Feature-Based Visual Sentiment Analysis of Text Document Streams

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This article describes automatic methods and interactive visualizations that are tightly coupled with the goal to enable users to detect interesting portions of text document streams. In this scenario the interestingness is derived from the sentiment, temporal density, and context coherence that comments about features for different targets (e.g., persons, institutions, product attributes, topics, etc.) have. Contributions are made at different stages of the visual analytics pipeline, including novel ways to visualize salient temporal accumulations for further exploration. Moreover, based on the visualization, an automatic algorithm aims to detect and preselect interesting time interval patterns for different features in order to guide analysts. The main target group for the suggested methods are business analysts who want to explore time-stamped customer feedback to detect critical issues. Finally, application case studies on two different datasets and scenarios are conducted and an extensive evaluation is provided for the presented intelligent visual interface for feature-based sentiment exploration over time.

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1. INTRODUCTION

In the last decade the amount of textual information readily available in digital form has increased enormously. Especially, the amount of user-generated content has grown at a fast pace lately, as the Web 2.0 has enabled easy participation for all

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Internet users. Large amounts of texts are provided through blogs, forums, wikis, twitter messages, companies' online surveys, and feedback forms and also through more formal publications like RSS news feeds and online news Web sites.

These text sources constitute a rich body of information that is valuable to exploit for different stakeholders with different information needs. Methods from text mining, natural language processing, and computational linguistics can help to extract interesting features out of the raw text data. However, not only automatic algorithms for data analysis are important, but also to appropriately convey detected peculiarities to the analyst and offer possibilities for interactive data exploration. In the case of such complex and ambiguous data as natural language text this requires possibilities to drill-down to the original text sources whenever needed in order to make sense of the automatic analysis, to enable an easy visual detection of interesting patterns, and to provide means to quickly generate or verify hypotheses. Methods from the fields of visual analytics and information visualization have been demonstrably shown to support such tasks.

In many concrete text analysis scenarios one crucial requirement is to extract sentiments or opinions contained in the documents. For example, companies might be interested in what their customers like or dislike about their products and services respectively what sentiments are associated with the brand or its products in news. Similarly, organizations or individuals of public interest have to be aware of what is reported about them in news and how their decisions and statements are reflected. Of course, many more related examples can be found, where opinions or sentiments on certain topics have a high relevance. The vibrant field of opinion and sentiment analysis is dedicated to detect these kinds of statements from text.

As Web communication and publishing happens in real time more and more, a further particularly interesting issue from the data analysis perspective is the involvement of the time dimension. Temporal aspects like the distribution of text features over time and potentially also analyses in real time can be critical in different real-world applications.

This article is devoted to integrating methods from text mining, sentiment analysis, and visual analytics to enable the analyst to detect interesting temporal sentiment patterns in text document streams. The main target group for the suggested methods are business analysts that want to perform a temporal analysis of feedback that customers directly send to a company via Web surveys.

For this purpose sentiments are extracted for features of different targets appearing in a text (e.g., products, persons, topics, etc.). In a next step, interactive visualizations are introduced that provide global temporal overview or allow detailed insights into temporal sentiment patterns about features. Furthermore, an automatic algorithm was designed that detects interesting sentiment patterns with a high temporal density and content coherence to guide the expert during analysis. Figure 1 gives an illustrating example.

Finally, application case studies are provided for two different analysis scenarios on document streams with different characteristics and an extensive evaluation is provided.

2. RELATED WORK

This section describes relevant related work on automatic and visual feature-based sentiment analysis (Section 2.1), and the visual analysis of text time series (Section 2.2).

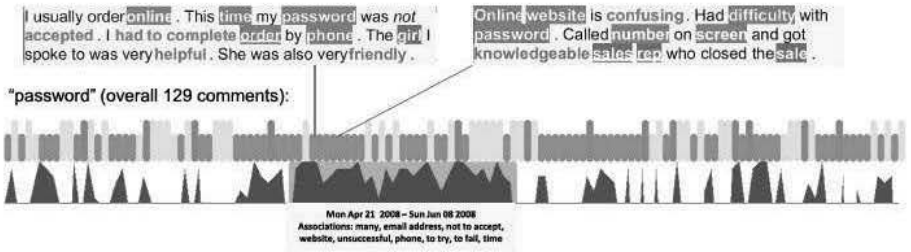


Fig. 1. *Time density plots* of an issue on the feature "password" with associated terms (bottom) and automatically annotated example comments (top). Among 50,000 customer comments, received within two years, all those are sequentially displayed that contain the noun "password". Each comment is represented by one vertical bar. The color indicates whether the noun "password" has been mentioned in a positive (green), negative (red), or neutral (gray) context. The height of a bar can encode another data dimension. In this case we experimented with the uncertainty involved in the sentiment analysis: the lower the bar, the more uncertain. The curve plotted below the *sequential sentiment track* is a *time density track*: the curve is high if the comments above have been relatively close in time. An automatic algorithm detects and highlights interesting portions of the visualization that analysts should explore in detail. Mousing over single comments, the content is displayed and the coloring of words indicates what the sentiment analysis has found. All nouns get a background coloring according to their sentiment context, sentiment words get font colors, and negation words are printed in italics. If the sentiment analysis of a noun was evaluated to be confident (little uncertainty) the corresponding word is underlined. Here, this is the case for "order" and "sales rep".

2.1. Feature-Based Sentiment Analysis

Feature-based sentiment analysis is a subtask of opinion and sentiment analysis. In literature the terms opinion and sentiment are often used interchangeably. For simplicity, in our approach we will use the term sentiment only.

Most approaches for feature-based sentiment analysis involve three or four consecutive steps.

(1) Features for different targets (e.g., persons, organizations, products, services, or topics) are detected either directly from the corpus or based on predefined word lists.
(2) Sentiment words that describe the extracted features are searched in the documents. Sentiment words are words that evoke positive or negative associations.
(3) A mapping strategy aims to detect which sentiment words refer to which feature, so that a sentiment score can be determined for each feature.
(4) Some approaches visualize the results of the feature-based sentiment analysis and enable the user to interactively explore the results in detail.

For the first two steps abundant research has been published in the last years. For the sake of brevity we refer to comprehensive summaries given in Pang and Lee [2008] and Liu [2010] for details. Both features and sentiment words can be either learned from the processed text documents themselves, from external resources (e.g., WordNet[1]), or they can be gathered from predefined lists. One special challenge is to identify sentiment words that have no general validity, but depend on the domain or even on the feature. For example, in a domain like "printer" an adjective like "fast" is feature dependent, that is, positive in the sentence "the printer prints fast" and negative in the sentence "the ink cartridge runs out fast."

Details about steps 3 and 4 are listed in Sections 2.1.1 and 2.1.2.

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

2.1.1. Sentiment-to-Feature Mapping. Different approaches have been suggested in the past to determine which sentiment words refer to which feature. Some of them use distance-based heuristics, that is, the closer a sentiment word is to a feature word, the higher is its sentiment influence on the feature. Such approaches operate on whole sentences [Ding et al. 2008], on sentence segments ([Ding and Liu 2007; Kim and Hovy 2004], or predefined word windows [Oelke et al. 2009].

Other approaches exploit advanced natural language processing methods, like typed-dependency parsers, to resolve linguistic references from sentiment words to features. There are several methods that resolve such references and thus can be used for feature-based sentiment analysis, although most of them were created for different purposes. Ng et al. [2006] use subject-verb, verb-object, and adjective-noun relations for polarity classification. Qiu et al. [2009] use dependency relations to extract both features (product attributes) and sentiment adjectives from reviews by a double propagation method. Popescu and Etzioni [2005] extract pairs (sentiment word, feature) based on 10 extraction rules that work on dependency relations and Riloff and Wiebe [2003] use lexico-syntactic patterns in a bootstrapping approach for subjectivity classification resolving relations between opinion holders and verbs. Our method differs from the previous ones in that we use a predefined set of syntactic reference patterns that are based on part-of-speech sequences only, in order to resolve references, instead of using typed dependencies. In cases where this linguistically motivated method is not able to resolve references, we rely on a distance-based heuristic. This approach also allows us to estimate a degree of uncertainty involved in the analysis.

