On the Way to a Science Intelligence: Visualizing TEL Tweets for Trend Detection

Peter Kraker[1], Claudia Wagner[2], Fleur Jeanquartier[1], and Stefanie Lindstaedt[1]

[1]Know-Center, Inffeldgasse 21a, 8010 Graz, Austria
{pkraker,fjean,slind}@know-center.at
[2]Joanneum Research, Steyrergasse 17, 8010 Graz, Austria
claudia.wagner@joanneum.at

Abstract. This paper presents an adaptable system for detecting trends based on the micro-blogging service Twitter, and sets out to explore to what extent such a tool can support researchers. Twitter has high uptake in the scientific community, but there is a need for a means of extracting the most important topics from a Twitter stream. There are too many tweets to read them all, and there is no organized way of keeping up with the backlog. Following the cues of visual analytics, we use visualizations to show both the temporal evolution of topics, and the relations between different topics. The Twitter Trend Detection was evaluated in the domain of Technology Enhanced Learning (TEL). The evaluation results indicate that our prototype supports trend detection but reveals the need for refined preprocessing, and further zooming and filtering facilities.

Keywords: science 2.0, trend detection, social media, qualitative analysis

1 Introduction

Twitter has high uptake in the scientific community. According to a recently published survey, personal email, Twitter, Skype, and project mailing lists are the most popular applications used for disseminating information by Semantic Web researchers [14]. The main motivations for publishing and sharing content on Twitter named by survey participants were: (1) to share knowledge about their field of expertise, (2) to communicate research results, and (3) to expand their network. The fact that the two main reasons for researchers to use microblogging services are communicating their research results and sharing information about their field of expertise makes Twitter a rich source of information, which can be exploited to detect research trends. It seems to be a reasonable assumption that the results of this study can be transformed to other technology-rich research fields such as Technology Enhanced Learning.

This paper presents an adaptable system for detecting trends based on the micro-blogging service Twitter, and sets out to explore to what extent such a tool can support researchers. In the context of this work we define a "trend" as a term belonging to a topic which gains considerable interest during a certain period of time. Similar to the TF/IDF measure from Information Retrieval, the interestingness of an item can be defined as the number of occurrences of that item in time interval i out of a larger interval j [6].

Our research revealed that there is a need to have a means of extracting the most important topics from a Twitter stream. According to our evaluation (see Section 3), there are too many tweets to read them all, and there is no organized way of keeping up with the backlog. Finding something interesting is more of a coincidence than the result of a structured search, even with tools that allow for various lists of users and hashtags. What makes it even worse is the large amount of noise generated by superfluous postings. Twitter's trending topics do not help with that as they are not related to research.

Following the cues of visual analytics, we use visualizations to show either the temporal evolution of topics, or the relations between different topics. We developed a focused Twitter Crawler which uses the Twitter Streaming API [20]. The crawler can be adapted to any domain, by either (a) specifying a taxonomy of keywords, (b) specifying a list of users, or (c) a combination of both. On the client-side, our system provides two explorative visualization components: a streamgraph for analyzing trends over time and a co-occurrence network for analyzing semantic networks of terms which may for example reveal which topics are popular at the moment or which topics are strongly correlated.

The Twitter Trend Detection was evaluated in the domain of Technology Enhanced Learning (TEL). The system was adapted to the domain using a taxonomy of 30 hashtags, and a list of 450 expert users from TEL. First, we conducted semi-structured interviews involving the use of the system with researchers from the domains of TEL and knowledge management. The outcomes from these interviews were used to further improve the system. It was then evaluated a second time at the 2nd STELLARnet Alpine Rendez-Vous, where the visualizations were used as a means of support. The evaluation results indicate that our prototype supports trend detection but reveals the need for refined preprocessing, and further zooming and filtering facilities.

1.1 Related Work

Past research, such as ThemeRiver [9], was exploring solutions for automatically detecting emerging trends from collections of documents. With the rise of user generated content, researchers started exploring to what extent social media can be used to detect and monitor emerging trends. Fukuhara [7], for example, presents a system which generates a daily trend graph of weblog articles containing any given keyword. Glance et al. [8] introduce a tool called BlogPulse which allows monitoring trends in weblogs. They show a correlation between "blog and real world temporal data" such as temperature and news articles. Hotho [11] presents an approach for discovering topic-specific trends within folksonomies, by adapting PageRank algorithm to the triadic hypeWeighted Graph structure of a folksonomy.

