Sentiment Analysis for Issues Monitoring Using Linguistic Resources

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Résumé L'identification et l'évaluation des avis, opinions ou jugements exprimés sur un sujet, une entreprise, ou un produit sont des tâches essentielles dans le domaine de l'analyse des médias. L'étude d'opinion est employée pour repérer de nouvelles tendances, mesurer le degré de satisfaction des clients ou pour alerter quand des tendances négatives risquent d'être défavorable à l'image de marque de l'entreprise. Dans cet article nous présentons un outil de veille économique qui permet de classifier très finement des documents publiés en ligne ainsi que d'identifier et d'évaluer les opinions exprimées dans des articles en ligne et des forums de discussions. Après la présentation des diverses composantes du système et des ressources linguistiques utilisées, nous décrivons en détail **SentA**, la composante d'étude d'opinions, et évaluons sa performance.

Abstract Sentiment analysis dealing with the identification and evaluation of opinions towards a topic, a company, or a product is an essential task within media analysis. It is used to study trends, determine the level of customer satisfaction, or warn immediately when unfavourable trends risk damaging the image of a company. In this paper we present an issues monitoring system which, besides text categorization, also performs an extensive sentiment analysis of online news and newsgroup postings. Input texts undergo a morpho-syntactic

analysis, are indexed using a thesaurus and are categorized into user-specific classes. During sentiment analysis, sentiment expressions are identified and subsequently associated with the established topics. After presenting the various components of the system and the linguistic resources used, we describe in detail **SentA**[1]**,** its sentiment analysis component, and evaluate its performance.

1   Introduction

In recent years the tendency to exploit the huge amount of information available on the internet, especially in form of news articles or newsgroup postings for marketing and corporate communication purposes, has increased considerably. Text mining techniques have been developed to find relevant texts, classify them into meaningful clusters and also to extract specific information from them. One of the more sophisticated information extraction tasks, which has proved to be extremely valuable for companies, is the identification of sentiments towards a topic, a company, or a product in online news and newsgroup postings. This is essential for evaluating trends in public opinion, determining the level of customer satisfaction and taking preventive measures in case the level of dissatisfaction risks damaging the image of the company.

Various approaches to automatic sentiment evaluation have been proposed in order to efficiently deal with the large amount of available data as well as to reduce the high costs associated with the manual evaluation of such information. On the one hand, statistical text mining approaches, especially machine learning methods such as support vector machines for finding minimum cuts in graphs, have been used in order to classify texts as either positive or negative (Pang, Lee, 2004; Mullen, Collier, 2004). The approaches are known to be effective but also of limited use in areas where a high precision of results is needed. On the other hand, more elaborate approaches use linguistic resources in order to identify (1) expressions indicating opinions, (2) the polarity of the detected expressions as well as (3) the entity or topic to which the opinion refers. Typical examples of such systems are the ones developed by the CELI group (Dini, Mazzini, 2002) which analyzes customer opinions about mobile phones and identifies the polarity of opinions about specific parts or functions as well as the **Sentiment Analyzer** of IBM and the University of Texas (Yi et al., 2003) which extracts opinions about a given subject from online documents. However, obtaining a more fine-grained classification of opinions in terms of both granularity and specificity would be of much interest for many companies or agencies. For instance, within the **DeepThought** project experiments were carried out in which the CELI approach was extended by integrating deeper processing steps involving HPSG (Beermann et al., 2004). In this way more specific information concerning topics or the causes that brought about a particular judgment could be identified.

In this paper we present an issues monitoring system which performs a fine-grained analysis and classification of sentiments related to user-specific topics or aspects of them. The aim of our approach is to establish not only the polarity of the sentiments towards a specific topic identified in the text - as done in the above mentioned systems - but also to identify the

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[1] **SentA**: **S**entiment **A**nalysis

degree of positive or negative orientation as well as quantify the degree of emotional implication carried by sentiment expressions. To this end, the system makes use of various linguistic resources. Thesauri, lexicons and specific patterns are used to identify topics in German online texts, detect sentiment expressions, establish sentiment orientation and strength of emotional involvement, as well as associate the detected sentiment expressions to the established topics.