Recently, another approach was published that takes uncertainty into account [Wu et al. 2010]. The authors consider if customers do not express clear opinions, that is, "customers' conflict and uncertainty about their opinions" as well as the uncertainty involved in the automatic opinion analysis processing. As a result a feature mention can be both negative and positive at the same time. Their uncertainty score is based on two parameters: The smaller the difference between the negative and positive sentiment on a feature within a sentence and the longer the sentence, the higher the uncertainty. We also capture uncertainty in our analysis, however, we limit the analysis to the uncertainty the algorithm has when evaluating a sentence. In contrast to the existing approach, our method relies on linguistic knowledge and not only on distance-based heuristics. In addition, the sentence length is not relevant in our analysis as we consider only sentence segments.

2.1.2. Visual Exploration of Feature-Based Sentiment Analyses. Several different approaches have been suggested to visualize the outcome of automatic feature-based sentiment analyses and enable further user explorations. The Opinion Observer [Liu et al. 2005] visualization enables users to compare products with respect to the amount of positive and negative reviews on different product features. A more scalable approach for the same purpose, that is able to display more products and features at once, is that of the Summary Reports presented in Oelke et al. [2009]. The same paper provides further visualizations to identify groups of customers with similar opinions and correlations between individual feature scores and overall ratings. The AMAZING System [Miao et al. 2009] also visualizes the sentiment of product reviews on certain products over time. The number of positive and negative reviews are aggregated over months and displayed with line charts. In Wanner et al. [2009] a visualization is suggested to track sentiments expressed in RSS news feeds on political parties and their candidates during a presidential election.

Recently, OpinionSeer [Wu et al. 2010], a novel visual analysis tool for hotel reviews, was introduced, where uncertainty contained in reviews is visually represented and aggregated analyses can be performed, for example, on day, week, and month scale.

In contrast to the previous work, our approach enables a much more detailed insight into the temporal development of sentiments on individual features.

2.2. Visual Text Time-Series Analysis

A comprehensive survey about the visualization and visual analysis of time series is given in Aigner et al. [2007]. Several further publications on the visual exploration of time-series data are related to the TimeSearcher Project[2]. Methods especially designed for text time series are often based on a linearly scaled time line, aggregating events according to predefined time bins. Many of these approaches have been inspired by the ThemeRiver method [Havre et al. 2002]. So-called History Flows are used by Viégas et al. [2004] to track collaborative authoring. Krstajic et al. [2010] visualize daily aggregates of entity occurrences in news with stacked time series.

One particularity of our approach, however, is that it deals with unevenly spaced data streams in which events (here: feature occurrences) may occur with an arbitrarily skewed temporal distribution. That means that the data includes short time spans with high amounts of incoming data and large time spans that are only sparsely populated. In Aris et al. [2005] several methods are presented to deal with unevenly spaced auction data. The (interleaved) event index method is the most similar one to our time density plots. It distorts the time axis in order to grant the same amount of space to each event. While the temporal order is preserved the exact temporal relations are lost. Since the exact time between two consecutive events is not conveyed, the authors try to support the user by shading the time axis segments.

Our visualization complements the previous work, in that it displays data records in sequential order without overlap and empty space, while still conveying information about exact temporal relations.

3. OUR APPROACH

Most of the previously mentioned feature-based sentiment analysis approaches deal with collections of customer reviews on a certain product, as can be found on retailer sides such as amazon.com. In contrast, this article focuses on customer reviews that are directly sent to a company via a Web survey. This direct feedback is not necessarily related to products but refers to any issue within the purchase and service process. Most importantly, not only the sentiment polarity but also the temporal and context coherence of customer comments are considered to detect critical issues that occur at certain points in time. This paper covers the whole pipeline of methods necessary to detect important sentiment pattern information in large document streams and contributes at different stages of the analysis process by suggesting novel automatic and visual analysis approaches; see Figure 2. The required input for our analysis is rather generic in order to guarantee a wide applicability. It consists of a set of time-stamped texts. To give an overview of the analysis steps, they are listed in the following. Contributions are briefly explained.

— Linguistic Preprocessing
— Feature Sentiment Identification. In the sentiment-to-feature attribution we aim to achieve a good coverage while being as accurate as possible. Therefore, we combine different methods to resolve sentiment-to-feature references and together with the analysis results we give an estimation for the uncertainty involved in the analysis. This is a minor contribution that is not central to the overall approach but was considered interesting to explore. For details see Section 4.
— Context Identification

[2]http://www.cs.umd.edu/hcil/timesearcher/

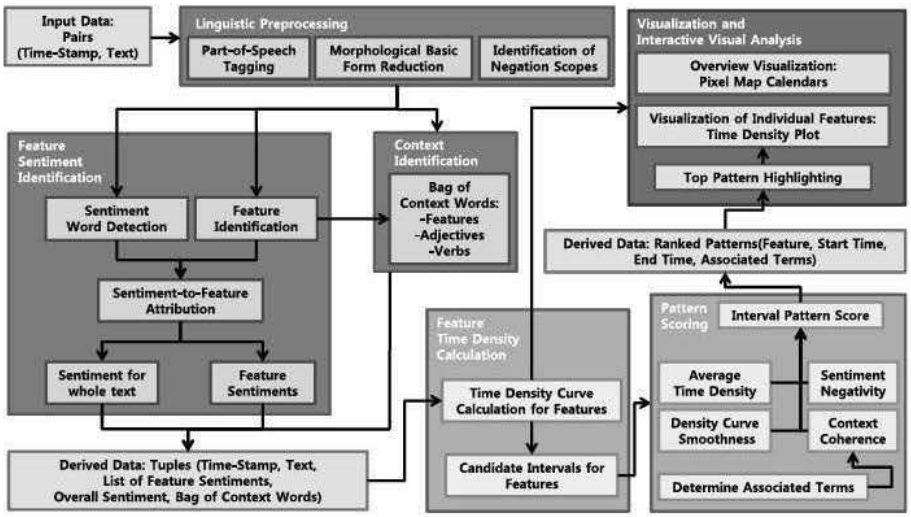


Fig. 2. Overview of the steps involved in the visual analysis.

— Feature Time Density Calculation. Along the temporal dimension, we try to detect shifts in the occurrence frequency of a certain feature which may indicate time-related issues. The time density is calculated relative to the overall occurrence frequency of the feature. This allows us to detect interesting time patterns also for infrequent features. For details see Section 5.2.
— Visualization and Interactive Visual Analysis. To visualize sudden temporal accumulations of comments on one feature, we propose an innovative visualization method: *Sequential sentiment tracks* together with *time density tracks* are able to display unevenly distributed feature occurrences without overlap and space-consuming gaps. Critical issues can readily be detected visually and explored in detail interactively accessing the relevant full text as a tooltip, as shown in Figure 1. To provide a global overview about the data distribution, pixel map calenders are applied. For details see Section 5.
— Time Interval Pattern Detection. In order to guide an analyst and advise her/him of critical issues, we further propose a new time pattern detection algorithm that operates both on past data and is also applicable in real time. Interesting time spans for features will be filtered and ranked according to their importance scores providing the basis for triggering real-time alerts. Patterns have to be comparatively dense in time, with a smooth time density curve, have to have a clearly negative sentiment connotation, and the feature has to appear in similar contexts within the documents of the pattern. With the purpose to determine the context coherence, terms are extracted that have a strong association with the pattern. Patterns are highlighted in the visualization and the associated terms are displayed in order to provide a quick insight. For details see Section 6.

To the best of our knowledge there are no other comparable approaches that offer a complete pipeline for the visual analysis of time-dependent sentiment patterns for text features. In Section 3 we discuss characteristics of two different datasets we use. Section 4 gives details about the feature-based sentiment analysis, Section 5 explains the visual analysis components, and Section 6 details the detection of interesting time interval patterns. In Section 7 we provide application case studies discussing

interesting results that were obtained on real data. An extensive evaluation of different parts of our approach including an expert user study is given in Section 8, where also advantages and limitations are discussed. In Section 9, we conclude the article with a summary.