Cheong et al. [5] describe an approach of analyzing trend patterns on Twitter. They explore the properties and features of a trending topic and the properties of the users (or 'trend setters') that contribute 'tweets' to a trending topic, which makes them a part of the trend. For analyzing trending topics versus non-trending topics, they used only the last 1500 tweets which one obtains from the Twitter search API when conducting a keyword search. Mathioudakis [15] introduces TwitterMonitor, a system that discovers "bursty" keywords[1] in Twitter streams and uses them as 'entry points' for trend detection. Finally, Benhardus [2] also presents a trend detection system based on Twitter. He uses term frequency-inverse document frequency analysis and relative normalized term frequency analysis to identify the trending topics.

Our work differs from previous work by focusing on supporting researchers during their daily work with domain-specific information. Most existing work deals with general trends on Twitter which are largely irrelevant to researchers. To the best of our knowledge, this is the first system that can be adapted to a certain domain. The prototype's UI is a web-based one that relies on web standards. Therefore the visualization can be displayed in a standard web browser, but also be easily integrated with any system that allows for widgets adhering to the W3C standard. This design is far more adjustable compared to existing solutions.

2 System

2.1 Twitter Stream Analysis

We developed a focused Twitter Crawler which uses the Twitter Streaming API [20]. The crawler can be adapted to any domain, by either (a) specifying a taxonomy of keywords, (b) specifying a list of users, or (c) a combination of both. The Twitter Crawler then logs only tweets which were either authored by a certain user or which contain at least one keyword of the taxonomy. Next, we lexically preprocess the logged tweets in order to extract "informative" tokens (mainly nouns and hashtags) from it, using a part-of-speech tagger (POS Tagger), namely TreeTagger [16]. Finally we store the tweets, their metadata, and their associated informative tokens in a Solr index [18] which is used by our Visualization Dataservices. Fig. 1 illustrates this architecture.

The Visualization Dataservices are REST-ful Webservices which enable client-side, lightweight visualizations to fetch and reload the data on demand. Since we provide two different types of visualizations, streamgraphs and weighted graphs, we also implemented two different types of Visualization Dataservices.

Both Visualization Dataservices take the following parameters as input: (1) a query consisting of one or several search terms (e.g., "conferences") (2) a time period of interest (e.g., 10.4.2010 - 15.5.2010), (3) the maximum number of co-occurring terms, and (4) the type of co-occurring terms (either nouns, hashtags, or users). Besides, the Streamgraph Dataservice optionally takes the number of

[1] Keywords which are frequently used within a short period of time.

time intervals as additional parameter. Both Dataservices translate the search query into a Solr query and preprocess the Solr result in different ways: the Streamgraph Dataservice focuses on analyzing the temporal evolution of topics over time; the Weighted Graph Dataservice focuses on relations between different topics.

The Streamgraph Dataservice splits the time-period of interest into the specified number of intervals. For each interval, the Streamgraph Dataservice returns the most frequent topics which co-occur with the query term within said interval. The Weighted Graph Dataservice returns the most important topics which co-occur with the query terms and the number of times they co-occurred.

