Visual Analysis of Real-time Social Media for Emergency Response

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Abstract. The prevalence of Social Media in sharing day to day information regarding all aspects of our life is ever increasing. More so, with access to cheap Internet-enabled devices and proliferation of Social Media applications. Among the variety of information shared, the most relevant, in the context of this paper is how individuals assess their surroundings and how they or their loved ones are affected by adverse events, disasters and crises. Traditional channels of communication often fall behind in providing timely information for emergency responders to formulate an accurate picture of the situation on the ground. The role of Social Media in complimenting such sources of information is thus invaluable and Social Media has been recognised as a key element of assessing evolving situations. Timely, accurate and efficient means to explore and query Social Media is essential for an effective response during emergencies, and hence this gives rise to a Knowledge Management issue. Our paper presents our approach to analysing Real-Time Social Media data streams using Visual Analytic techniques. We discuss the highly visual and interactive approach we employ to provide emergency responders means to access data of interest, supporting different information seeking paradigms.

Keywords: Social Media, Emergency Response, Visual Analytics

1 Introduction

The challenge of gathering a good understanding of large volumes of Social Media data streams is a significant one. The nature of Social Media itself, being highly dynamic, multi-lingual, geographically distributed, and highly relevant to the short-term zeitgeist poses enormous challenges. Additionally, the highly repetitive and noisy nature of Social Media also adds significant challenges to analysis efforts. In spite of these challenges, the potential of Social Media is immense and has been recognised as significant in Emergency Response by various organisations. Social Media empowers analysts with better means to understand public perception of events and situations on the ground as well as facilitating decision making processes for planning rescue operations[1 2] [20, 31]. The Emergency Response domain, owing to the need for the efficient delivery of critical information for decision makers, requires the assimilation, analysis and visualisation of Real-Time information. How such information can be presented to end users is a significant research challenge, as evolving situations require means to ensure the dynamicity of information is communicated. Social Media is multi-dimensional and hence, the information delivered to users must be communicated in a multi-faceted paradigm.

The goal of our research is to facilitate exploration of large volumes of Social Media information for gathering a very quick understanding of a situation at hand. It is important to note that this paper discusses events and situations from a broader perspective – events refer to anything that occurs[3] that is of interest to an analyst, while situations relate to the conditions and state of affairs (including events that occur to shape situations). To this end, we have developed a system, TUI (Tracking User Intelligence) [13] that exploits various visualisations and employs different interaction paradigms and approaches to help users improve their Situation Awareness [11, 32] by exploring various facets of Social Media. The context of our paper is all types of emergencies (major and minor) and events, but the effectiveness of our solution depends on the volume of Social Media generated. For example, low scale events such as small accidents in less populated areas would generate less interest, and hence, minimal Social Media posts. Our system also explores how users can have access to information based on temporal windows and can observe the evolution of events.

This paper is structured as follows: the next section describes related work. Section 3 presents an overview of the TUI interface. Section 4 describes how various types of information needs are addressed by elements within the framework, and how they are relevant to Emergency Response. Section 5 briefly discusses several field studies we conducted in real world examples and we conclude the paper with lessons learned and a discussion of future work.

2 Related Work

We present related work in two areas: Situational awareness and Visual Analytics. Situational Awareness in emergencies is paramount to deliver a timely and effective response [9]. To achieve effective Situational Awareness, emergency services must collate information from multiple sources and use it to build an understanding of the current situation and how this may evolve over time [11]. Leveraging data from citizens to build a form of collective intelligence [26], during emergencies or for security purposes, is becoming a vital resource for Situation Awareness [22]. During the 2007 southern California wildfires, two bulletin boards were set up to facilitate the exchange of information between citizens

[1] http://www.unocha.org/top-stories/all-stories/disaster-relief-20-future-information-sharing-humanitarian-emergencies
[2] http://www.unocha.org/hina
[3] http://www.complexevents.com/2011/08/23/event-processing-glossary-version-2-0/

and authorities [24]. A later analysis of Twitter postings during the 2009 Red River flooding [27] indicated that the service was being used by citizens and communities to collate and propagate information in a concise and responsive manner. Several systems have been developed to support citizen participation during emergencies that either directly foster data from citizens through custom apps [19] or analyse public data stream to extract real-time knowledge [2,29,30]. Existing techniques for searching Social Media involve exploiting entity-based semantic features [28]; entity mentions, hashtags, URLs and metadata [17]; and entity annotations coupled with user models for personalised searches [1]. Recommendations and filtering systems are used to help users reduce information overload, i.e. recommending links that users may find interesting; using dynamic semantic models of user interests [2]; recommending posts and friends based on categories [10, 21].

