companies in Belgium, since many of their customers write online messages in Dutch, French or English. We emphasize that the number of languages that can be analyzed for sentiment is less important than the quality of the analysis itself. On the basis of the challenges listed in section 2.1.2 and 2.4.1, we recommend that future tools should focus on analyzing online messages at the entity-level since one mention often contains multiple opinions. In addition, it is important to determine the negation scope as this is said to drastically improve sentiment predictions (Councill et al., 2010). Since social media messages are sources of noisy data, we recommend to further study contextual features so that sarcasm and irony, for example, can be detected efficiently.

These particular challenges make social media content a fascinating subject that merits additional study. The rapid emergence of social media imposes that companies need to adapt their marketing strategy accordingly to remain competitive. The right tools to monitor online content can make a significant difference in how companies realize their new strategy. Thanks to efficient tools, they can take business from conversation to conversion (http://conversity.be/en/).

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7.2 List of informants

Joachim De Beule, Data scientist at Engagor, e-mail March, 27, 2013

Kattoo Hillewaere, E-commerce consultant at Indie Group, e-mail February 22, 2013

Reed David, Customer Support at Simply Measured, e-mail March 29, 2013

Thierry Meerschaert, Senior Research Manager Technology & Services at InSites Consulting, November 27, 2013

8 APPENDICES

8.1 Overview of tools

	ENGAGOR	OPENAMPLIFY	SENTIMENT 140	SOCIALMENTION	FACEBOOK INSIGHTS
ASSETS					
Tool/API	Tool, also API	API	Tool, also API	Tool, also API	Tool, also API
Origin	Belgium	USA	USA	USA	USA
Sentiment Analysis	✓	✓	✓	✓	Only negative mentions
Scientific techniques	✓	✓	✓	?	?
Social Media Monitoring	✓	✓			✓
Interactivity	✓	✓			
Graphic visualization	✓	✓		?	✓
Multilingual	✓		✓	✓	✓
Filters	✓	✓		✓	✓
Export data	✓	✓	?	?	?
Continual improvements	✓	✓	Not certain		✓
Clear online manual	✓	✓	✓		✓
Free trial	✓	✓	Tool is free	Tool is free	
Price	€450-€1750	On demand	$200 for API (±€155)	API on demand	Free

8.2 Overview of respondents

Colour-code: respondents in grey have participated in the survey.

MEDIA	WEB SHOPS	
Newspapers	**Beverages/Food**	**Other**
HET NIEUWSBLAD	COLRUYT	GAMMA
GAZET VAN ANTWERPEN	DOUWE EGBERTS	ICI PARIS XL
HET BELANG VAN LIMBURG	DUVEL-MOORTGAT	PLOPSA
HET LAATSTE NIEUWS	LIEFMANS	STANDAARD BOEKHANDEL
DE STANDAARD	UNILEVER	VERTROUWELIJK
DE MORGEN		
	Clothing	
Magazines	3 SUISSES	
FLAIR (Sanoma)	BEL & BO	
NINA	BONPRIX	
FEELING	E5 MODE	
LIBELLE	LA REDOUTE	
HUMO (Sanoma)	SNAPSTORE	
GOED GEVOEL	TORFS	
MARIE-CLAIRE	VANDEVELDE	
	VENTE EXCLUSIVE	
Television channels	ZALANDO	
SBS	ZEB	
VMMA		
VRT	**Electronics**	
2BE	FREE RECORD SHOP	
TMF	NECKERMANN	
Radio stations	**Furnishing**	
Q-GROUP (Vmma)	AXESWAR DESIGN	
MNM (VRT)	UNIGRO	
RADIO 2		
RADIO 1 (VRT)	**Travel**	
STUDIO BRUSSEL	JETAIR	
KLARA	NECKERMANN	
	THOMAS COOK	
Media conglomerates		
DE PERSGROEP ADVERTISING	**Transport**	
SANOMA	DE LIJN	
CORELIO	NMBS	
CONCENTRA		
ROULARTA MEDIA		