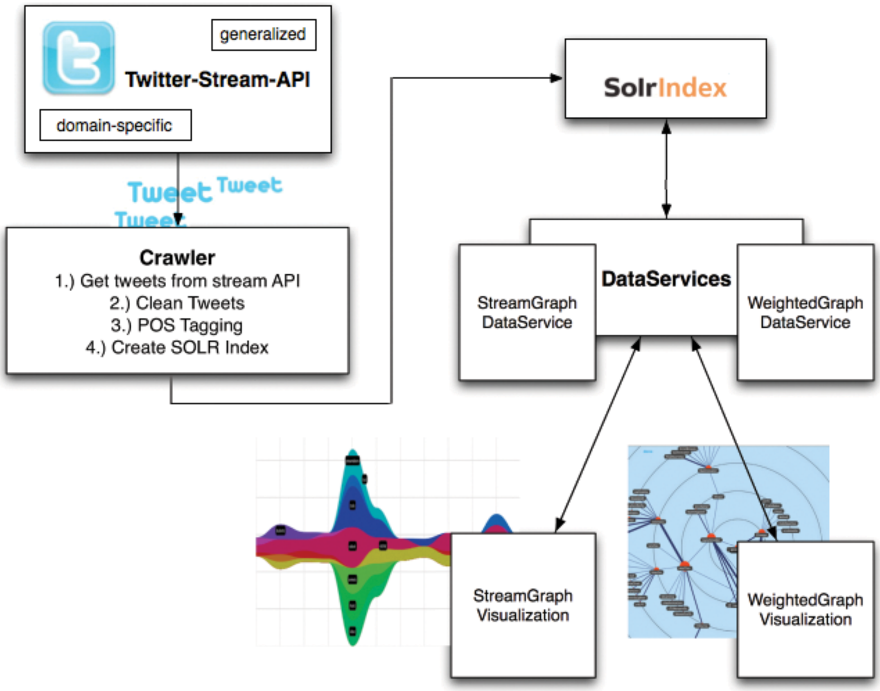

Fig. 1. Architecture

2.2 Visualizations

Following the cues of visual analytics [12], we use visualizations to show both the temporal evolution of topics, and the relations between different topics. First, we studied existing visualization techniques to identify those that are suitable for our purpose.

Heer et al. [10] describe a stacked graph as a classic method for visualizing change in a set of items, where the sum of the values is as important as the individual items. While such charts have proven popular in recent years, they do have some limitations such as the fact, that stacking may make it difficult to accurately interpret trends that lie atop other curves. The authors in [9] describe a more enhanced visualization technique that is suitable for visually describing thematic variations over time within a large collection of documents. This technique makes use of a river metaphor for revealing patterns and trends. One of the major advantages of this technique is little dependence on the number of documents; furthermore, the stacked areas are suitable for observation and comparisons. Inspired from the visualization technique mentioned before, Byron and Wattenberg further describe the Streamgraph design, a unified approach to stacked graph geometry and algorithms [4]. We therefore identified this special stacked graph design technique called "streamgraph" as one suitable approach to visualize Twitter-data over time. Lamping et al. [13] describe a focus+context visualization technique that is intended for displaying hierarchies, which is the basis for our second visualization approach: visualizing the relations between topics.

We further extended our visualization study to comparing existing web script libraries for the two visualization techniques described above that could be used in our prototype. The Streamgraph Visualization builds on top of the Grafico javascript library [22] while the Weighted Graph Visualization is based on the Javascript InfoVis Toolkit [1]. An HTML-based frontend offers the possibility to type in one or several search terms, furthermore specifying a facet such as "hashtags that occurred with the term above". Furthermore, the UI provides a date selection to narrow the search to a specific date range, and a field to specify the maximum number of co-occurring terms.

Fig. 2 shows a screenshot of the Streamgraph Visualization, displaying the co-occurring hashtags for the query "conferences" from 20/2/2011 to 14/04/2011. On the x-axis, the time intervals are outlined, whereas on the y-axis, the relative number of occurrences is shown. Each colored stream represents one co-occurring hashtag. The visualization shows that the hashtag for the South-by-Southwest conference (#sxsw) is trending around the actual event on March 15.[2] The #pelc11 hashtag was trending around April 7, with the Plymotuh E-Learning conference taking place from April 6-8. Another conference that is trending is the PLE Conference in Southhampton which has not taken place yet (#PLE_SOU). The other co-occurring hashtags are not tied to a certain conference (such as #mlearning and #edchat), but they denote hashtags in the TEL area which

[2] The conference took place from March 13-20.

contain a large amount of tweets about conferences. These hashtags could therefore be used to find out about other conferences in the area. An example for the Weighted Graph Visualization is shown down below in section 3.2.