Visual Analytic techniques have been proposed to represent and filter Social Media at different levels of specificity [15] [4] and to convey information evolution in the crisis management domain [23]. When visualising large scale Social Media data, Visual Analytics is mainly used to provide high level overviews. [14] explores information regarding Social Media campaigns, [23] uses Twitter to understand the progression of earthquakes and [33] explores trends in emergency medicine. While these systems manage to efficiently display the chosen information, they are limited in the amount of data displayed. Systems with a broader focus try to capture the properties of generic data, allowing users to filter the data to items of interest. [15] for example, is a system for visualising and summarising events on Twitter. [8] allows users to explore Real-Time data streams relating to a given keyword. [3] is a system that improves Situation Awareness during small-scale crisis response, such as factory fires or music festivals by focussing on geotagged tweets and employing classification algorithms to identify messages relevant to specific events. Whilst most Social Media visualisation approaches rely on geographical and temporal features such as [18], some systems are starting to exploit the semantic of the data to enhance the visualisations. Examples of such systems are [6, 12, 15]. [15] uses features such as sentiment and link popularity to geographically plot the data. [12] uses features such as sentiment to create news flow diagrams that analyses the evolution of keywords and sentiments over time. [5] also focuses on interactive colour-coded timeline displays. [6] cluster groups of users and their evolution over time for a particular topic.

3 Tracking User Intelligence – An Overview

We designed our solution centering to the different modes of Information Seeking proposed by Bates [7]. Figure 2 presents the four modes: Searching, Monitoring, Browsing and Being Aware.

TUI is a multi visualisation platform that consists of multiple views over different facets of Social Media data. Users can interact with the system via each visualisation widget or a set of generic query elements to define filters. The user interface is separated from the backend processing, in order to deliver a more responsive performance, and hence our solution consists of two independent solutions. Several interaction paradigms govern how users can interact with the system, and therefore, provides multiple ways of engaging with the data. While being founded on the four information seeking models of Bates, TUI supports Schneiderman's well-known information seeking paradigm "overview first, zoom and filter, and details on demand" [25].

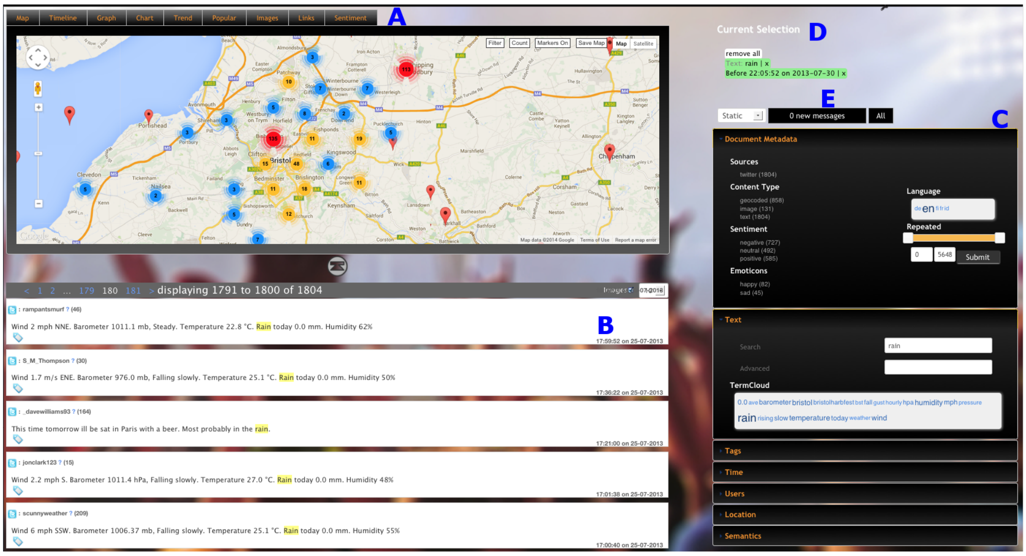

Fig. 1. A Screenshot of the developed system, Tracking User Intelligence (TUI). Five main sections can be observed (A: Contextual Information Visualisation; B: Content Presentation; C: Filters; D: Current Selection/filters; and E: Real Time Updates)

