

# State-of-the-Art Report of Visual Analysis for Event Detection in Text Data Streams

F. Wanner, A. Stoffel, D. Jäckle, B. C. Kwon, A. Weiler, and D. A. Keim

University of Konstanz, Germany

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## Abstract

*Event detection from text data streams has been a popular research area in the past decade. Recently, the evolution of microblogging and social network services opens up great opportunities for various kinds of knowledge-based intelligence activities which require tracking of real-time events. In a sense, visualizations in combination with analytical processes could be a viable method for such tasks because it can be used to analyze the sheer amounts of text streams. However, data analysts and visualization experts often face grand challenges stemming out of the ill-defined concept of event and various kinds of textual data. As a result, we have few guidelines on how to build successful visual analysis tools that can handle specific event types and diverse textual data sources. Our goal is to take the first step towards answering the question by organizing insights from prior research studies on event detection and visual analysis. In the scope of this report, we summarize the evolution of event detection in combination with visual analysis over the past 14 years and provide an overview of the state-of-the-art methods. Our investigation sheds light on various kinds of research areas that can be the most beneficial to the field of visual text event analytics.*

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## 1. Introduction

With the advent of Social Media, event detection from text data streams has gained popularity in the past decade. Especially for analysts event detection plays an important role for their success. Thus, it is vexing that no single, precise definition of events has been presented so far. Within this paper, events are regarded as unexpected and unique patterns extracted from text data streams, valuable to users.

In the past, many approaches have been developed to detect events from various types of text data streams. Due to recent advancements in information science and technology, event detection has been brought a big step forward by means of its main data sources. In particular, data sources evolved from a relatively limited amount of well-written news articles to rapidly generated, user written, and in some cases unstructured textual data from social media services. This trend has been initiated with the emergence of the Web 2.0. This term was publicly introduced in 2004 and identifies a new era of the web, allowing user interaction and collaboration (Social Media).

One of the very first works on event detection was presented by Yang et al. [YPC98] in 1998. The authors carried

out a study where they make use of text retrieval and clustering techniques in order to detect events in chronologically ordered news story streams. Within the same year, Allan et al. [APL98] presented a modified single-pass clustering approach for on-line event detection and information filtering. This technique was then used to track events.

Accurate event detection from user-generated text data streams posits unprecedented challenges. Regardless of the used visualization and data, all approaches define an event as something surprising, abnormal, or even unexpected that can be identified within the analysis and visualization process of the data. However, the characteristics of the event definition as well as the used approaches vary. We identified some of the most important questions that rise when talking about events. For example: “How and why did the event happen?”, “Where did the event happen?”, or “How did the event evolve over time?”. Furthermore, the tasks addressed by various visualizations occur diverse. Dou et al. [DWRZ12] defined task according to “New Event Detection”, “Event Tracking”, “Event Summarization”, and “Event Associations”, but we expect that tasks can be even more diversified including geographic dimension which were not explored yet. Another challenge represents the unstructured, diverse

textual data. It mandates extensive processing and preparation in order to properly employ it.

This survey aims to take first steps towards deriving meaningful insights on the issue by investigating existing visual text event detection approaches from the past decade. With this paper, we present – to the best of our knowledge – a categorization as well as an overview of a reasonable number of the most important publications, that describe any approaches associated with visual event detection in text streams. In contrast to the work of Rohrdantz et al. [ROKF11], we concentrate on research works that focus on event detection and identification in particular.

This paper is structured as follows. First, we present related work which motivates tasks and challenges within this domain. Then, we describe our methods to select and survey papers in Section 3. From the selected papers, we first derive some trends on text data sources in Section 4. Then, Sections 5, 6, and 7 summarize automatic methods for visual text event detection and diverse visualizations of events. Finally, we present various evaluation methods in Section 8. In Section 9, we summarize our findings, discuss their implications, and highlight possible future work.