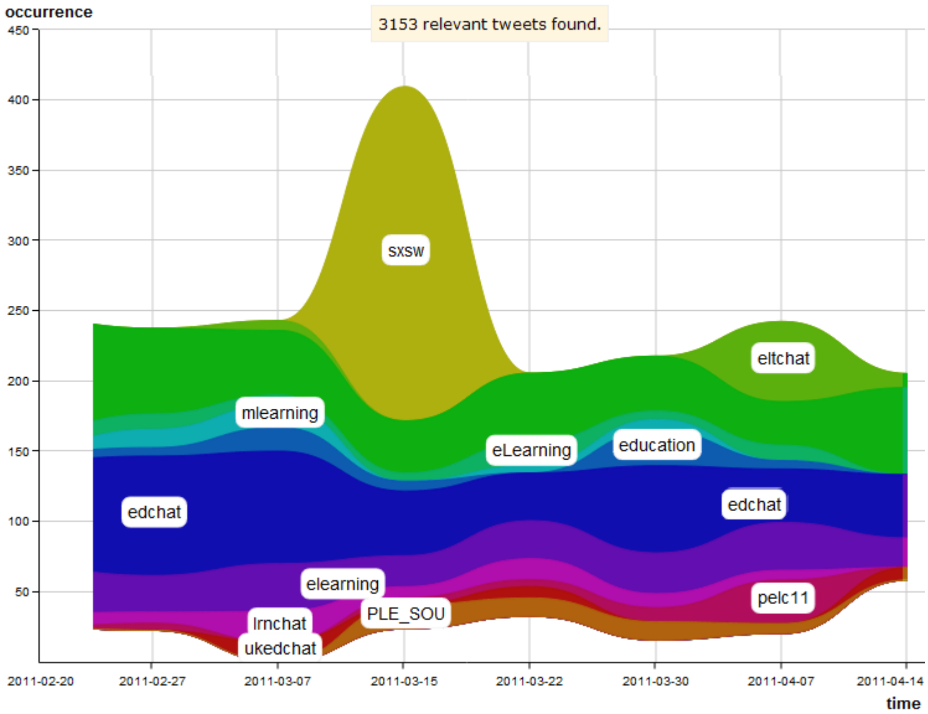

Fig. 2. Streamgraph Visualization

3 Evaluation

The Twitter Trend Detection was evaluated in the domain of Technology Enhanced Learning (TEL). The system was adapted to the domain using a domain-specific taxonomy of 30 hashtags. That removes the noise that is generated when taking all tweets into account, or when using general keywords such as "learning" and "training". In an early prototype using general keywords, we found that there is a strong correlation between "training" and "dog"; this is interesting as a fact, but irrelevant to the domain of TEL. The taxonomy was created (1) by analyzing hashtags that occur with the more general keywords, and (2) by searching Twapperkeeper [19] for relevant archives. Besides the taxonomy, we also created a list of 450 user accounts from various lists related to Technology Enhanced Learning which belong to well-known domain experts, researchers, and students. The system is part of the STELLAR Science 2.0 infrastructure [21]. The visualizations are also integrated as early-stage widgets on the TELeurope platform [17].

The evaluation of the Twitter Trend Detection is based on the creative thinking method PMI [3]. PMI stands for Plus, Minus, and Interesting. Instead of asking participants to take an objective stance in the evaluation, their attention is guided to think separately about (a) the positive aspects of the system (Plus), (b) the negative aspects of the system (Minus), and (c) the neutral but noteworthy aspects of the system (Interesting). This terminology was not only used in the instruments, but also later in the analysis, guiding the qualitative coding scheme.

The Twitter Trend Detection was evaluated in two settings: first, we held semi-structured interviews involving the use of the system with five researchers from the domains of Technology Enhanced Learning and knowledge management. The new system was then further evaluated at the 2nd STELLAR Alpine Rendez-vous where the visualization was used as a means of support. We utilized them in a reflection session in one of the workshops; this was accompanied by three in-depth interviews with conference participants.

3.1 Evaluation 1

In the first evaluation, we held semi-structured interviews involving the use of the system with five researchers from the domains of Technology Enhanced Learning and knowledge management based in Austria. Among the participants were one professor, three senior researchers, and one PhD student. Two had a background in computer science, two in psychology, and one in business administration. Participants were interviewed about their use of Twitter in research, and specifically in relation to trend detection. Afterwards, they were introduced to the visualizations. Following a short tutorial, we asked participants to search for trends in their area of interest. The interviews were recorded on tape, and later transcribed. We qualitatively analyzed the transcripts using a reducing and interpreting approach. Codes were divided into three sections, following the PMI terminology: Plus, Minus, and Interesting. Each of these sections was subdivided into the codes "General", "Weighted Graph", and "Streamgraph". To capture the general remarks on Twitter, we added "Usage of Twitter", "Advantages of Twitter", and "Disadvantages of Twitter" to the scheme. Initially, the transcripts were coded with these general codes. In a second iteration, we refined these codes to paraphrase the content of marked statements. In the last step, we merged similar paraphrases to remove redundancy in the scheme.

The goal of the first evaluation was to collect feedback on the usability and the general applicability of the system to trend detection. In this phase, the system contained three different visualizations: two competing streamgraph visualizations, and one Hypertree Visualization. Table 1 shows the top two recommendations that resulted from this first evaluation. The evaluation showed that users were struggling with the interface. It proved to contain too many parameters that were labeled with technical terms. Furthermore, users had a hard time interpreting the co-occurring terms, and they were unclear about the underlying data. As a result, the user interface was completely overhauled, and we started to display the first 100 analyzed tweets alongside the visualizations.