Data and Applications

Our target users are industries, companies, and small businesses who want to explore their customer feedback. In addition to Web surveys, we also can readily apply our visualization and pattern detection methods to time-stamped news, twitter data, hotel reviews, movie/recreations reviews, etc., as long as the quality of the sentiment analysis in that domain is reasonable. We use mostly standard methods for the automatic sentiment analysis that were suggested for mining customer reviews.

To apply our methods to datasets with different analysis scenarios and characteristics, in addition to customer Web surveys also RSS news feeds were explored.

— *Customer Web Surveys*. Web surveys give users the opportunity to directly comment, in a detailed way, on issues they liked or disliked about the product itself and its purchase, service, delivery, payments, etc. This kind of information can be especially valuable for companies as it might point them to problems that they had been unaware of beforehand, having negative effects on their business performance if the problems are not detected and eliminated in time. We gathered a dataset containing about 50,000 Web survey responses sent to a company between 2007 and 2009.
— *RSS News Feeds*. RSS news feeds redistribute and spread current news in real time. For example, they are interesting for political analysts who want to see when and why political parties and persons are mentioned in negative contexts. To explore the applicability of our methods for such a related task, we analyzed about 16,000 RSS news items collected from 50 feeds about the U.S. presidential election in 2008. The collection started about one month before the election and ended on the election day. The dataset was also used in Wanner et al. [2009].

4. FEATURE-BASED SENTIMENT ANALYSIS IN DOCUMENT STREAMS

The kind of data we deal with does not have a predefined limited topic coverage. There is no fixed set of features, that is, we are interested in any kind of feature for any kind of target (persons, organizations, products, services, topics, etc.). This also implies that we cannot define a domain- or attribute-dependent sentiment word list, but have to rely on sentiment words with general validity. The feature-based sentiment analysis comprises several steps where we apply standard methods.

(1) Linguistic Preprocessing. In a preprocessing step we apply part-of-speech tagging[3] and lemmatization. Next, predefined negation words and their scope are detected in sentences. Later, the polarity of sentiment words occurring after negations is inverted. The negation remains valid in the same sentence until one of the words or punctuation marks typically marking the end of a negation frame is encountered (e.g., ",", "-", "but", "and", "though", "however", etc.).
(2) Feature Extraction. All nouns and compound nouns are extracted as candidate features. Whether a feature is interesting or not will only be determined in the later time-related analysis. Features and further content-bearing context words

[3]http://opennlp.sourceforge.net/

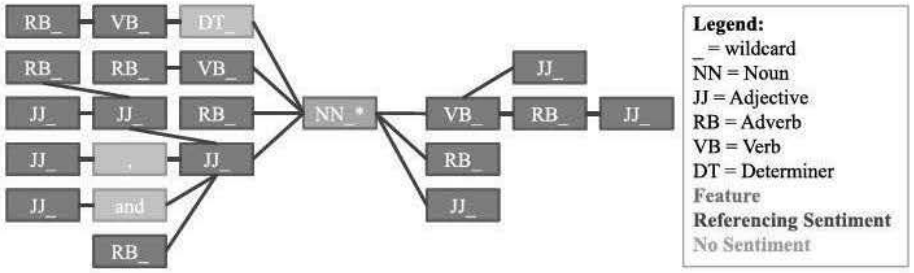


Fig. 3. Syntactic sentiment reference patterns. Word order patterns go from left to right, the level indicates the exact position. The first pattern at the top left, for example, would match a sentence like " I/PRP really/RB like/VBP this/DT printer/NN". The positive polarity of the verb "to like" would then be attributed to the noun "printer". The graph summarizes the most frequent reliable patterns we could detect in our data and we therefore regarded in the analysis. In total, the graph covers 18 different patterns, one for each blue node.

(verbs and adjectives) are saved together with the information whether they appeared in a negated context. The context words are used when evaluating context coherences of interesting feature time interval patterns (see Section 6).

(3) Sentiment Word Detection. The polarity categories (positive, negative) from the Internet General Inquirer[4] are applied in order to find sentiment words. The lists have been manually enhanced by removing some arguable words and adding further colloquial words. The positive word list contained 1594 words after removing 40 and adding 90. The negative word list contained 2018 words after removing 14 and adding 138.

(4) Sentiment-to-Feature Mapping. While the processing steps 1–3 are very similar to what has been done by other approaches before, this step includes novelties in that it relies both on syntactic reference patterns and distance-based heuristics. It is described in detail in Section 4.

Sentiment-to-Feature Mapping in Document Streams

As outlined in the related work there are distance-based methods for sentiment-to-feature mapping and methods based on typed-dependency parses. The first set of methods has the problem that it does not involve any linguistic knowledge and the latter type suffers high computational complexity and error-proneness. A series of simple tests we conducted indicates that such a parsing is not feasible for large amounts of text documents possibly coming in at real time. To illustrate the effect we sent three requests to the Stanford Parser[5] and retrieved the quickest response time out of 20 trials: (1) *It rains.* (0.006s), (2) *It rains quite often.* (0.020s), (3) *It rains quite often here these days, but still not as much as in other places that I have visited during my last trip.* (0.824s).

On the other hand, it is not very accurate to rely only on distance-based heuristics. Therefore, we chose to have a hybrid sentiment attribution approach and also account for the uncertainty involved.

In the first step, we make use of a set of manually defined syntactic reference patterns (see Figure 3) that previously have been used successfully for resolving sentiment references in photo corpora [Kisilevich et al. 2010]. The only preprocessing

[4]http://www.wjh.harvard.edu/~inquirer/
[5]http://nlp.stanford.edu:8080/parser/index.jsp

requirement is part-of-speech tagging, which was already performed to extract features. We determine three levels of certainty.

(1) If a sentiment word stands in one of the syntactic pattern relations from Figure 3 to a feature, then this mapping is considered to be correct with a high certainty, that is, we assign certainty level 1. In this case the certainty value is 1.
(2) If no sentiment word could be found in such a syntactic relation, then we use the distance-based mapping from Ding et al. [2008]. We modify this mapping by not considering the whole sentence, but sentence segments [Ding and Liu 2007] and word windows. First, we try to detect sentence segments by searching typical segment borders ("but", "except", ",", "though", "however", etc.). Next, we consider only the segment containing the feature and introduce a threshold for the maximal distance that is still to be considered, like in Oelke et al. [2009]. In a set of experiments with manually annotated data, we determined the best threshold to be 10. If only sentiment words of one polarity, that means either only positive or only negative words, can be found within that sentence segment, then the certainty level is 2. In this case the certainty value is 2/3.
(3) If both polarities are encountered, the polarity with lower distance from the feature is assigned, but only with a certainty level of 3. If the feature itself is a sentiment word, for example, "problem", it is only regarded if no other sentiment words could be found in its reference window. In this case, again we assign the feature-polarity with certainty level 3. In this case the certainty value is 1/3.

Finally, a sentiment value is saved for each feature occurrence. The sentiment value corresponds to the certainty value (1/3, 2/3 or 1) of an analysis multiplied with the assigned polarity (+ or -). The sentiment value can then be conveyed to the user as part of the visualization of the analysis results. While this straightforward choice of certainty levels is not sufficient to exactly reflect the uncertainty involved in the analysis (see Section 8.2), it is a first meaningful step in that direction that brings two advantages: (1) These three levels can be deduced from the analysis and easily be distinguished in a visualization. (2) We observed that it is important to sensitize analysts that the accuracy of an automatic sentiment analysis is not nearly 100%. In addition, they are pointed to cases where they should manually assure the correctness of analysis result if crucial to them. This can be done reading the annotated tooltips, as shown in Figure 1.

5. VISUAL ANALYSIS

For the visual analysis of feature sentiment developments over time two complementary visualizations are used. In order to provide global overview of the overall data distribution, *pixel map calendars* are used [Hao et al. 2008]; see Section 5.1. To track concrete temporal developments of single features, with a focus on time spans with high data frequency, novel *time density plots* are applied; see Section 5.2. It has to be pointed out that in both visualizations each individual document gets a visual representation. Such a plotting on record level allows details, like the full text and further data attributes, to be accessed and explored by mouse-over interaction, which is crucial to get a deeper understanding of the data.