## 2. Related Work

Event has been defined in various ways because it has different values for different purposes. Becker [Bec11] shows interesting work about event detection in social media. She divides an event using three dimensions: 1) “planned” vs. “unplanned”; 2) “trending” vs “non-trending”; 3) “exogenous” vs. “endogenous”. The last dimension aims to detect events within the data in a real-life context. This is interesting, because it raises the question which events are present in the text data and *what are their specific features and why text events occur in text streams*. The basic question here is why people write about an event. That could be partially answered for the professional news creation process by having a look into communication sciences literature. The concept of *news values* or *news criteria*, respectively were introduced by Galtung and Ruge in 1965 [GR65] and were “revisited” by Harcup and O’Neill [HO01]. Research on the question why an event reflected in a text stream is newsworthy enough to be noticed by a reader did [Kep98] by presenting the concept of *selection criteria*.

There have been some surveys on text mining methods. Hotho et al., [HNP05] define text data mining in general and explain the functionality of different natural language processing, data mining and information retrieval and information extraction methods. Berry and Castellanos [BC08] discuss text mining methods like clustering, classification, filtering, and anomaly detection methods for text collections. Anomaly detection is also a kind of event detection. In the described method the anomalies are labeled with event types which come out of the text.

Visualizations coupled with data mining methods have also been reviewed by Šilić and Bašić [ŠB10]. They characterize each text document as a form of a text stream, because it consists of smaller textual components (paragraphs, sentences, etc.). Some examples of visual social media analysis is shown in Schreck and Keim [SK13]. With screenshots of the different visualizations, the authors explain the underlying data, analysis methods, and functionality of various applications in visual social media analysis. Some of the papers in this publication are included in our survey. There exists a survey on semantic sensemaking by Bontcheva and Rout [BR12]. Though their focus was on the semantic aspects, a subsection refers to visualization approaches. Some of the mentioned papers fit also in our survey.

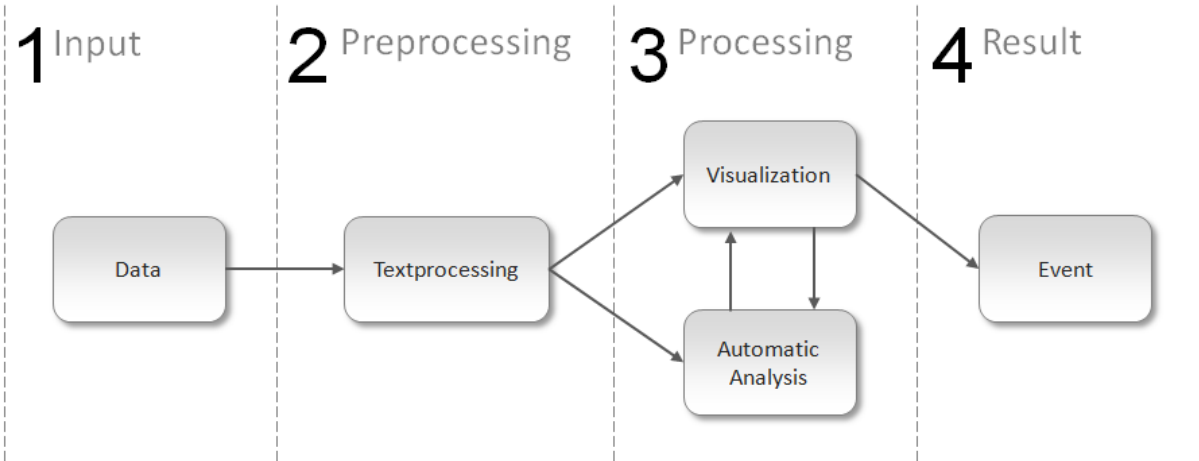
Especially visual analytics can be a viable method to perform various domain tasks that are related to event detection. Rohrdantz et al. [ROKF11] mention tasks for the “Real-Time Visualization of Streaming Text Data”. They call tasks that are relevant in terms of the scope of our paper “monitoring”, “change and trend detection” and “situational awareness”. After examining their examples for each particular task, we subsumed them under event detection for our purposes. The relevant visualization tasks regarding our paper are described in Section 7. Though all of these papers are highly related, they do not focus on visual analysis for event detection. Therefore, we conduct this study to investigate the delicate issues of visual analysis for event detection.