Table 1. Recommendations from first evaluation

General:
Redesign the user interface to make it more accessible to the user
Include more metadata for the co-occuring terms
Streamgraph:
Keep Grafico streamgraph as it is more clearly laid out and has a better usability
Highlight meaning of the axis to the user
Hypertree:
Replace visualization with a version that is more clearly laid out
Position search term more prominently

The initial Hypertree Visualization was replaced by the Weighted Graph Visualization, and from the two streamgraphs, only the Grafico Streamgraph was developed further. Axis descriptions were added to the Grafico Streamgraph, and in the Weighted Graph Visualization the search term was highlighted.

3.2 Evaluation 2

The new system was further evaluated at the 2nd STELLAR Alpine Rendez-vous, where the visualizations were used as a means of support. Fig. 3 shows the Weighted Graph of hashtags for the main conference hashtag "arv11" from 27/03/2011 to 14/04/2011. This covers the conference which took place from 28/03 to 01/04 as well as the discussion afterwards. The size of the circles indicates the number of occurrences, while the line thickness indicates, how often two hashtags co-occurred. The visualization is centered on "arv11". The hashtags on the first level are directly related to arv11, namely "ngtel", "arvmupemure", "multivocalanalysis", "datatel11", and "arv3t". They all represent different workshops that were held during the conference. "jtelws11" represents the JTEL Winter School which was co-located with the Alpine Rendez-vous. For each of the workshops, as well as the winter school, a number of co-occurring hashtags are identified on the second level that tell a bit more about the individual workshops.

In the dataTEL workshop, we presented the corresponding visualizations in a reflection session on the workshop. During the course of the presentation and the ensuing discussion, participants were asked to list positive (Plus), negative (Minus), and neutral but noteworthy (Interesting) aspects on post-its. This evaluation was complemented with three in-depth interviews with participants from the Alpine Rendez-vous involving the visualizations. The interviewees were all tweeting in the course of the conference, and were specifically asked about the usefulness of the system. Among them were one professor, one senior researcher,

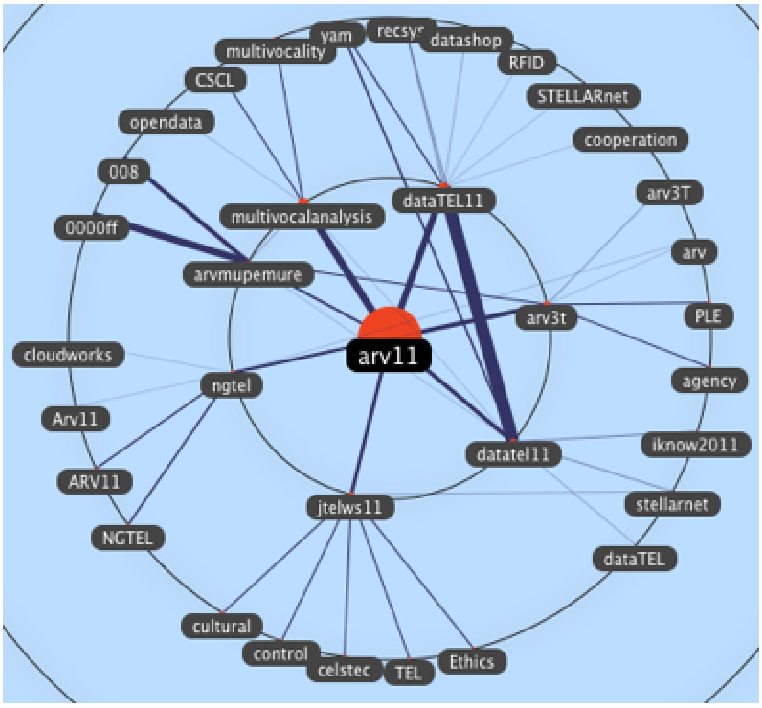

Fig. 3. Weighted Graph Visualization

and one PhD student. Two had a background in education, and one in computer science. Participants came from Europe, the United States, and Canada. The results were recorded, transcribed, and analyzed in the same manner as described in the first part of the evaluation above.

The evaluation showed that Twitter is regarded as an important means of communication among the participating TEL researchers. Interviewees found it interesting (a) to follow and to contribute to the backchannel discussion in their own workshop, thus enriching their experience, and (b) to follow what is going on in other workshop. They also used Twitter to document parts of the workshop, and to keep their teams at home up-to-date, sometimes even using designated hashtags for that.[3] Among the uses outside of conferences were (1) to use it as a source of information, (2) to ask for feedback on one's own work, and (3) to directly communicate with other researchers.