8.3 Example of surveys

8.3.1 Survey A

1. Is uw bedrijf/organisatie actief op sociale media?

#	Answer	Bar	Response	%
1	Ja		1	100%
2	Neen		0	0%
	Total		1	

2. Op welke sociale netwerken/media is uw bedrijf actief?

#	Answer	Bar	Response	%
1	Twitter		1	100%
2	Facebook		1	100%
3	LinkedIn		1	100%
4	Google+		0	0%
5	Andere		0	0%

Andere

3. Hoe vaak per week (maandag tot vrijdag) beheert u uw account/persoonlijke bedrijfspagina?

#	Answer	Bar	Response	%
1	1 keer per week		0	0%
2	2 keer per week		0	0%
3	Iedere dag		1	100%
4	Andere (specifieer)		0	0%
	Total		1	

Andere (specifieer)

4. Waarvoor gebruikt uw bedrijf zijn persoonlijke pagina? Verschuif het pijltje om uw activiteit weer te geven. 0 betekent 'ik gebruik mijn persoonlijke pagina hiervoor niet', 1 betekent 'dit is mijn voornaamste activiteit op mijn persoonlijke pagina'.

#	Answer	Min Value	Max Value	Average Value	Standard Deviation	Responses
1	Informatie geven over het bedrijf	94.00	94.00	94.00	0.00	1
2	Reclame maken	80.00	80.00	80.00	0.00	1
3	Wedstrijden opzetten	52.00	52.00	52.00	0.00	1
4	Vacatures openstellen	58.00	58.00	58.00	0.00	1
5	Als maatstaf voor het aantal fans	38.00	38.00	38.00	0.00	1
6	Andere	0.00	0.00	0.00	0.00	-

5. Is er iemand specifiek aangesteld om de bedrijfspagina op sociale media te beheren?

#	Answer	Bar	Response	%
1	Ja		1	100%
2	Neen		0	0%
	Total		1	

6. Is er mogelijkheid tot dialoog op uw persoonlijke bedrijfspagina? Bijvoorbeeld: reageert u op reacties zoals klachten?

#	Answer	Bar	Response	%
1	Ja		1	100%
2	Neen		0	0%
	Total		1	

7. Gebruikt u de verzamelde informatie op sociale netwerksites in uw marketingstrategie?

#	Answer	Bar	Response	%
1	Ja		1	100%
2	Neen		0	0%
	Total		1	

8. Beschrijf kort hoe u deze informatie verwerkt in uw strategie (bijvoorbeeld: inspelen op het aantal fans, inspelen op reacties,...)

Text Response
Uitgebreidere artikels schrijven over onderwerpen die vaak aangeklikt worden.

9. Wordt sociale media in het algemeen gescreend in uw bedrijf? Wilt u, bijvoorbeeld, een algemeen overzicht krijgen van wat er zich op sociale media afspeelt? (Het gaat hier dus niet specifiek om de persoonlijke bedrijfspagina).

#	Answer	Bar	Response	%
1	Ja		1	100%
2	Neen		0	0%
	Total		1	

10. Heeft u al eens gehoord van sentiment analyse (ook wel: sentiment detectie, opinion mining)?

#	Answer	Bar	Response	%
1	Ja		1	100%
2	Neen		0	0%
	Total		1	

11. Gebruikt u bepaalde tools voor sentiment analyse? Specifieer welke tools.

#	Answer	Bar	Response	%
1	Ja		0	0%
2	Nee		1	100%
	Total		1	

Ja

12. Hoe evalueert u uw aanwezigheid op sociale netwerksites als een meerwaarde voor uw bedrijf? Indien u op meerdere netwerksites actief bent, kunt u meerdere evaluaties invullen.

#	Question	Helemaal geen meerwaarde	Nauwelijks meerwaarde	Neutraal	Gemiddelde meerwaarde	Absolute meerwaarde	Total Responses
1	Facebook	0	0	0	0	1	1
2	Twitter	0	0	0	0	1	1
3	LinkedIn	0	0	0	1	0	1
4	Google+	0	0	0	0	0	0
5	Andere (specifieer)	0	0	0	0	0	0

Andere (specifieer)

13. Wat is de naam van uw bedrijf/organisatie?

Text Response
Lana Eeckhout

8.3.2 Survey B

1. Is uw bedrijf/organisatie actief op sociale media?

#	Answer	Bar	Response	%
1	Ja		1	100%
2	Neen		0	0%
	Total		1	

2. Op welke sociale netwerken/media is uw bedrijf actief?

#	Answer	Bar	Response	%
1	Twitter		1	100%
2	Facebook		1	100%
3	LinkedIn		1	100%
4	Google+		0	0%
5	Andere		0	0%

Andere

3. Hoe vaak per week (maandag tot vrijdag) beheert u uw account/persoonlijke bedrijfspagina?

#	Answer	Bar	Response	%
1	1 keer per week		0	0%
2	2 keer per week		0	0%
3	Iedere dag		1	100%
4	Andere (specifieer)		0	0%
	Total		1	