## 3. Methodology

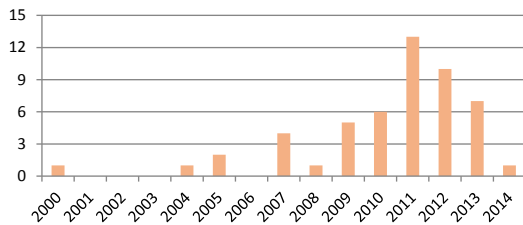
This review provides an overview of the state-of-the-art techniques to detect events in text data streams. To achieve the goal, we show the evolution of event detection in text streams over the past ten years. In particular, we investigate visual analysis approaches to derive the analysis results and detect common patterns and events. Therefore, we selected research papers that show visual analysis approaches detecting any type of events in text data using visualization for analysis and communication. We particularly paid our attention to papers which include significant contributions, such as a new algorithm, a new visualization, or a new data set.

To the best of our knowledge, there is no visual analysis pipeline specifically designed for event detection. To conduct this survey, we first started reviewing papers without any particular models in mind. While reviewing event detection and visual analysis from multiple papers, we slowly conceptualized high-level components and individual task processes. Based upon our insights, we created our own the event detection and exploration pipeline in Figure 1 adapting from Keim et al. [KAF\*08]. Then, we retrospectively surveyed papers to adjust and improve this pipeline. We believe that this pipeline reflects both the visual analysis process and the more interactive visual analytics process for event detection to a reasonable extent.

In the first step of the pipeline, the documents are prepared



**Figure 1:** The event detection and exploration pipeline used to structure this report.



**Figure 2:** Distribution of surveyed papers over publication year. The majority of papers were published between 2007 and 2013. We consider only one paper from 2014, because this report was written in early 2014.

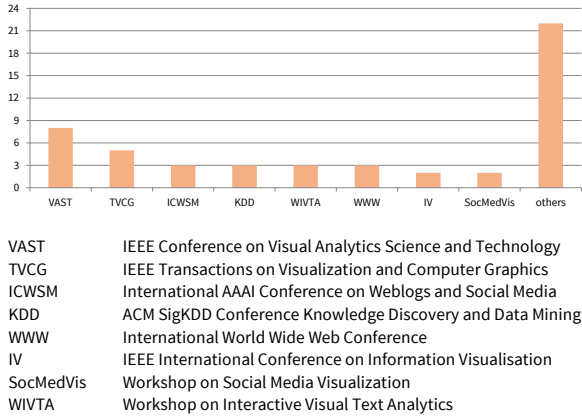
for the analysis. In this step the documents are parsed to get the plain texts and standard text preprocessing methods, such as sentence detection, tokenizing, and stemming and lemmatizing are applied. In addition to these standard methods, methods from the computer linguistic field can be used in the preprocessing step to annotate the texts with additional information. For instance, part-of-speech tagging, named entity extraction, or syntactic parsing can be used to identify types of words, persons and places, or structure of sentences. The standard preprocessing techniques are required to work with text data in any case. We therefore focus on the usage of computer linguistic methods in this review.

After the preprocessing step different approaches are used to detect events (see two branches in Processing in Figure 1). The first group of approaches applies automatic methods to detect patterns in the data. The detected patterns are then used to create a visual analysis interface for the data set, what we call visual analysis. The interaction between visualization and the automatic part shapes a visual analytics approach. The second group of approaches skips the automatic analysis and directly visualizes the outcome of the prepro-

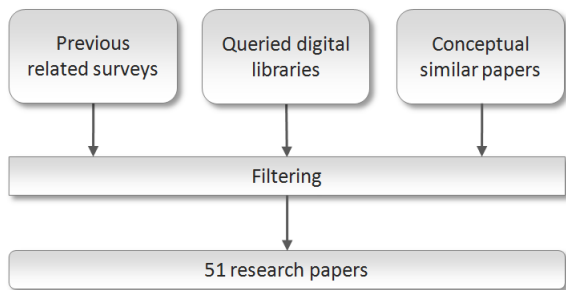
cessing, what also is only visual analysis because of the lack of interaction possibilities of a certain extent. The used visualization and interaction techniques depend on the type of data and the requirements of the different approaches. This report investigates the applied automatic data analysis methods as well as the visualization methods.