Figure 1 shows the four main components of the TUI interface. The interface is designed to enable users simultaneously access the most important information that is relevant to their present session. We enable this by providing a set of tabs (Section A: Contextual Information Visualisation), each presenting a piece of contextual information depending on the user's information need. The tabs (most relevant ones are discussed in the paper) are as follows: Map View ('Map'), Timeline View ('Timeline'), Graph view ('Graph'), Chart View ('Chart'), Trend View ('Trend'), Freq View ('Popular'). Map view provides contextual spatial information on a geographical map, while timeline provides visual summaries on a temporal scale. Graph view provides topical information, presented as a graph of topical relation among Social Media messages, where each topic is visually encoded based on the number of occurrence, associated collective sentiment or any other parameter that is decided as appropriate. The type of graph that is deployed depends on the particular use case, and TUI can select from a set of candidate graphs based on the number of topics. For example, a typical node-link graph can present a lower number of topics, but can provide an easier way of communicating relational information between co-occurring topics. The Context and Hierarchy chain [16], on the other hand presents a larger number of topics along with their hierarchical relations but requires a greater amount of interactivity to understand co-occurring topics. Chart view provides an overview of the entire dataset, presented as a series of pie charts. Trend view and Freq view provide advanced scatterplot visualisations to display which topics are trending and the most shared Social Media posts. The last two views are hidden from a typical Emergency Responder's profile, as they are presently under development and more investigation is needed into the best possible visualisations. These contextual tabs address the first part of Schneiderman's paradigm 'overview first'.

The Social Media posts section (Section B: Content Presentation) shows the data instances, where each Social Media post is presented as a snippet, chronologically listed. The display of Social Media posts is designed to address the last part of Schneiderman's 'details-on-demand' paradigm, where the session of user exploration dictates the relevant content to be displayed. The central part of Schneiderman's paradigm, 'zoom and filter' is the final filtering section (Section C: Filters). The filtering interface provides two functions – visual communication and overviews, and filtering. This section presents tag clouds of several facets of the data such as authors, places, type of post (photo, video, audio, link etc.), keyword or hashtag. Additionally, other interaction mechanisms such as text entry boxes, sliders, calendar widgets and buttons are presented to users for entering specific filters (or queries). Overall, interactions within Section A and C result in defining the context of the user's information needs and eventually retrieve the content for Section B. The Real-Time Updates section (Section E) provides a real-time reflection of the background data collection: this informs the user that in the time that has passed since the last time the visualisations have been refreshed, there has been a number of new messages that have been collected. The user has three choices: ignore the message, view only the new messages, or view all the data that has been collected. The final component presents the filters and selections that are active on the present exploration session of the user. These filters are generated by the user by interacting with visualisations and interface elements from the Sections A and C. Users can disable each filter by clicking on the (x) button if required.

4 Supporting Multiple Modes of Information Seeking

Within the scope of Emergency Response, Searching involves directed and active information seeking activities, where the user has a very specific information need, and knows the information exists. For example, an emergency responder is investigating a situation at hand (such as a flood) and is looking for more information related to the state of rivers overflowing. Monitoring involves the user having a specific information need, but is unsure if the information exists and hence monitors for relevant information. For example, an emergency responder is aware that flooding is a regular occurrence in a city, and is monitoring the condition of the city with a higher than usual predicted rainfall. Browsing, on the other hand involves the user actively looking for any relevant information, but in an undirected manner. An example of browsing would be an emergency responder looking for any occurrence of floods within a large geographical area. Being aware involves the user being passively looking for relevant information in an undirected manner. For example, an emergency responder looking for anything which can indicate an incident occurring that might be of interest to be further investigated.