In the following section we describe the issues monitoring system: we present its architecture, the resources used during the monitoring process, and illustrate its way of functioning by means of an example. Then, in Section 3, we focus on the various steps involved in the sentiment analysis with **SentA**, whereas in Section 4 we present an experiment carried out to evaluate the sentiment analysis process and discuss the results. Finally, we present our conclusions and point to future work.

2   The Issues Monitoring System

2.1   Architecture and Resources

In order to perform a fine-grained analysis and classification of sentiments related to user-specific topics, we have adapted an automatic indexing tool described in (Ripplinger, Schmidt, 2001). The modified architecture is shown in Figure 1.
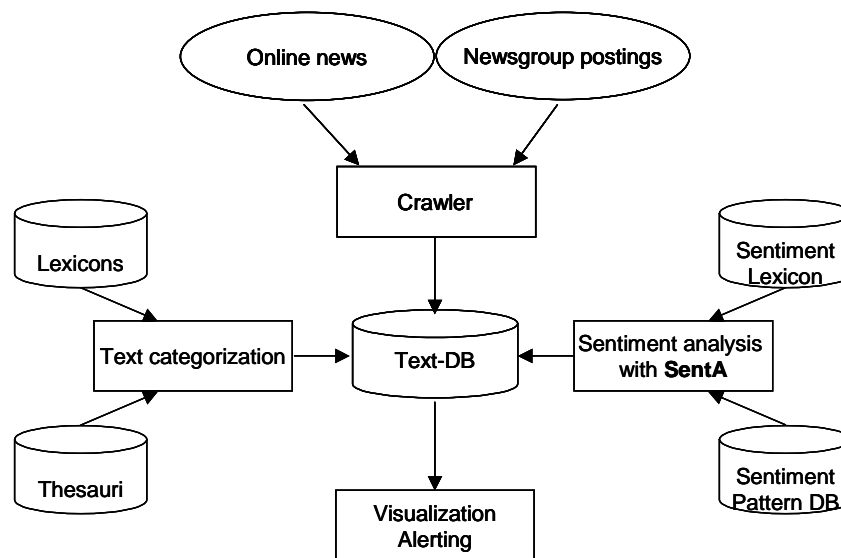

Figure 1 : Architecture of the issues monitoring system

The crawler downloads hourly news articles and newsgroup postings from specific websites. Then, in order to classify the retrieved texts, the input undergoes linguistic processing. The first step consists in the morphological analysis of the input with the package MPRO (Maas, 1996). It involves lemmatization, part-of-speech tagging and homograph analysis. Monolingual lexicons are used in order to assign information concerning word class, semantic

features, as well as derivation or decomposition in case of compound words. Then, shallow parsing is carried out to disambiguate the input and identify multiword terms and their respective variants. Eventually, a list of descriptors defining the topic of the text or aspects of it is generated by statistically evaluating the semantic load of the text and by weighing this information against a thesaurus. At this stage the text is classified using either a classification scheme provided by the user or the predefined codes assigned to terms in the lexicon (Ripplinger, Schmidt, 2001).

The next processing step is the analysis of the sentiments expressed in the input texts with **SentA**. Two types of resources are involved in this process. The first one is a sentiment lexicon in which expressions are encoded together with a manually assigned sentiment orientation. In some entries word stems are fully specified whereas in others regular expressions are used in order to ensure a broader coverage. The second resource is a sentiment pattern database including an ordered set of typical patterns involving sentiment expressions. Such patterns are used to establish if the sentiment orientation of an expression has been changed by certain features revealed during the analysis or by the immediate context. As will be shown in Section 3.2, sentiment orientation might be reinforced, attenuated, or even reversed depending on the context. Moreover, specific patterns are used to associate sentiment expressions either to the main topic or to aspects of it.