Andere (specifieer)

4. Waarvoor gebruikt uw bedrijf zijn persoonlijke pagina? Verschuif het pijltje om uw activiteit weer te geven. 0 betekent 'ik gebruik mijn persoonlijke pagina hiervoor niet', 1 betekent 'dit is mijn voornaamste activiteit op mijn persoonlijke pagina'.

#	Answer	Min Value	Max Value	Average Value	Standard Deviation	Responses
1	Informatie geven over het bedrijf	94.00	94.00	94.00	0.00	1
2	Reclame maken	80.00	80.00	80.00	0.00	1
3	Wedstrijden opzetten	52.00	52.00	52.00	0.00	1
4	Vacatures openstellen	58.00	58.00	58.00	0.00	1
5	Als maatstaf voor het aantal fans	38.00	38.00	38.00	0.00	1
6	Andere	0.00	0.00	0.00	0.00	-

5. Is er iemand specifiek aangesteld om de bedrijfspagina op sociale media te beheren?

#	Answer	Bar	Response	%
1	Ja		1	100%
2	Neen		0	0%
	Total		1	

6. Is er mogelijkheid tot dialoog op uw persoonlijke bedrijfspagina? Bijvoorbeeld: reageert u op reacties zoals klachten?

#	Answer	Bar	Response	%
1	Ja		1	100%
2	Neen		0	0%
	Total		1	

7. Is er mogelijkheid tot dialoog op uw persoonlijke bedrijfspagina?
Bijvoorbeeld: reageert u op reacties zoals klachten?

#	Answer	Bar	Response	%
1	Ja		1	100%
2	Nee		0	0%
	Total		1	

8. Gebruikt u de verzamelde informatie op sociale netwerksites in uw marketingstrategie?

#	Answer	Bar	Response	%
1	Ja		1	100%
2	Nee		0	0%
	Total		1	

9. Beschrijf kort hoe u deze informatie verwerkt in uw strategie (bijvoorbeeld: inspelen op het aantal fans, op reacties,...).

Text Response
Inspelen op het aantal fans dat een Facebook-bericht leuk vindt.

10. Wordt sociale media in het algemeen gescreend in uw bedrijf? Wilt u zo, bijvoorbeeld, op de hoogte blijven van de concurrentie? (Het gaat hier dus niet om de persoonlijke bedrijfspagina.)

#	Answer	Bar	Response	%
1	Ja		1	100%
2	Nee		0	0%
	Total		1	

11. Heeft u al eens gehoord van sentiment analyse? (Ook wel: opinion mining, sentimentdetectie)

#	Answer	Bar	Response	%
1	Ja		1	100%
2	Nee		0	0%
	Total		1	

12. Doet u binnen uw bedrijf aan sentiment analyse of besteedt u deze taak uit?

#	Answer	Bar	Response	%
1	Binnen mijn bedrijf is er een verantwoordelijke aangesteld.		1	100%
2	Ik besteed deze taak uit.		0	0%
	Total		1	

13. Gebruikt u bepaalde tools voor sentiment analyse? Specifieer welke tools.

#	Answer	Bar	Response	%
1	Ja		1	100%
2	Nee		0	0%
	Total		1	

Ja
Engagor

14. Ondervindt u problemen met deze tools? Zo ja, welke?

#	Answer	Bar	Response	%
1	Ja		0	0%
2	Nee		1	100%
	Total		1	

Ja

15. Wat verwacht u van sentiment analyse? U kan meerdere antwoorden aanvinken.

#	Answer	Bar	Response	%
1	Ik verwacht dat ik zo kan nagaan wat er over mijn bedrijf geschreven wordt.		1	100%
2	Ik wil inspelen op positieve of negatieve commentaar (vb. door campagnes aan te passen).		1	100%
3	Ik wil weten hoe vaak mijn bedrijf vernoemd wordt op een sociaal netwerk.		1	100%
4	Ik wil een hogere return on investment behalen.		0	0%
5	Ik wil onze positie ten opzichte van de concurrentie nagaan door online inhoud te analyseren.		1	100%
6	Andere: specifieer		0	0%

Andere: specifieer

16. Wat heeft u concreet gerealiseerd met sentiment analyse? Heeft u via deze weg, bijvoorbeeld, al ingespeeld op wat er online over uw bedrijf verspreid werd? Licht kort toe.