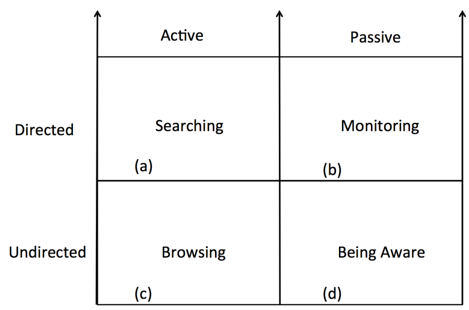

Fig. 2. Four modes of Information Seeking, proposed by [7]

As explained previously, Schneiderman's information seeking paradigm was central to the design of the interface. Bate's information seeking model provided a basis for understanding how users may need to search/explore/monitor existing situations using the system. During initial design phases, Bate's model along with interviews and focus groups with emergency responders and practitioners provided realistic scenarios that can explain what are the information needs of users at different stages of an emergency situation. This section presents four main scenarios that relate to the different elements of Bate's model, and how TUI can be typically used to identify data of interest. It is to be noted that while all of the aspects of the model requires active searching, the manner in which the user can trigger the searches and the follow up tasks play a role in addressing different types of information needs.

The filters section (Section C) is key to this task, where the user can drill-down to a set of data instances of interest, based on the information need of the user. The selection can be done using different interaction techniques and via a variety of facets. The variety of facets can be observed on the accordion menu on the right – three levels of filters are provided to users. Figure 3 describes how these filters are organised - Content filters, Immediate Context filters and Wider Context filters. Information that can be easily extracted from the content of the Social Media posts are referred to Content Filters. The content filters are the features that are aligned the closest to the Social Media post itself. A minimal analysis of the Social Media posts can provide a few more features, which have been organised into Immediate Context. While some features like Language or Type can be easily retrieved from the data provider, they may require some basic analysis to interpret content and infer. The Wider context filters indicate the features that require a further level of analysis/interpretation/query. Features such as identifying locations may be easily provided by geolocated posts, but the process may be considerably more difficult if there is a need to analyse text to interpret locations. Information surrounding a post such as the relevant users (who posted, who replied or who were mentioned) can be retrived by further queries to the data providers and may require further processing.

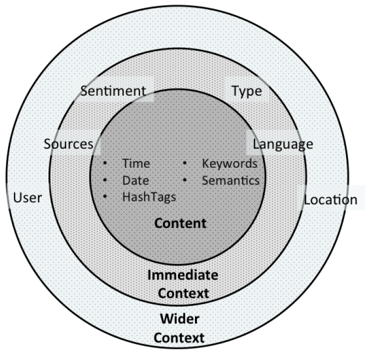

Fig. 3. Three levels of filters: Content filters indicate elements that can be quickly retrieved from the content of the Social Media posts; Immediate Context filters indicate information that can be inferred from the Social Media posts with minimal analysis; and Wider Context filters refer to the information that can be derived from the user who are relevant to the post, or the locations related to the posts.

A combination of filters can be used to identify an initial subset of the data, and then users can progressively apply further filters to reach the data instances that are of interest. For example, if the user is interested in the negative/positive messages that have had a high impact among the users, he/she can make a combination of selections of emotions/sentiments as well as selection of a high number of repeated messages. Observing the hashtags or keywords can then provide a rough summary of the topics of discussions and provide a greater overview of the situation.

4.1 Searching – Active and Directed

The first, and possibly most relevant to most Semantic Web applications is the ability to search for existing information, when there is a highly specific information need. Within the context of Emergency Response, the need to search for information, plays a significant role once an incident has been identified. Another role searching plays is post-event analysis where all data is searched to understand how an event evolved from different perspectives. Effectively, searching provides answers to questions that are already known by analysts and to facilitate follow-on analyses. In order to perform searching tasks, users simply enter (or select) an appropriate set of filters and reach the data of interest. Section C (filtering section) is the most appropriate in this context, as it provides direct means for users to search. Interactions within Section A (visualisations) also generate filter queries but such features are more pertinent to browsing activities. The search terms that are involved in this process are highly dependent on the evolution of the event as well as the event itself. Hashtags and keywords vary on how they have propagated within Social Media, and therefore, it is difficult to predict which terms would best suit the scenario being investigated. This calls for the need to monitor situations based on an initial 'guess' to encapsulate possible terms, and then fine-tuning queries to capture and retrieve more relevant information.