The last step is visualizing the analysis results. The sentiment values are cumulated for each user-specific issue. On the basis of such information, the issues monitoring system is able to show the development of attitudes or opinions towards a specific subject for a given period of time. The charts in Figure 2 show the results of the categorization and sentiment analysis processes. The chart on the left hand side (LHS) presents the three most negative issues over an interval of seven days (*7 Tage*) in online news. In the case shown here the three issues are *Sicherheit* (*safety*), *Pünktlichkeit* (*punctuality*), and *Mehdorn*, who is the chairman of the executive board at the German railway company *Deutsche Bahn*. The y-axis shows the sentiment value from neutral (*neut*) to negative (*neg*) on the LHS whereas on the right hand side (RHS) the same values are visualized through the changing colours of the column from yellow (neutral) to red (negative). A dot at the end of a line in the chart represents the position of an issue during the current week while the other end indicates the position of the same issue the week before. The x-axis shows the *media presence value* (*Medienpräsenz*) of an issue. This value is calculated by taking into account the length of the articles relevant for that issue and specific website frequency scores. The more an issue is located at the RHS the more spread it is among the public. The chart on the RHS illustrates the development of an issue, i.e. *railway* (*Bahn*) over a period of 12 months. The y-axis shows media presence values on the LHS as well as negative sentiment values with colours changing from yellow (neutral) to red (negative) on the RHS. The x-axis shows the 12-month time period[2].

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[2] Since the system has been in use only since October, the RHS chart does not contain any information for the previous months.
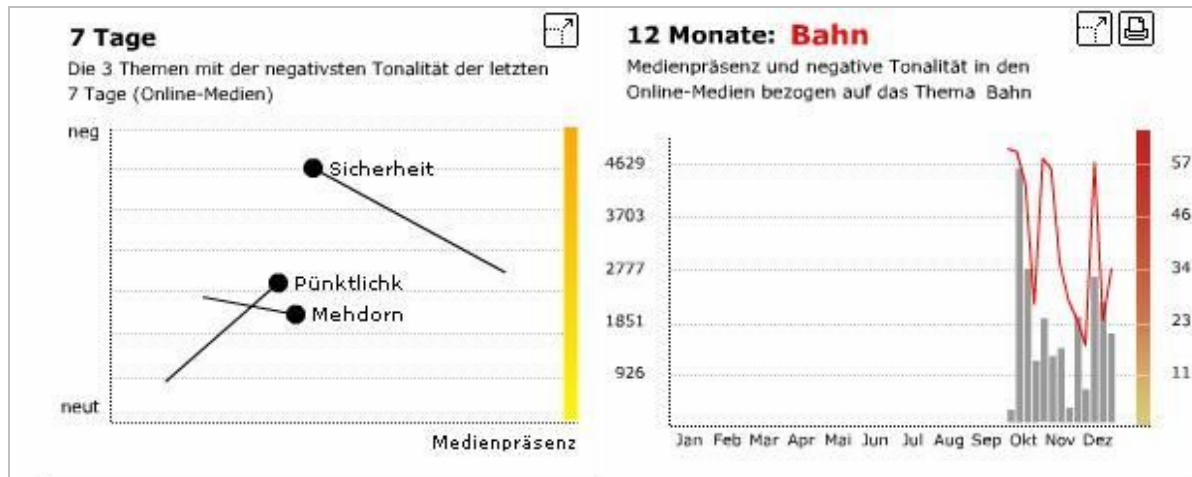
Figure 2 : Visualizing the results of the categorization and sentiment analysis processes

2.2 Example

Example (1)[3] illustrates the text categorization and the sentiment analysis processes for a given sentence. As described in Section 2.1 the descriptors *Fernverkehr* (*long distance traffic), Nahverkehr* (*short distance traffic)*, and *Preis* (*price*) are computed as being relevant to the main topic of the text. In the field *Oberbegriff* (*Hyperonym*), the hyperonyms of these descriptors are listed. Hyperonym information as well as the data concerning general categorization schemes listed in the *Special Field* are encoded in the thesaurus.