5.1. Pixel Map Calendars

Each data point is represented by one pixel and displayed in hierarchical bins along x and y dimension. For example, in Figure 4, x axis bins correspond to days and y axis bins to years with months, but also any other combination of time units (seconds, minutes, hours, days, weeks, months, years, etc.) is possible. Within the bins of

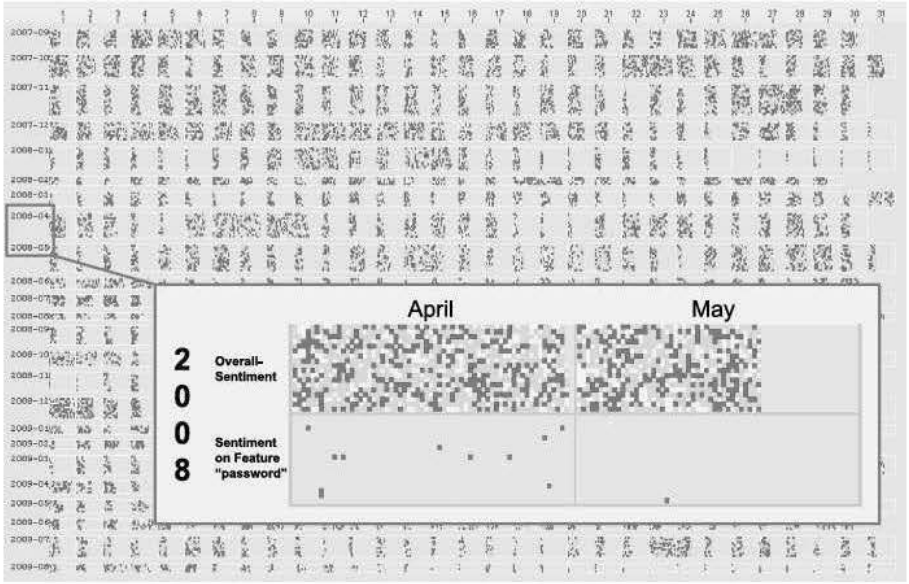
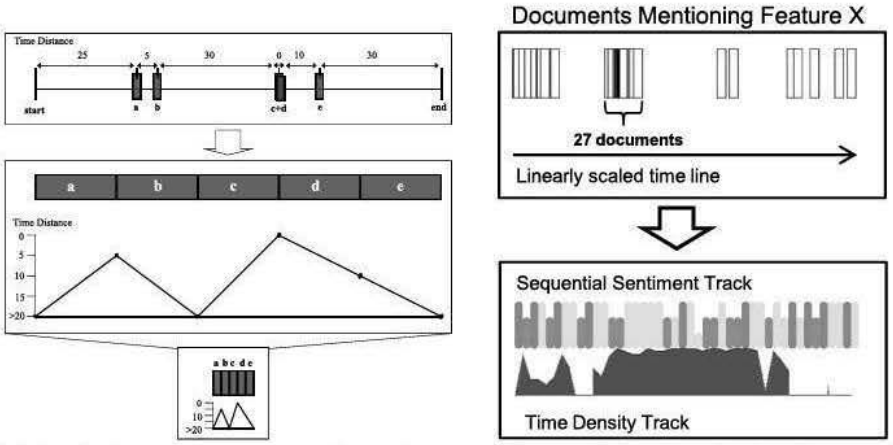


Fig. 4. *Pixel map calendar*: Each document corresponds to one pixel and the color of the pixel indicates the overall sentiment of the document, which corresponds to the average of all contained feature sentiments. If the overall sentiment is positive, the pixel is colored in green, if it is neutral, the pixel is colored in yellow, and negative sentiments lead to a red pixel coloring. In the background the x-axis bins correspond to days and y-axis bins to years with months. Additionally, an enlarged view of April and May 2008 is provided, where the x-axis bins correspond to months and the y-axis bins to years. In this visualization the overall sentiment (top) can be compared to the sentiment on the feature "password" (bottom). It can easily be seen that "password" is a relatively infrequent term that mostly occurs in negative contexts.

the *pixel map calendar*, pixels (documents) are plotted in temporal order based on their arrival sequence from bottom to top and left to right. There is always enough space to place the documents in the corresponding bins, because the size of each bin is calculated from the maximum number of documents in a day as illustrated in Figure 4. All bins have equal width in the *pixel map calendar*. Different bin heights are used for the different months according to the maximum number of documents in a day. As a result empty space is visible in the bins which do not have enough documents to occupy the bin; see Figure 4. While temporal distances within bins are no longer visible, this method is very scalable with respect to the amount of data that can be displayed: Each document requires one pixel only. This makes pixel calendar maps a very suitable overview visualization and point of entry for further analyses. Feature occurrences can be explored in the context of selectable temporal granularities and in the context of the overall data distribution.

5.2. Time Density Plots

The basic idea of the *time density plots* is similar to the event index method [Aris et al. 2005], described in related work, as it does not use the x axis for conveying exact temporal relations but grants the same amount of space to each event (document containing a certain feature). In this article, however, we suggest a *time density track* displaying both the temporal order of events on the x axis and the detailed temporal coherences among events on the y axis. In addition, we omit the, for our purpose, mostly useless information about the exact lengths of the time intervals during which no events occur, and focus on areas with a high density of events. These interesting time



(a) details about the construction of time density curves

(b) example for a beneficial application of *time density plots*

Fig. 5. In the upper parts, all documents about one specific feature are plotted as they occur over time. The documents are shown in temporal order along a linearly scaled time line, each document being represented by one rectangle. In the dense areas many rectangles (documents) may overlap which does not allow an appropriate analysis. In the lower figure, our new approach is shown that overcomes these problems and provides further insight for analysts.

intervals get much more space than they would with linear time scaling and can easily be analyzed in detail without any overlap. For each feature one individual *time density plot* is created. The threshold that determines when detailed temporal relations are displayed depends on the average frequency of the respective feature. Thus, data streams and features of very different temporal resolutions and granularities (as they appear in our data) can be readily handled in the same manner. This novel approach can be generalized for application scenarios, where such temporal accumulations of comments are the main interest. Our basic visualization consists of two parts that require the same space each, a *sequential sentiment track* on top and a *time density track* below; see Figure 5(b) for an example. The sequential sentiment track contains all documents mentioning a feature of interest in sequential order as they occur along the time dimension. The exact point in time is not relevant in this upper track, only the temporal order is maintained, so that both space-consuming gaps and overplotting are inherently avoided. Each rectangle bar encodes one document that contains the feature and indicates by its color the polarity of the feature. The height of a bar depends on the certainty level of the analysis, that is, the more certain the analysis, the higher the bar. The space that is needed in horizontal direction thus depends linearly on the number of documents in which the feature appears. Figure 5(a) provides details and an example on how the time density track is created. In the upper box, documents a, b, c, d, and e are plotted as rectangles on a time line. Document c and d have exactly the same time stamp and are thus plotted one on top of the other. The time distance between each pair of consecutive documents is given in the figure; for simplicity let us assume we have an overall time interval of 100 minutes. Then, a appears after 25 minutes, b after 30 minutes, and so on. As we observe 5 documents within 100 minutes we assume that if they were equally distributed over time, every 20 minutes we should be able to observe one document, as this is the average time distance between successive documents. Therefore, we define that if the time gap between two documents is larger than the average (here: 20 minutes) there is no noteworthy temporal connection

between both. If the time gap is smaller, then the temporal connection is interesting and reaches a maximum level of interestingness at a time gap of 0 (same point in time). This temporal density is plotted as a curve below the document rectangles as indicated in the second box of Figure 5(a). When shrinking the document rectangles to their original size (lowest box of Figure 5(a)), we observe that we potentially save a lot of space without losing the relevant information, that is, c and d occur at the same point in time, a and b are very close together, and e is still close to c and d. The only information we lose is how long exactly the gap between b and c is and the gaps at the beginning and ending of the time interval. For our task this information is irrelevant; it is sufficient to know that in this case there is no interesting temporal proximity between two successive documents. In addition, we are now able to display the documents c and d without overplotting. This is a major advantage since the document contents can easily be explored by mouse-over interaction, and patterns become visible in detail.