In the last step of our pipeline, users interact with the visualization and derive the requested knowledge. As our selection of papers requested visual approaches, all surveyed papers use visualizations to communicate results. The papers often show the validity and usefulness of their approach by comparing with different techniques. In this report we summarize the used evaluation techniques and give an overview of their usage. We used the pipeline to review individual papers; we derived subcategories (e.g., POS tagging for text processing methods), and checked whether individual papers include them. Following sections are structured in the same way so that readers can easily follow.

We used the following procedure to select papers for our review (Figure 4). We first archived papers from previous survey papers, e.g. [ŠB10, BR12]. Then, we used the digital libraries of IEEE Xplore, ACM and AAAI to search documents that include all the following terms in their title or abstract (for AAAI we used Google Scholar): “visual”, “text”, “event” and “analysis”. This querying process resulted in more than 280 research papers. In addition, we took research on visual text event analysis into account which does not calling it explicitly analogous. After the collection step, we refine our paper pool by filtering papers out using the following criteria: 1) papers were published from 2000; 2) papers should describe visualization methods as well as event detection (an event has to have a time dimension); 3) a newer paper was selected when multiple versions of similar methods were available from the same research group. As a result, we included 51 papers in total for our review. Figure 2 shows



**Figure 3:** Number of papers selected by venue. The category “others” summarizes all venues with a single paper.



**Figure 4:** The paper selection process. In a first step we collected the papers from several sources. Then we applied a filter step to get the result of 51 papers.

the distribution of the papers over publication year and Figure 3 shows the number of papers selected by venue.

#### 4. Text Data Sources

We derived twelve distinctive text data sources used in the 51 papers, as Table 1 shows. We summarize characteristics and trends of such data sources, which could be useful for future researchers.

##### 4.1. Characteristics

News is a well-known text data source. News captures information of a real world event or happening. It consists of a title, often followed by a short summary and the body containing details about the event. News goes through a professional gatekeeping process which in the end forms the agenda of media. Whitney and Becker [WB80] describe the process as follows: “[...] the agenda being presented by the media audiences is influenced by the newsgathering procedures of the media and the relationships among the media.”

During this process, the published news has to pass different “gates”. Each gate could shut down in case the news is not newsworthy enough. At the beginning of a simplified publication process the first gate is the reporter himself. As he investigates an event in detail, he has to decide if it is worth to become news or not. Later in the paper we will show some criteria for such a decision. In case the information about an event is proven newsworthy by the journalist, it has to pass the next gate which is the editorial journalist. If the news is not interesting or newsworthy enough, does not fit to the agenda or there is no space left, the news will not be published. Since news is also published on the Internet, the space limitation does not form a large barrier anymore. However, it is still limitation for the printed version of a newspaper.

A typical electronic document is email. Its ancestor is postal mail which is sent to real postboxes close to the entrance doors of houses and apartments. Emails are used for personal conversations, advertisement or business information exchange. They consist of a header and a body. The header contains information about transaction: sender, receiver, timestamp, and other meta data. The body contains the textual content of the email. An email body can be of arbitrary length which is one of its characteristics.

Weblogs, shortly named blogs are used for information purposes of a more or less undefined audience. Beside other providers, WordPress for example provides software to create, maintain and design weblogs in an easy and convenient manner (Software available at <http://en.wordpress.com/features>). A blog can have a specific topic or can be open for various topics. There are personal or non-personal blogs [KLS\*05, EdR08]. In the scope of the survey we take personal blogs as a matter of private citizens whereas non-personal blogs are written by non-governmental organizations (NGOs), companies, enterprises or professionals in general.

RSS feeds are a standardized format to broadcast short news snippets. They consist of a title and a description. RSS feeds can be used by news agencies, newspapers and blogs. In contrast to former pull services, RSS was developed as push communication. If users want to receive a feed, they need a RSS reader and have to subscribe for a feed that they are interested in. The reader aggregates all the incoming messages. The standardized format allows the easy integration into other applications.