1. Die Preise im Fernverkehr sind seit Sonntag um 3,1 Prozent, im Nahverkehr sogar um durchschnittlich 3,6 Prozent teurer.
   (*Ticket prices in long distance traffic increased by 3.1 percent, in short distance traffic actually by an average of 3.6 percent.*)

Descriptors:	Fernverkehr[100]; Nahverkehr[100]; Preis[50];
Special Field:	n6021 (Personenbeförderung)[100]; n6000 (Landverkehr)[100];
Oberbegriff:	Verkehr[100]; Preis[50];
Opinions:	{ori=teurer,opinion=S-1+2,desc=fernverkehr;nahverkehr}

The field *Opinions* contains the results of the sentiment analysis process. The sentiment expression *teurer* (*more expensive*) is assigned a semantic orientation value (*opinion=S-1+2*) and is associated with the descriptors *Fernverkehr* and *Nahverkehr* (*desc=fernverkehr; nahverkehr*). Section 3 provides a more detailed description of the sentiment analysis process.

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[3]In order to keep explanations simple, only those aspects of the output are presented that are relevant for our paper. In all examples the results of the sentiment analysis are given in form of attribute-value pairs grouped in a feature bundle. The attributes used for illustration have the following meaning: *ori* – surface form of the input word, *opinion* – sentiment orientation, *desc* – descriptor.

3   Sentiment Analysis with SentA

In this section we describe the various steps involved in sentiment analysis and illustrate them with examples. The first step of the analysis is the matching of the sentiment lexicon against an input text (cf. Section 3.1). Secondly, the patterns concerning change in sentiment degree are applied in order to identify contexts reinforcing or attenuating sentiments (cf. Section 3.2). In a third step negation patterns, which are used to discover contexts that change the polarity of sentiment orientation, are considered. Eventually those patterns are applied that try to associate the discovered sentiment expressions to the main topic or to one of the aspects of a topic identified in the analyzed text.

3.1   Lexical Matching

When matching the sentiment lexicon against the input text, the sentiment expressions detected in the text are associated with the corresponding sentiment orientation values found in the lexicon. In Example (2) the verb *hofft* (*hopes*) is identified as sentiment expression and associated with the sentiment orientation value *S+1+2* (*opinion=S+1+2*). The sentiment orientation value involves two dimensions: the first dimension is the degree of positive or negative orientation measured on a scale from -6 to +6; the second one quantifies the degree of emotional implication on a scale from 0 to +6. The latter dimension was introduced in order to quantify how strong the preference or aversion towards a specific topic is. In our example these two dimensions are: +1, indicating a slightly positive orientation, respectively +2, marking a somewhat increased emotional involvement.

2.   Jetzt hofft die Bahn AG auf Verkehrszuwachs.
    (*The Bahn AG hopes that traffic will increase*)
    {expression=hofft, opinion=S+1+2,desc=bahn}

3.2   Pattern Matching

Pattern matching in **SentA** serves various purposes. After identifying sentiment expressions in input texts, **SentA** examines if the marked items are actually relevant for sentiment analysis. For example specific patterns are used to identify and filter out items that appear in questions or in the vicinity of particular structures. Then, typical patterns are applied in order to determine if the orientation of the detected sentiment expressions has been altered. We consider two categories of patterns to detect such cases: degree patterns and negation patterns. A third category of patterns called topic-relevant sentiment patterns is used in order to determine possible associations of a sentiment expression with one or several descriptors. The patterns are implemented in KURD[4], a flat pattern matching formalism (Carl & Schmidt-Wigger, 1998).

Degree Patterns

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[4] KURD is an acronym representing the first letters of the basic actions of the formalism : Kill, Unify, Replace, Delete.