5.2.1. Creation of the Visualization. All documents containing a certain feature are extracted and ordered by time. They are plotted in sequential order represented by vertical bars (the *sequential sentiment track*) and colored according to the feature polarity. Positive contexts are encoded in green, neutral ones in gray, and negative ones in red. The height of a red or green bar depends on the uncertainty involved in the analysis and corresponds to the certainty value: For certainty level 1 the bar has the default height, for certainty level 2 it has 2/3 of the default height, and for certainty level 3 it has 1/3 of the default height. That means the higher the certainty, the higher the bar, the stronger the visual impact. Next, a time density track is plotted below the sequential sentiment track. The height of the time density curve below the border of two successive document bars is determined by the normalized temporal distance between the time stamps of both documents (see formula (1)).

$$timedensityheight(f, a, b) = max\left(0, \left(1 - \frac{timedist(a, b)}{avgtimedist(f)}\right)\right), \quad (1)$$

where feature f, preceeding document a, succeeding document b.

The calculated time density values determine the height of the curve below the border of the two corresponding documents. In the area between two borders the curve is linearly interpolated. For obtaining the average gap time (avgtimedist) in live data streams, we use simple moving averages.

6. TEMPORAL SENTIMENT PATTERN DETECTION

The visualization of temporal developments through the combination of a time density curve and the sentiment polarity coloring draws the eye to interesting time spans. However, if all reasonable features have to be considered, an analyst still has to skim through the time density plots of several hundred features. Visually scanning all time density plots with the eye is exhaustive, time consuming, infeasible on live streams, and error-prone in the sense that details might be overlooked. Consequently, we developed an automatic algorithm to preselect interesting patterns and guide the analyst. This algorithm is based on a scoring function that approximately encodes the criteria an expert would use while skimming through the time lines in search for critical issues. The algorithm automatically detects interesting portions of the visualization and shows them to the user, who can manually verify if they really form patterns that bring useful new information. In order to discover patterns the algorithm tries to analyze the data according to the questions of a data analyst.

(1) Does a set of documents mentioning a certain feature appear accumulated in a relatively short time range?

(2) Is this subset dominated by negative sentiments about the feature?
(3) Is the feature mentioned in similar contexts, that is, do people report about the same issue or about different ones?

The first question can be answered separating documents according to the occurrence of features and investigating their temporal distribution. In order to detect interesting time patterns within the documents mentioning a specific feature, first candidate time pattern intervals have to be identified. A candidate pattern is any pattern that corresponds to a relatively large interval of documents with high time density. Time-dense means that all time distances between consecutive documents in this interval are smaller than the average (for the current feature). Visually this corresponds to a portion of the time density curve that is constantly above zero, without interruption. An interval is considered to be large if it is at least twice as long as the average time-dense interval for the same feature. In addition, as the main goal is to detect problems, intervals that are dominated by negative feedback are of prior interest. Thus, if an interval according to our criteria is both time-dense and large, and if it contains more negative than positive comments, it is inserted into the candidate pattern list and regarded for further analysis. The following algorithm details the detection of such candidate intervals.

```
Algorithm to extract candidate patterns for individual features:
Definition
   pattern = list of tuples (time distance, sentiment value);
Input
   L_t := List of ordered time stamps (for one feature)
   L_s := Corresponding list of sentiment values
          multiplied with certainty values
Derived
   L_d := List of pairwise time distances of succeeding
          time stamps (calculated from L_t);
   d_avg := Average pairwise time distance of succeeding
            time stamps (calculated from L_d);
   L_p := new empty list of patterns;
   p_tmp := pattern, initialized with null;

   for d at k in L_d
      if d < d_avg
         if p_tmp is null
              p_tmp := new empty pattern;
         endif
         add (d, L_s[k]) to p_tmp;
      endif
      else
         if p_tmp is not null
            if isNegative(p_tmp)
               add p_tmp to L_p;
            endif
            p_tmp:= null;
         endif
      endelse
   endfor
   deleteShortPatterns(L_p)
```

```
Output
   L_p

where
- isNegative(pattern p) returns true if the sum of all sentiment
values in pattern is negative
- deleteShortPatterns(List of patterns L_p) deletes patterns that have
less than 2 times the average pattern length for the same feature.
```

Next, all candidate interval patterns for a feature F are scored and ranked with respect to their importance for analysts. The score was empirically designed and consists of four factors.

(1) DENSITY: The average height of the time density curve for a candidate pattern. The higher the curve is on average, the more densely the documents appear in time. In order to account for the undesired influence of uninteresting events on the time density, the fraction of uninteresting events is incorporated as a compensating weight. In the detection of negative sentiment patterns, for example, uninteresting events correspond to documents mentioning a feature F with positive sentiment S. In general, the smaller the relative time distance $D(x)$ of a document x to the next document within the pattern P, the higher the density value of P. The time distance is normalized with the average time distance $avg(D(F))$ among consecutive documents mentioning feature F.

$$\text{density}(P) = \frac{1}{|\{x \in P\}|} \sum_{x \in P} \left(1 - \frac{D(x)}{avg(D(F))}\right) \cdot \left(1 - \frac{|\{S(x) : S(x) > 0\}|}{|\{S(x)\}|}\right)$$

(2) SMOOTHNESS: The time density curves of many interesting patterns have a shape that clearly shows an increase, a plateau, and a subsequent decrease. On the other hand there are larger patterns of events that are rather loosely connected in time, showing a zigzag pattern. The latter ones are usually less interesting, and this is why we give a higher score to patterns with smoother time density curves. The smaller the average normalized difference of succeeding time distances D among the documents x within the pattern P, the higher is the smoothness value of pattern P. Note that all time distances D necessarily are smaller than the average time distance for the same feature F as this is a criterion for being a candidate pattern.

$$\text{smoothness}(P) = 1 - \frac{1}{(|x \in P| - 1)} \sum_{i=0}^{i<(|x \in P|-1)} \left| \frac{D(x_i)}{avg(D(F))} - \frac{D(x_{i+1})}{avg(D(F))} \right|$$

(3) SENTIMENT-NEGATIVITY. The more negative the documents in a candidate pattern are, the more it might point to critical issues. The higher the certainty of the sentiments, the more interesting. Therefore, the sentiments S on the feature in individual documents x are summed up. To get a positive score when having mostly negative sentiments, values are multiplied with -1.

$$\text{sentiment-negativity}(P) = \sum_{x \in P} -S(x)$$

(4) CONTEXT-COHERENCE. There may be accumulations of negative comments on a feature that do not necessarily refer to the same issue. On the other hand, those candidate patterns are of most interest for which all documents apparently report about the same issue, that is, they mention the feature in similar contexts.

Table I. Contingency Table Showing the Number of Documents *DOC* Depending on a Certain Term *T* and a Certain Pattern *P*

	$DOC \in P$	$DOC \notin P$
$T \in DOC$	A	B
$T \notin DOC$	C	D

A simple but effective heuristic was designed to take this context coherence into account. For every potentially content-bearing term (adjectives, nouns, verbs) in an candidate pattern it was evaluated how strongly this term T is associated with the documents *DOCS* of a pattern P. To measure the significance of an association the *log-likelihood ratio test* was used, which operates on a contingency table (see Table I) and has been used before to measure the strength of word collocations [Manning and Schuetze 1999].

The document counts were used to calculate the log-likelihood ratio (see Eq. (2)), where A, B, C, and D correspond to the four cells in Table I.

$$\begin{aligned} \text{log-likelihood ratio} = A \log\left(\frac{A/(A+B)}{(A+C)/(N)}\right) + B \log\left(\frac{B/(A+B)}{(B+D)/N}\right) \\ + C \log\left(\frac{C/(C+D)}{(A+C)/N}\right) + D \log\left(\frac{D/(C+D)}{(B+D)/N}\right) \\ \text{with } N = A+B+C+D \end{aligned} \tag{2}$$

Next, the top 10 associated terms for a pattern are determined and their log-likelihood ratios are summed up. This sum will be higher for patterns that have a number of terms occurring significantly more likely within the documents of the pattern than within the other documents. This is the case for patterns with a coherent context for a feature.

$$\text{context-coherence}(P) = \sum_{i=1}^{10} \text{log-likelihood ratio}(T_i, P)$$

$$\textit{where } \text{log-likelihood ratio}(T_i, P) \geq \text{log-likelihood ratio}(T_{i+1}, P)$$

OVERALL SCORE. All four outlined factors get equal influence in the score of a pattern P, as shown in the formula that follows.

$$\text{score}(P) = \text{density}(P) \cdot \text{smoothness}(P) \cdot \text{sentiment-neg.}(P) \cdot \text{context-coh.}(P)$$

In a series of experiments on different test datasets (customer Web surveys, RSS news, and Twitter data) this score function yielded a very satisfying performance. However, it is possible for the analyst to adapt the weighting among the factors according to the current focus of search. The default score makes it possible to find interesting patterns quickly without requiring any preknowledge about the data or deeper insight into the algorithm. The effectiveness of the scoring function is described in Section 8 (evaluation), where also the influences of the individual factors on the overall performance are shown.