Recently, microblogging providers are becoming more and more popular. The messages are limited with respect to their length of 140 characters. So-called “hashtags” are used in order to characterize the membership of a tweet to a certain topic. In addition, more meta data is provided, e.g. geo-location, author, place etc. That depends on whether users have these meta data fields enabled. The largest service is Twitter (<https://twitter.com/>). Since its birth in March 2006, it has more than one billion of registered users [Koe13] and more than 232 million monthly active users [Con13]. The to-







methods (as shown in the second column of Table 2), many other elementary methods (e.g., tf-idf) have been excluded. Diverse research topics emerged recently, which require in-depth analysis of text, perhaps about the quality of a subset of text (e.g., topics, sentiments). Thus, we believe that many research papers started absorbing more natural language processing techniques to further generate their event metrics.

## 6. Automatic Methods for Text Event Detection

We observed four categories of event detection techniques; they are further subdivided into 15 categories (see Table 3). In a big picture, we have seen few papers that adopt any automatic event detection methods. The two most popular method categories were clustering and statistical methods. The popularity may be highly correlated to how the event is defined in the papers. For instance, many research papers defined the event as an irregular activities compared with average signs across the temporal dimension in given data. Thus, such papers seek to find statistically significant difference in textual data, which naturally leads to the popularity of statistical methods. Given that many topic modeling techniques were also adapted with respect to temporal dimension to narrow down events in fine granularity (e.g., Zhao and Mitra [ZM07]). However, very few papers incorporated classification, prediction, knowledge modeling, or pattern mining.

### 6.1. Event Detection Methods

A widely used family of algorithms to detect events is based on clustering techniques. Clusters are generated for different time windows based different properties in the document, e.g., co-occurrence of terms, frequency in time, or metadata. Events are generated when the set of clusters changes, e.g., a new cluster arise or two existing clusters merge. With clustering based methods users do not need to specify the type of events but the algorithms detect changes in the data.

Other approaches to detect specific events are based on classifiers. Users provide a set of example documents and classifiers learn to detect the annotated events. Classifier-based techniques are used in similar cases with rule-based ones, but have the advantage that users do not need to create rules by themselves. In our surveyed papers, only two papers use classifiers to detect user specific events. This accords with the finding of the rare usage of rule-based methods and indicates that visual analysis approaches are mainly used to explore new events in text streams.

Statistical methods such as correlation or detection of outliers and significant difference are used to identify events. Correlation based methods examine collection between terms or between terms and time and detect events by changes in the correlation measures. A different type of statistical methods calculate term-wise deviation from an expected value or use other measures to identify rare or unique

occurrence of terms. These statistical abnormalities are then assessed and events are identified.

Prediction-based methods predict the occurrence of following documents based upon past history. We found one paper using Kalman filters [SOM10] for prediction. Based upon many geo-tagged documents, predictions can be made on the location of newly added documents. Thus, this method can detect abnormal events which deviate from prediction. Thus, prediction-based methods require archived past events to precisely anticipate the future events. We found only one paper that applies a prediction method to detect natural disasters.

Methods based on ontologies [HHSW09] are suitable for event analysis in single domains. Specific ontologies are generated with full- or semi-automatic methods. The only paper in our set using ontologies aims to identify concepts appearing in documents and time frames. Using this type of methods, events can then be detected from changes in activated concepts.

Pattern mining algorithms, such as the A-priori algorithm of Wu and Chen [WC09] applied to text in [WSJ\*14], are used to extract common sequential patterns in document streams. Patterns can be found based on documents themselves or time intervals. In both cases, features extracted from documents are then used to define patterns. Instead of identifying single events, pattern mining algorithms aim to derive recurring patterns in data. In our selected papers, we found only a single paper using pattern mining technique, which does not only identify events but characterizes these events based upon their pattern.

Models of the recurring characteristics of data streams can be used to detect events. An event is detected when a stream deviates significantly from its expected characteristics. We only found one paper [BGAC11] using Fourier analysis to model the base frequencies of a data stream and using them as model to detect events.

Rule-based approaches detect events with manually created rules. For instance, users specify rules based on terms and/or frequency to detect a particular event. The events that can be detected by these approaches are only limited by the expressiveness of rule languages. In contrast to other techniques are events detected with these approaches predictable for users but require precise knowledge of the data and the events. To our surprise is only one paper [GS05] using rule-based definition of events and allows expert users to define events by queries.