Degree patterns are used to establish if the sentiment orientation value of an expression has been reinforced or attenuated. In certain cases the meaning of a sentiment expression is modified through specific features such as the use of the comparative or the superlative degree in case of adjectives or adverbs. Context may also have such an influence on meaning. In (3) for example, the negative meaning of the noun *Protest* is reinforced through the use of the modifying adjective *heftig* (*fierce*).

3. Dies führte zu heftigen Protesten.
   (*This lead to fierce protests.*)
   {ori=Protesten,opinion=S-4+3}.

Specific patterns relying both on morphological and contextual information have been implemented in **SentA** in order to recognize such contexts and adjust the value of the sentiment orientation feature accordingly. In (3) the original sentiment orientation of the word *Protest*, *opinion=S-2+2*, is augmented to *opinion=S-4+3*. After detecting contexts of sentiment reinforcement or attenuation, the next step in the sentiment analysis process is applied.

Negation Patterns

Negation within an utterance changes the semantic orientation of sentiment expressions. Therefore, negation patterns are applied to the modified input, in order to detect negation markers and adjust the semantic orientation of the corresponding sentiment expressions accordingly. In (4) the semantic orientation of the adjective *zufrieden* (*satisfied*) is changed from *S+1+1* to *S-1+0* under the influence of the detected negative marker *nicht*.

4. "Wir werden uns damit nicht zufrieden geben", so Kohl.
   (*"We won't be satisfied with that", said Kohl*)
   {ori=zufrieden,opinion=S-1+0}

Topic-Relevant Sentiment Patterns

Once the sentiment orientation value of an expression has been established, **SentA** tries to associate the identified sentiment expression to the corresponding topic or issue. In Section 2 we mentioned that during the text categorization process, so-called descriptors, indicators of the topic or of its aspects, are computed. The topic–relevant sentiment patterns try to associate these descriptors to the sentiment expressions marked in the text. Some of these patterns are linguistically motivated. However, when no linguistically motivated pattern applies and the utterance contains both descriptors and sentiment expressions, other patterns relying on information concerning general sentence structure or vicinity try to associate them. As shown in examples (2) and (5) the base form of the descriptors detected in the sentence are assigned as values to the attribute *desc*.

5. Die Preise im Fernverkehr sind seit Sonntag um 3,1 Prozent, im Nahverkehr sogar um durchschnittlich 3,6 Prozent teurer.
   (*Ticket prices in long distance traffic increased by 3.1 Percent, in short distance traffic actually by an average of 3.6 Percent.*)
   {ori=teurer,opinion=S-2+3,desc=fernverkehr;nahverkehr}

In case of example (2) the association of the descriptor *Bahn* to the sentiment expression *hofft* was motivated by a linguistic pattern, i.e. a verb expressing sentiments is likely to refer to the grammatical subject of the sentence. On the other hand, in (5), patterns relying on information concerning coordination and sentence structure in general are used to associate the predicatively used adjective *teuer* to the descriptors *Fernverkehr* and *Nahverkehr*.

In the next section we evaluate the overall performance of **SentA**. Besides, the reliability of the various resources involved in the sentiment analysis process is tested.

4   Evaluation of SentA

For the evaluation of the system we used two classes of texts dealing with the German Railway Company *Deutsche Bahn*. The first category, henceforth *Bahn-News*, consists of 25 news texts automatically retrieved by the issues monitoring system from the internet. The second category of texts, *Bahn-Group*, includes 25 texts retrieved from various newsgroups on the net.

We established gold standards by manually annotating the text segments expressing opinions in all texts. Besides identifying the sentiment expressions (SE) in the test texts, the manual annotation also includes information concerning degree of sentiment orientation (D), negation (N) and the association of sentiment expression to particular topic descriptors (SE-TD). The following figure summarizes the characteristics of the two text classes.