6.1. Possibilities for Live Alerting

The whole pipeline of suggested methods (see Figure 2) is able to work on live datasets with continuous updates. The only prerequisite is to have a limited amount of past

data in order to determine the moving average time density values for the different features. Then, each new customer feedback comment can be aggregated to the corresponding feature time lines as soon as it comes in. Alerts can be sent out right away if a feature reaches considerably high scores. This automatic tracking of large numbers of different features puts analysts into the position of being able to instantly detect emerging trends and problems. The analyst is then able to react immediately on issues that otherwise might not have been discovered until the comments had a negative impact.

7. APPLICATION CASE STUDIES

One difficulty in the evaluation of an approach that helps to visually detect interesting temporal sentiment patterns in large documents streams is the lack of appropriate ground truths. For two datasets, however, we were able to get at least some basic ground truth. In the following application case study we provide empirical evidence and examples for the good performance of our method, by comparing its results with these basic ground truths.

7.1. Customer Web Surveys

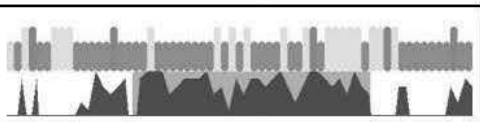
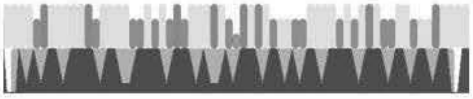
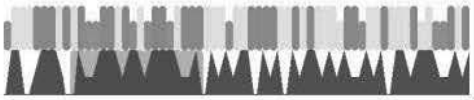
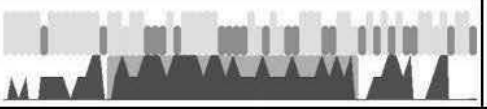
With the help of the data manager, who had provided the customer Web surveys, we were able to construct a ground truth of known issues that had occurred in the time span of the dataset (about 2 years); see Section 8.1 for details. We ran our automatic pattern detection algorithm and extracted the top 10 patterns; see Table II. One of those patterns was a false positive (issue 6) and two further patterns relate to known general problems that could not in particular be related to the determined time span (issue 4 and 8). The remaining issues had all been contained in the ground truth. It can be seen that patterns are detected in the feature time series of both frequent features, like “phone”, overall 1650 comments, and infrequent features like “packing list”, 44 comments, or “customs”, 26 comments. The two latter ones can otherwise easily remain undiscovered because of their infrequency. Even the top issue “password”, 129 comments, is relatively infrequent considering the overall amount of documents (see Figure 4). The spike is only visible in the time density plot and coincided with a login issue that was not immediately corrected because it was not known at the time. Further detected issues cannot be discussed in detail, because of the confidentiality of the data. The data manager stated that he learned several interesting things about his data and, during the ground-truth construction, discovered issues with help of the tool that he had not been aware of. In general, it can be observed that patterns may have varying time spans. In this dataset the available time resolution is on day basis and discovered issue time spans range from single days to several weeks. In Table II it can be seen that the wrong detection of issues 4, 6, and 8 is an artifact of having a time resolution on day basis. All of the wrongly discovered features are comparatively frequent and mostly negative. One feature mention per day is enough to keep their time density curves above 0. Apparently, this increases the chance to produce meaningless patterns.

7.2. RSS News on Electoral Campaigns

RSS news feed items mentioning the presidential candidates and their parties were collected in the three weeks before the U.S. presidential election in 2008. With the former approach three interesting events with negative sentiment connotation were identified in this time range (see Wanner et al. [2009]).

(1) Sarah Palin was accused of abusing her power as Alaska’s governor firing the state’s public safety commissioner (“Troopergate”).

Table II. The Top Ten Issues Discovered by the Automatic Pattern Detection

Feature & Description	Visual Pattern	Associated Terms
1. password Mon Apr 21 2008 - Sun Jun 08 2008		many, email address, not to accept, website, unsuccessful, phone, to try, to fail, time
2. packing list (packing slip, charge) Tue Apr 08 2008 - Thu Jun 05 2008		wrong, total, to show, first, order confirmation, amount, to disappoint, confusion, accessory
3. phone (hour) Fri Nov 28 2008 - Fri Nov 28 2008		hour, many, technical, same, basic, first, service person, to try, hard
4. india (english) Tue Sep 18 2007 - Thu Oct 04 2007		courteous, american, not to understand, someone, personnel, world, people, folk, not good
5. customs Mon Nov 10 2008 - Wed Dec 03 2008		to hold up, to delay, paperwork, sure, day, indianapolis, paper work, not correct, to hold
6. software Mon Nov 26 2007 - Sat Dec 15 2007		not same, same, product spec, false, csr, promise, photos, computer, call
7. envelope Mon Mar 16 2009 - Mon May 25 2009		not to recycle, cartridge, not to include, to recycle, new, not to dispose, not to print, photosmart c6380, recycle
8. english Tue Nov 27 2007 - Thu Dec 06 2007		not to speak, poor, to speak, wrong, new, not nice, not to understand, hour, rep
9. windows vista Thu Sep 06 2007 - Thu Oct 11 2007		on, happy, old, basic, program, other, not new, new, not compatible
9. minute Sat Nov 24 2007 - Tue Dec 11 2007		first, wrong, able, india, rep, to take, to call, few, hour

In the left column issues contained in the ground truth are colored in red, general issues in yellow, and false positives in green. If two discovered features relate to the same issue, that is, they shared at least 50% of the documents contained in their patterns, they are regarded as one issue and only the plot of the higher-scored feature is displayed. The lower-scored features are added in parentheses.

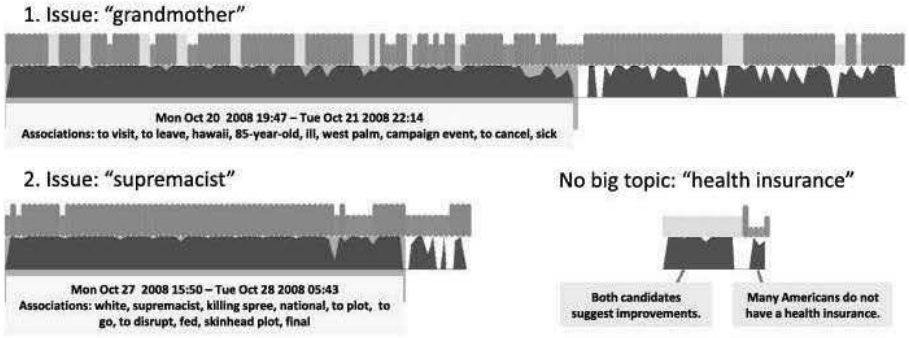


Fig. 6. Time density plots of the two top issue features and of a further feature "health insurance" that apparently did not play a big role in news about the electoral campaign.

(2) A plot of white supremacists to assassinate Barack Obama was uncovered.
(3) Obama and McCain attacked each other and battled fiercely in a TV debate.

Surprisingly, the top pattern detected by our algorithm (feature "grandmother") corresponds to a negative event (see Figure 6), that had not shown up in the previous analysis: Barack Obama interrupted his campaign to visit his gravely ill grandmother. Further patterns among the top 10 dealt with the known assassination plot and the Troopergate scandal. Another new issue was discovered at rank 10: Barack Obama's aunt was living illegally in the US. In the top 20 patterns further previously undiscovered issues were detected: Palin and McCain accused Obama of not being honest about his association with a former war protester. In a further issue they accused the *Los Angeles Times* of withholding a videotape showing Obama attending a party for a Palestinian-American professor and critic of Israel. Furthermore, one issue reveals that Palin took a prank call from a Canadian comedian posing as French President. Also, a voter registration fraud is reported.