### 6.2. Trends

We cannot find any correlation between text analysis and event detection methods. All event detection methods are used with basic text tokens and also with text processing results. Interestingly, only two papers build classifiers







		Visualization														
		Basic Charts	2D-Scatterplots	Pixel-Based	Timeline	Parallel	Cloud	River	Coordinates	Treenaps	Cyclic	Node-Link	Force directed	Glyph	Map	Information Landscape
Clustering	Topic Modelling															
	Graph-based															
	k-means Clustering															
	Hierarchical Clustering															
Classific. <sup>1</sup>	Regression															
	Decision Tree															
	Linear classifier															
	SVM															
Stat <sup>2</sup>	Correlation															
	Sig. Diff./Unique <sup>3</sup>															
Others	Kalman Filter															
	Ontology															
	A-priori															
	Fourier Analysis															
	Rules															

<sup>1</sup>Classification; <sup>2</sup>Statistic; <sup>3</sup>Significantly Different / Unique

**Table 6:** Usage of visualization and event detection techniques. Statistical event detection methods are used with any kind of visualization. In contrast, the clustering based methods are mainly visualized with the river metaphor. The exception are topic modeling techniques, which are often used to generate labels in visualizations or legends.

and classified according to the table we designed (see Table 7). In particular, we identified nine different evaluation categories across a representative number of papers that address visual text event detection. We subdivided these categories into two classes: *qualitative* and *quantitative* evaluation methods.

The table reveals one common trend at first glance: Use cases are very popular, especially since 2011. In this chapter we will highlight the main differences between common evaluation methods and unfold significant patterns.

We subdivide qualitative methods into the following categories: *case study*, *usability evaluation*, *use case*, and *anecdotal evaluation*. Table 7 accentuates the popular usage of use cases; except for 16 of all considered papers the authors make use of this method. Typically, a use case validates through the description of a fictitious scenario that pinpoints main features whereas a case study involves a domain expert and therefore is more time-consuming [DNKS10, MBB\*11]. This may be one of the reasons why use cases are more popular. Anecdotal evaluation describes how the suggested system could be used, but do not provide sufficient evidence to judge the general efficacy of the presented technique. Usability evaluations involve users performing particular tasks with the given system and asks for comments on usability.

Despite the fact that many systems suggests automatic event detection methods, quantitative evaluation are seldom used. The most prominent quantitative evaluation methods are comparisons of the detected events with a ground truth set. Often event databases are used as ground truth that are enriched by the authors with missing entries. Missing reliable ground truth might be the major reason why algorithms are in many cases not evaluated. A different evaluation form of algorithms are comparison with existing algorithms and reporting quality measures. In some cases not the results of the algorithms are evaluated but the performance in the sense of runtime or memory consumption is assessed, which is important for systems working in near real-time scenarios. We also found only four papers using a user study for evaluation. We expected more papers using user studies, because many systems present novel visualization techniques and user studies can verify the strength and weakness of the application [HHN00, LYK\*12, RHD\*12].

We come to the conclusion that qualitative evaluation methods, especially use cases, are used frequently, since papers with respect to visual systems are application-driven and demand validation through description of fictitious scenarios. We also believe that there need more user evaluation, especially when testing the efficacy of systems for time-critical tasks.



data [Bec11], which means that there is no real world event related in space and time. To overcome such problems, according to [Kep98] user's *selection criteria* could be taken into account. In step 3 of Figure 5 selection criteria are applied by a consumer (reader) in order to decide whether a broadcasted event is newsworthy or not. Especially in news analysis could those criteria of news creation and selection lead to new filters expressing user's intents.