This question was not answered by the respondent.

17. Hoe ziet u de aanwezigheid op sociale netwerksites als een meerwaarde voor uw bedrijf? Indien u op meerdere netwerksites actief bent, kunt u meerdere evaluaties invullen.

#	Question	Helemaal geen meerwaarde	Nauwelijks meerwaarde	Neutraal	Gemiddelde meerwaarde	Absolute meerwaarde	Total Responses	Mean
1	Twitter	0	0	0	0	1	1	5.00
2	Facebook	0	0	0	0	1	1	5.00
3	LinkedIn	0	0	0	0	0	0	0.00
4	Google+	0	0	0	0	0	0	0.00
5	Andere (specifieer)	0	0	0	0	0	0	0.00

Andere (specifieer)

18. Wat is de naam van uw bedrijf/organisatie?

Text Response
Lana Eeckhout

Dissertatiegegevens bij fiche

Titel van de scriptie

From conversation to conversion
An explorative study on the adoption of social media and the application of sentiment analysis in Flemish media and web shops

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Taal van de scriptie

Engels

Vrije trefwoorden

Sentiment Analysis
Social Media
Marketing Strategy
Opinion Mining Tools
Web 2.0
User-generated Content
Machine Learning

Trefwoorden en annotatie

Trefwoord:
Taaltechnologische studie

Annotatie:
Geen centraal werk

Iwetocodes

H350-linguïstiek
S191-marktstudie
S190-bedrijfsbeleid

Doelstelling, methode en resultaten

Doelstelling:
In deze masterproef wordt onderzocht of bedrijven afhankelijk zijn van hun online imago en hoe ze dit imago proberen te bewaken. Daarbij komen de volgende deelvragen aan bod: zijn bedrijven actief op sociale media en passen ze met tools sentiment analyse toe om een inzicht te krijgen in de zogenaamde Web 2.0 content? Een uitgebreide literatuurstudie van het domein van de sentiment analyse en een verkennende marktstudie laten toe om een eventuele kloof te ontdekken tussen de verwachtingen van bedrijven omtrent deze technologie en de mogelijkheden die de huidige tools bieden.

Methode:
Aan de hand van een grondige literatuurstudie wordt eerst de status quaestionis in het onderzoeksdomein samengevat. Na deze wetenschappelijke bespreking volgt een kritische analyse van een aantal tools en applicaties zodat de lezer ook een inzicht krijgt in de praktische toepassingen van sentiment analyse. Aan de hand van een marktstudie wordt ten slotte nagegaan of bedrijven actief zijn op sociale media en of ze sentiment analyse tools ook effectief gebruiken om hun online imago te bewaken. Als doelgroep werd gekozen om te werken met Vlaamse media en web shops.

Resultaten:
Uit de resultaten van de marktstudie blijkt dat alle respondenten, 7 uit de Vlaamse media en 8 uit web shops, actief zijn op ten minste één sociaal netwerk. Daarnaast stelden we vast dat de eigenlijke content op deze netwerken bij beide doelgroepen, i.e. 90%, al een deel uitmaakt van de online marktstrategie.Toch zien we dat slechts 1 op 15 respondenten sentiment analyse toepast om een meer gedetailleerd beeld te verkrijgen van wat er online over het bedrijf wordt verspreid. Deze kloof tussen de activiteit op sociale media en de integratie van sentiment analyse tools, wijst erop dat dit medium nog niet optimaal geïntegreerd is in de bedrijfsstrategie. Als we deze bevinding plaatsen naast de grote wetenschappelijke ontwikkelingen in het veld en het veelvuldig verschijnen van nieuwe tools kunnen we stellen dat we ons op een keerpunt bevinden. Deze studie is dan ook een goed vertrekpunt voor bedrijven die wensen hun online marktstrategie verder uit te bouwen of voor ontwikkelaars van sentiment analyse tools om nieuwe inzichten te verkrijgen in de markt.