However, the tv debate issue did not make it among the top patterns because it was not very negative. In general it could be observed that many different sources post very similar news within short time spans that are only slight variations of news agency messages. This facilitates the discovery of patterns.

It is also possible to track any topic of interest and try to visually detect patterns. Figure 6 shows the example of the feature "health insurance": It can be seen that it was not a big topic and did not mainly have negative connotations.

8. EVALUATION AND DISCUSSION

In addition to the application case study, further parts of our approach are evaluated individually: the automatic pattern detection (Section 8.1) and the modeling of uncertainty (Section 8.2). In Section 8.3 an expert user study is provided to give further insight into the real-world applicability and usability of the system. Along the evaluation different features and limitations of our approach are discussed.

8.1. Automatic Pattern Detection

For the customer Web survey dataset a ground truth of important issues was constructed. The data analyst who provided the dataset and had been working with it during data collection was able to name 9 important issues that he was aware of. In addition, among the automatically extracted issues, he was able to identify 8 further issues interesting to him. With this ground truth of 17 time-related issues to be found we evaluated the precision and recall of the automatic pattern detection algorithm. To

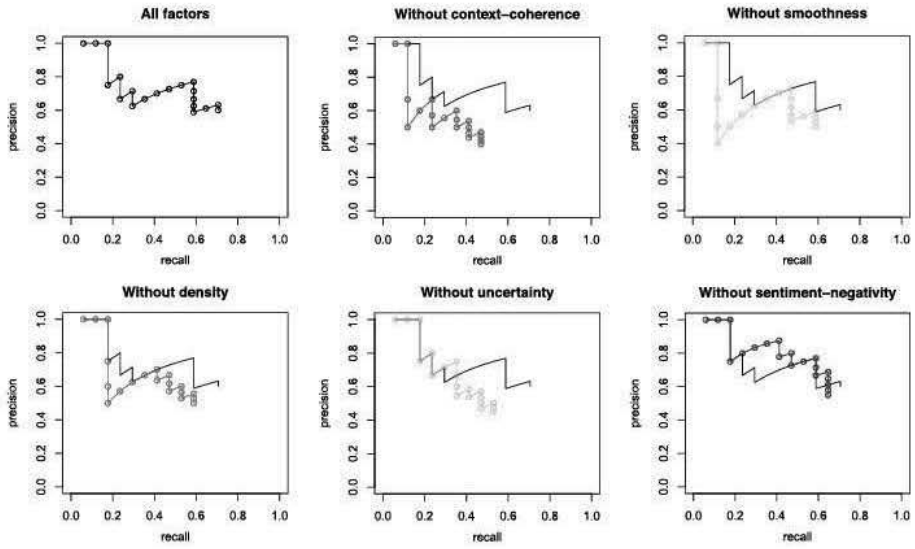


Fig. 7. Recall-precision diagrams for the score containing all factors (upper left) and modified scores where one factor is excluded. In these diagrams the recall-precision curve for the score with all factors is additionally displayed in black to enable comparison.

Table III. Precision and Recall Values when Extracting the Top 20 Patterns

Method	Precision	Recall
Original Score	60.00%	70.59%
Without Sentiment-Negativity	55.00%	64.71%
Without Density	50.00%	58.82%
Without Smoothness	50.00%	58.82%
Without Uncertainty	45.00%	52.94%
Without Context-Coherence	40.00%	47.06%

this goal, the top 20 patterns according to the overall score were extracted and it was verified whether these patterns actually pointed to one of the 17 known issues. The recall-precision diagram for the overall score is displayed in the upper left of Figure 7. Taking all 20 results, the precision is 60.00% and the recall 70.59%. In addition, the results for modified scores are provided, performing a sensitivity analysis. For each of the other scores one factor of the overall score was left out and again a recall-precision diagram was created (Figure 7). The purpose of this sensitivity analysis was to validate that each factor in the score is actually beneficial, which is true if all top 20 results are considered; see Table III. However, the version that does not consider the *sentiment-negativity* partly outperforms the overall score when returning less than 20 results, as can be seen in Figure 7. Apparently, the exact negativity of a pattern is not that important as long as it is assured that the negative comments dominate. Even more astonishing is that the *uncertainty* has a beneficial influence on the overall score, although it just modifies the *sentiment-negativity*. We could observe that the *uncertainty* was preventing features that at the same time were sentiment words (e.g., problem, waste, error) from being weighted too much. The uncertainty modeling causes these kind of features to get certainty value 1/3 if no other sentiment words can be found in their surroundings. From Table III and Figure 7 it can also be deduced which among

Table IV. Results of the Sentiment Analysis Dependent on the Certainty Level

Dataset	Level 1	Level 2	Level 3	No Sentiment
Customer Feedback Accuracy	85.7%	84.8%	80.0%	19.7 %
Customer Feedback Proportions	27.9%	39.3%	2.5%	30.3%
RSS Feeds Accuracy	80.0%	52.9%	62.5%	74.6%
RSS Feeds Proportions	14.9%	51.7%	4.0%	29.4%

All values are rounded to one decimal. The proportions show the fraction of all feature mentions the algorithm assigned with the corresponding certainty level. The accuracy shows which fraction of the feature mentions of one certainty level have been assigned to the correct sentiment category (positive, negative, neutral).

the factors are most valuable when trying to detect interesting patterns. Surprisingly, the *context coherence* has the strongest positive effect on the score, which becomes evident by the much worse performance when leaving it out. Next, the *uncertainty* has the second best influence, although it is not a real factor in the formula, but just a modifying element of the *sentiment-negativity*. *Density* and *smoothness* both cause the same improvement which still is a considerable contribution. Only the *sentiment-negativity* cannot unambiguously be classified as being beneficial. Interestingly, the good performance without this factor is due to the fact that some issues have been identified that had not been detected in any of the other settings. This was the case when the automatic sentiment analysis could not detect many negative statements, but the corresponding issue still was in the ground truth. While sentiment analysis apparently is rather simple for some features, other features contain many implicit sentiments and get higher scores when the *sentiment-negativity* is not even considered. It can be concluded that whenever the sentiment analysis is accurate it is beneficial to include *sentiment-negativity*.

8.2. Uncertainty Assessment

It is well-known that automatic sentiment analyses cannot be 100% accurate, due to different reasons (ambiguity, implicitness, etc.). To enable analysts to judge how confident analysis results are, in our approach the uncertainty involved in the analysis is assessed and visually conveyed. To evaluate the uncertainty modeling, for both the customer Web surveys and the RSS news feeds, 201 feature mentions were annotated manually. For each dataset the first 3 mentions of the 67 most frequent features were considered. This was done in order not to bias the results, because sentiments appear to be easier to detect for some features than for others. The resulting values are provided in Table IV. The numbers are quite different for both datasets and in general better for the customer Web surveys, for which the analysis had been designed first of all. For these surveys there are no considerable differences in accuracy among the three levels, which would be a good argument to omit them. However, as shown in the evaluation of the pattern detection (Section 8.1), it is still beneficial to consider the uncertainty, because it works better for the special case where words are features and sentiments at the same time. The value in the category “No Sentiment” shows how many of the feature mentions, for which no sentiment could be identified, actually did not have any sentiment. In other words a low accuracy here indicates that quite a number of sentiments have not been detected, which is the case for the customer Web surveys. This is quite different for the RSS feeds dataset. Apparently, this contains many more nouns not mentioned in relation with a sentiment than the customer surveys. In addition, a clear difference between level 1 and the two other levels is visible. Considering the fact that the algorithm has three options for sentiment labels (positive, negative, neutral), the 52.9% accuracy for level 2 is still

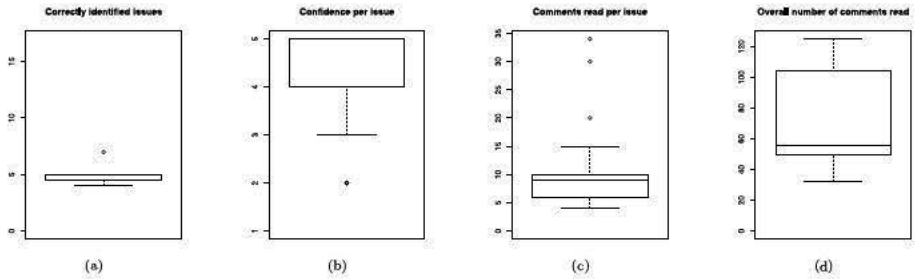


Fig. 8. Numerical results of the study: (a) time-related issues detected correctly within 20 minutes (average per person), (b) confidence in discovering time-related issues (per issue) on a scale ranging from 1 (not very confident) to 5 (absolutely confident), (c) estimated amount of comments read (per discovered time-related issue), (d) overall amount of comments read by each participant including comments that did not lead to the discovery of time-related issues.

much better than chance but at the same time not quite satisfying. One reason is that in news about electoral campaigns the different political camps are often named in the same sentence, either comparing them or citing representatives of one camp talking about the opponents. In these cases our automatic sentiment analysis has problems attributing sentiments to the correct entity. For the automatic pattern detection, however, this flaw typically is not a big problem as *sentiment-negativity* was shown to be less influential than the other parameters.