Text class	Texts	Sentences	Words	SE	D	N	SE-TD
Bahn-News	25	484	8420	266	39	15	148
Bahn-Group	25	183	2863	160	15	6	59

Figure 3 : Characteristics of the test texts

We used the *Bahn-News* texts to tune our system to the specific topic *railway*. During tuning we extended the sentiment lexicon and the sentiment template database in order to cover as many sentiment expressions and typical patterns found in the *Bahn-News* texts as possible. Then, we compared the gold standards for both text classes with the automatic annotation of the test texts and computed precision and recall (cf. Figure 4) for detecting sentiment expressions and the corresponding sentiment orientation values. The association of sentiment expression to topic descriptors was evaluated at a later stage (cf. Figure 5).

Text class	Recall	Precision
Bahn-News	99%	97%
Bahn-Group	75%	92%

Figure 4 : Recall and precision values for the test texts

As expected, recall and precision for the *Bahn-News* texts are very high. Precision in case of the *Bahn-Group* texts is fairly high whereas recall is considerably lower than for the *Bahn-News* texts. Decrease in recall is mainly due to sentiment expressions that are not covered in the sentiment lexicon. Many of these expressions are rather colloquial and thus more typical to newsgroup postings than to the online articles on which the system was trained. Other missing sentiment expressions as *einfach* (*simple*) are ambiguous and can be used with different polarity depending on the context.

Figure 5 presents recall and precision values for all the resources involved in the sentiment analysis process considered independently. For all resources both recall and precision values for the *Bahn-Group* texts decrease. Decrease in recall is mainly due to sentiment expressions or patterns not yet covered in the resources. Precision in case of the degree and negation patterns is relatively high, 88% respectively 80%. However the number of such patterns detected in the test texts is too low to attempt any kind of generalization at the moment.

	SE		D		N		SE-TD	
Text class	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
Bahn-News	99%	97%	97%	97%	93%	100%	82%	61%
Bahn-Group	75%	92%	88%	88%	67%	80%	64%	57%

Figure 5 : Recall and precision values SE, D, N, und SE-TD

As shown in Figure 5 recall and precision values in case of the topic relevant sentiment patterns are quite low. In many cases, templates based on vicinity information lead to wrong associations which could be avoided by implementing more templates that are linguistically motivated.

5   Conclusions and Outlook

In this paper we described an issues monitoring system which uses linguistic resources to perform a fine-grained analysis and classification of sentiments related to user-specific topics. The evaluation of the sentiment analysis component shows that the performance of **SentA** can be compared to that of the CELI system (Dini, Mazzini, 2002) and **Sentiment Analyzer** (Yi et al., 2003). Even though a direct comparison of the approaches is not possible due to the differences in the technical approach, development, test corpora or covered patterns, figures show that the overall precision for the *Bahn-Group* texts (92%) is comparable to the values obtained with the CELI system (92%) and the **Sentiment Analyzer** (87%). Recall with **SentA** is, however, higher: 75% vs. 52% with the CELI system and 56% with **Sentiment Analyzer**. The evaluation also shows that the patterns associating sentiment expressions to the main topic of a text or to its various aspects need to be further refined. This seems to be a major problem in the CELI approach, too (Beermann et al., 2004). The experiment reported in (Beermann et al., 2004) showed that by integrating deep analysis with HPSG inappropriate sentiment expression – topic associations could be filtered out and thus noise could be reduced. However, the fact that recall could not be increased and the relatively high percentage of non-parsed text units (27%) along with longer processing times required by

deep analysis in general raises the question if deep analysis is the appropriate technique to be used to increase the overall efficiency of an issues monitoring system. Therefore, future work on **SentA** will rather concentrate on further refining the resources used for shallow processing, more specifically on the implementation of further linguistically motivated templates for the assignment of sentiment expressions to specific topics. Moreover, topic association needs to be extended to the text level and therefore, such phenomena as anaphora resolution or ellipsis must be addressed.

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