4.2 Monitoring – Passive and Directed

Perhaps most relevant to Emergency Response is the notion of monitoring, where the analyst needs to monitor an evolving situation, and looks out for information that may be relevant. This is achievable by setting queries and filters, and during standard data exploration via visualisations (Section A) and reading Social Media content (Section B), users can be updated when new relevant content is made available after harvesting recent Social Media posts. Once new content is available that is relevant to the present search criteria, users are communicated by a clickable label which states 'X new messages available'. The analyst is faced with one of three options in such situation: the first being, continue exploration and ignore the update. This would have no effect on the present exploration, and the user can proceed with finishing his/her analysis. With more information being made available, the notification is updated. This is enabled/disabled via the dropdown (session type) selection option 'Static' (the other options are 'dynamic' and 'batch-update'). The second option the user has is to proceed with analysing only the new content that has been retrieved. This notes the time when the previous analysis had started (the time when the last query was triggered). Selecting 'batch-update' from the dropdown enables this option and the user can then click on the button to view the relevant data instances that have been recently added. The third option the user has is to proceed analysing all of the data, with the new instances added to the analysis. This is performed by selecting 'static' and clicking on the click-able label.

The last option is a dynamic monitoring option, which regularly updates with new posts continually appearing during exploration sessions. This options is the least used, and hence is presently not encouraged to be used – more work is needed to understand how continuously evolving data can be presented to users without causing confusion and loss of analysis effort.

4.3 Browsing – Active and Undirected

Browsing involves users looking for information as and when their interests evolve. This is a mode which is also highly relevant to Emergency Response. Monitoring continuously evolving data, and searching existing data can indicate interesting events, keywords, or hashtags that might be relevant to improve the understanding of an evolving situation. In our approach, interactive Visualisations are key to this: while exploring a relevant dataset, users have the possibility to add new filtering terms by clicking elements from tag clouds, charts, timelines or maps. Clicking on sensitive areas of the visualisations immediately triggers queries, which result in a new filter being added and the system to drill-down into a more relevant subset of the data being explored. The user can remove the recently added filter by deselecting the filter from Section D (Current Selection).

4.4 Being Aware – Passive and Undirected

The most complex of information seeking modes is the state of being aware. TUI facilitates this by easily combining some of the approaches that are employed in the other three modes. The state of being aware in Emergency Response implies that an analyst is aware of the wider context of his/her analytic activity, but unaware of what event/situation may arise. This is often perceived to be the precursor to some of the modes and is conducted as a part of an initial or continued survey of the broader area (geographic, temporal or topical). In a typical ER (Emergency Response) activity, it is expected that an instance of the interface is continuously dynamically updated to provide overviews, based on query terms that are most likely to retrieve interesting events – generic terms such as 'flood', 'accident', '911' or 'fire' could form a good candidate set of keywords to look for[4]. Identifying any relevant interesting event would then initiate monitoring, browsing and searching activities on other instances of TUI.

5 Architecture and Implementation

The TUI interface is the second part of two systems - the first being a Social Media harvesting system which enables gathering of Social Media posts, and the second being a system which interfaces with the harvesting system and a local data store. While the first system (harvester) involves querying multiple sources of data continuously for new information and storing the results in local datastores following several iterations of backend processing, the second (TUI) is the interactive interface that users can use to access the data being stored/analysed/harvested. TUI is implemented as a standard web application, and written completely in HTML and Javascript. Several toolkits have been used

[4] It is to be noted that several of such 'generic' terms can also occur in posts that are highly irrelevant such as song lyrics, quotes from speeches etc. The decision to select relevant terms is mostly left with the analysts, based on their interpretation of the content being currently monitored.

within TUI to facilitate interactions such as jQuery[5], and provide customised look and feel such as jQueryUI[6], Less[7] and BlockUI[8]. Visualisations are provided by D3.js[9], Highcharts[10], Google Maps[11] and Javascript Infovis toolkit[12]

6 Discussions and Continuing Work

Over the summer of 2013, as a part of multiple projects, TUI was used to monitor several large events across the UK. Several Emergency Response organisations, Police, City Councils, event organisers and authorities were involved in the events. During the events the different types of information seeking modes were employed, and the system was used to monitor by several analysts at the same time. One of the key findings was the need for supporting multiple types of information seeking at the same time. Analysts need to explore, query, browse and be aware of situations at the same time, and hence, several instances of TUI are necessary to be active for improving Situation Awareness.

The TUI system is currently being redesigned to provide support for multiple tasks within one interface. Several layouts are presently being evaluated to understand which layout from a set of candidate layouts would be the most effective. The system is also planned to be evaluated with emergency responders during planned and unplanned events. Several techniques such as focus group, contextual inquiry and shadowing are planned to be used in the evaluations to understand how the system compliments traditional techniques for Emergency Response.

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