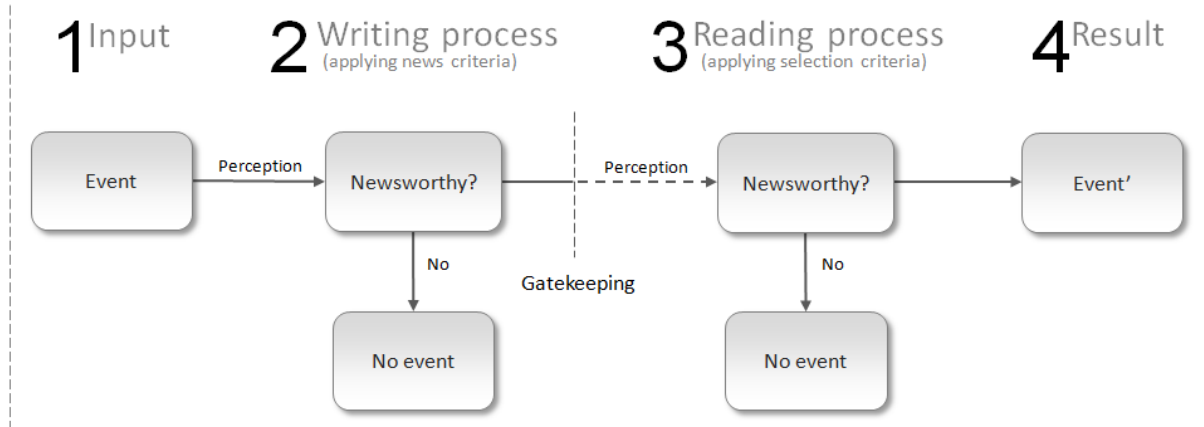
In general, news and selection criteria could be merged into one concept we call *event values*. Event values are a concept including the text data producer's and user's perspectives. They could be implemented in the data analysis process by means of new features (feature engineering) and interactive elements, which comes along with the call for more visual analytics functionality. In (visual) text event analysis applications, this concept could help to improve and generalize the underlying event definition and the process of event detection. It could also enable different user groups to adapt the same application for their needs. Then, event criteria would help to understand which events are in the data and what is relevant to certain users. Anyway, further interdisciplinary research is needed on how a general concept can be developed and which news and selection criteria can be transferred to social media analysis [Jah12].

As a side note we did not find any paper within our selection judging the trustworthiness or credibility of the textual documents.

These lessons from our reviews shed light on various areas we need to fill in the next decade. Our review shows that we have an ill-defined concept of event, which may distract the focused effort from this community. On the other hand, we also show some interesting perspectives of news and selection criteria that can be used to detect events that are defined by users. We believe that this paper takes the first step towards clarifying this concept.

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**Figure 5:** A simplified process of news creation and consumption. During news creation (step 2) news criteria [GR65, HO01] are used to judge newsworthiness of an event by a human. During reception (step 3) a reader applies selection criteria [Kep98] to decide whether the broadcasted event is newsworthy enough to get attention. The process is appropriate for conventional news and could also be appropriate for social media, but not without further research [Jah12]. Note, social media have typically no gatekeeping process.

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## Biography

**Franz Wanner** is PhD student in computer science. He is working for years in the Information Visualization and Data Analysis Research Group at the University of Konstanz. His main research interests include visual text event detection, visual analytics of heterogeneous datasets in conjunction with text and document visualizations.

**Andreas Stoffel** received his PhD degree in computer science in 2013. He is currently working in the Information Visualization and Data Analysis Research Group at the University of Konstanz. His main research interests include visual analytics, document visualization and automatic document analysis methods.

**Dominik Jäckle** is PhD student at the Data Analysis and Visualization Group at the University of Konstanz. His main research interests include the development and application of new visualization techniques and algorithms for the exploration of vast amounts of data.

**Bum Chul Kwon** received his PhD degree specializing in information visualization and human computer interaction at Purdue University in 2013. He is currently working in the Information Visualization and Data Analysis Research Group at the University of Konstanz. His main research interests include information visualization, visual analytics and human-based computation methods.

**Andreas Weiler** is PhD student at the Database and Information Systems Research Group at the University of Konstanz. His main research focuses on processing, analyzing, and visualizing of Social Media Data Streams for Event Identification and Tracking.

**Daniel Keim** is a full professor and the head of the Information Visualization and Data Analysis Research Group in the University of Konstanz's Computer Science Department. Keim received a habilitation in computer science from the University of Munich. He has been program cochair of the IEEE Information Visualization Conference, the IEEE Conference on Visual Analytics Science and Technology (VAST), and the ACM SIGKDD Conference on Knowledge Discovery and Data Mining. He's on the steering committees of IEEE VAST and the Eurographics Conference on Visualization.