8.3. Expert User Study

In order to gain a better understanding of the usefulness and usability of the system for target users an expert user study was conducted. We were able to get hold of 7 experts willing to participate. The participants were asked to use the system to identify important time-related issues contained in the Web survey dataset. To this end, they were first given explanations about the underlying concepts of the visualizations contained in the tool and were given the chance to become familiar with the possibilities for interaction. This introductory phase took about 5 to 10 minutes depending on the questions a participant had about the techniques and the tool. Then, the participants were given 20 minutes to find as many time-related issues as possible. Moreover, they were asked to speak their thoughts aloud during the whole study, so it would be easier for the observing person to learn more about their strategies, assumptions, and problems when using the tool. For each time-related issue a participant believed to have found she/he should provide further information: the feature that had helped to discover the issue, a short description of the issue, the start and end time, the estimated number of comments read to identify and understand the issue, and finally the confidence in this analysis. The purpose of asking for a description of the issue as well as the start and end was to assure that the participant actually had gained an understanding of the issues he or she discovered and was able to identify time ranges. The further information was collected to evaluate the reading efforts required and the confidence participants had gained in their analysis. As well, participants were given the option to state that they had discovered an issue that did not appear to be time-related but rather general. Finally, the participants were asked whether they considered the tool as being useful and if so what they liked the most. Further questions were what they disliked about it and what suggestions for improvement they had. Also, they were asked whether they ran out of time and thought they could have discovered more issues easily or if already within the given time they had problems discovering further issues.

Table V. The Aggregated Results for All Participants

	Truly time-related	Truly general	Truly nothing
Time-related (participant)	35	0	3
General (participant)	2	10	0
Nothing (participant)	1	1	7

The choices of the participants (rows) in comparison with the ground truth (columns), only for those features participants actually had a chance to look at before running out of time.

Results and Discussion. First, we want to look at the quantitative performance shown in Figure 8. In average participants were able to discover 5 time-related issues within 20 minutes and had to read 9.84 comments to verify them. They were pretty confident in the analysis with an average of 4.45 (with 5 being the maximum and 1 the minimum). Only 3 (7.9%) false time-related issues were identified, aggregating results for all participants. The 3 false hits correspond exactly to those that were identified with a confidence of 3 or lower. The overall amount of comments read (Figure 8(d)) varies considerably. It could be observed that some participants read comments only superficially focusing on the sentences containing the feature, while others read comments completely. The 74.57 comments participants read in average during the study only correspond to about 0.15% of the overall data (50,000 comments). Next, Table V shows the aggregated performances of all participants for all features which they managed to investigate within the 20 minutes. The overall precision is 88.14%, the precision for time-related issues 92.11%. The 5 time-related issues participants were able to detect in average correspond to a recall of 29.41%. However, the trade-off introduced by the fixed time constraint is decisive here. All 7 participants were confident that they would have discovered more issues if having more time. At the same time, one participant commented that if it was critical in a real-world analysis he would have read every single comment of an interesting time interval pattern, which he did not during the study. All in all, the numerical evaluation of the performance proved that the system is actually usable and suitable for the outlined task of identifying time-related issues in large sets of documents minimizing the reading efforts for analysts.

More interesting than the numerical performance, however, were insights gained when observing the experts using the tool. A basic strategy all participants shared was starting to have a closer look at the intervals automatically detected by the automated analysis. Yet, to our surprise participants applied quite different individual strategies to deal with these intervals. One participant first had a look at different interesting time density plots without exploring them in detail, in order to gain a better feeling for the visualization. In general, users got faster and more accurate the longer they worked with the tool. When running out of time one user commented that he probably had misinterpreted something at the beginning and had just realized this after researching further time density plots, which was actually true. When it came to exploring potentially interesting intervals, one user preferred reading negative comments with a high level of certainty while another user first read the comments at the beginning and end of the highlighted area to see whether they were similar. Several users tended to ignore comments with neutral rating and rather read the other comments. A further user preferred to first read the associated terms of a highlighted area and only then started reading; he was the one that read the least number of comments to identify issues. While 4 participants focused mainly on reading comments within highlighted intervals the other 3 also read a considerable number of comments outside intervals to see whether the reported issue might have persisted in time but just with

a lower frequency. In general it could be observed that the more homogeneous in content the comments within an interval were, the quicker an issue was detected. This was more often the case when dealing with generally infrequent features than with frequent ones.

The answers to the survey questions at the end of the study revealed further details. All participants found the tool useful and when asked what they liked most made the following responses (several things could be named by one participant): 6 mentioned the automatic scoring and highlighting of interesting intervals, 3 mentioned the quick access to the documents via mouse-over, and 2 named the combination of sentiment and time density track. Not liked about the tool was that when zooming out too far, objects could disappear from the screen. This was mentioned by 4 participants and could be fixed in the meantime. Another complaint was about the insufficient description of the interface and one user would have liked an auto-size functionality to see a whole time density plot on the screen without zooming by himself. Further suggestions for improvement were given. One participant would have liked to be able to search and highlight keywords, respectively highlight comments in which these keywords appeared. She wanted to see whether certain keywords appeared more frequently within the comments of an interval than outside. Another participant would have liked to be able to combine two features to one time density plot, containing only documents where both selected features appeared.

As mentioned before, the target user group for our approach and also within the user study were experts. Of course, experts in data analysis are a very experienced user group, so the results cannot simply be generalized to common computer users. The similar level of experience of the participants may also have contributed to the relative homogeneity in performance, though their strategies were quite diverse. In conclusion, the basic concept was well-received, participants gave a mostly positive informal feedback, and were able to identify time-related issues without larger reading efforts. Apart from fixing minor interaction problems further methods for filtering and selection should be integrated in future versions.

9. CONCLUSION

In this article, we address a feature-based sentiment analysis process that tightly couples methods from automatic text processing, visual analytics, and information visualization. Our intelligent visual interface for several reasons is especially beneficial to explore sentiments over time. First, the uncertainty involved in automatic analysis due to the complex and ambiguous nature of language requires further exploration: The textual content of customer comments can easily be accessed by mouse-over interaction for detailed insight and to derive meaning. Second, the fact that it is not quite clear beforehand what kind of interesting temporal patterns might be included in the data demands a broad feature coverage and visual exploration. To quickly analyze vast volumes of text documents over time, we use two complementary visualizations: *pixel map calendars* for general overview and sequential *time density plots* for detailed insights. Features of interest can be selected and visually explored for salient patterns, combining both visualizations. Furthermore, interesting interval patterns are automatically detected and scored. The score measures the importance of an interval based on the height and smoothness of the time density curve, the sentiment negativity, and the context coherence. Analysts can use this score to automatically detect top issue patterns potentially also for early prevention in real time. Our new solutions were tailored for direct customer feedback through Web surveys and further tested on RSS news feeds. Previously unknown issues were discovered and features of interest could be explored in detail. In an extensive evaluation we were able to demonstrate the applicability, usability, and good performance of the

approach, learned about the impact of different parameters, and discussed limitations. Our future research will be in the areas of real-time visual sentiment comparison and reasoning.

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