What had already surfaced in the first evaluation, was also repeatedly noted in the second evaluation: there is a need to have a means of extracting the most important topics in a Twitter stream. According to the participants, there are too many tweets to read them all, and there is no organized way of keeping up with

[3] One of these hashtags "#yam", can be seen in Fig. 3 as a co-occurring hashtag of "#dataTEL11".

the backlog. As one of the interviewees put it so aptly, "If I get up to get coffee, I could have already missed something important." For the interviewees, finding something interesting is more of a coincidence than the result of a structured search, even with tools that allow for various lists of users and hashtags. What makes it even worse in the eyes of the participants is the large amount of noise generated by superfluous postings ("I am having breakfast now"). Twitter's trending topics do not help with that as they are not related to research.

3.3 Discussion

Participants liked the looks of the visualizations, and the idea behind them. In both evaluations, they noted that the interface is visually appealing. They also noted on several occasions that the system might be a useful way to deal with the backlog in their Twitter streams. The two visualizations are complementing each other very well; participants were interested in the connections between topics as well as the temporal evolution. Participants noted that both of them condense a lot of information in one view. They enjoyed the fact that the visualizations operate on live data with the ability to go back in time. Another feature that was well received was the consistency between the two visualizations, as the visualizations always operate on the same set of tweets for a given search term and a given time range.

As for the Weighted Graph, people were easily able to understand the basic visual metaphor, albeit it's sometimes crowded nature, and the fact that the weighted Graph is not always centered on the initial search term. Most interviewees could instantly interpret the size of the nodes and the thickness of the edges correctly. It was only the different levels that were hard to grasp in some cases. Participants noted that edges between topics are useful to determine the connection between the two, and the kind of clustering that is provided by the Weighted Graph in that way. They recognized topics from the discussions in their workshops, as well as users which participated in the backchannel discussion. An additional use that they saw was to get a quick overview of a field that they were not familiar with.

In the case of the Streamgraph, participants that were not accustomed to the visual metaphor needed a bit more time to understand the concept. Especially the alignment and the color-coding were often mis-interpreted. After a short introduction though, they liked that topics are shown in such a way that one can clearly see the bursty terms. They were able to reconstruct the time wise evolution of certain discussions from their workshops. One participant said it would be interesting to have such a visualization running on several screens at a conference to keep everyone updated about the current sessions. Another possible use that was mentioned is the detection of pivotal moments in online discussions.

Despite all the positive feedback, the evaluation also pointed out several shortcomings of the visualizations. First and foremost, users would like to be able to zoom into the results. They would like to be able to click on a co-occurring term to see its metadata, and they want to be able to not only see a full list of tweets but rather a filtered one. This revealed the need to implement zooming and filtering and the need to provide more details on demand. This should be complemented by a short help page on either visualization to make the metaphor crystal clear. In addition, users demanded more meaningful terms. They found the co-occurring terms to be too broad and generic. In addition, we need to get better at filtering out hashtags and mentions, and ignoring the case in the output. This revealed the need for refined preprocessing.

On a meta-level, participants sometimes criticized Twitter as a data base, as they trust only certain experts with trends. To address those concerns, we need to find a way to include only certain user accounts in the search. Finally, users would like to be able to integrate the visualizations with their existing Twitter applications.

4 Outlook

The evaluation results indicate that our prototype supports trend detection, but we still need to address several issues. First and foremost, we will provide more insight into the data in connection with further filtering mechanisms to allow users to view only a portion of that data. We will also improve the data quality by changing our crawler so that it does not count users and hashtags as nouns, and by applying lowercase to all output terms. To weed out the generic terms, we will look into applying the TF-IDF measure, and/or blacklists of common and broad terms.

Moreover, we will look into ways of integrating the visualizations with existing platforms emerged. We already took a first step into that direction by creating a W3C compliant widget, which can be included into any system that allows for such widgets; a first version has already been deployed to the social network TELeurope. Furthermore, it would be interesting to have a kind of self-evolving taxonomy of hashtags and users which semi-automatically adds new pieces of information to the taxonomy. On the front-end side, we are constantly looking into new meaningful visualizations, which can be adapted for system.

With the ever increasing amount of tweets, scalability becomes an issue; in a little over three months, we have collected over 500.000 tweets. Nevertheless, Solr has proven to be able to go way beyond that number of documents. The system is currently tailored towards Technology Enhanced Learning, but it could easily be adapted to other fields of research. The only precondition is to produce a list of hashtags and/or users from the field. If such a taxonomy does not exist, the system itself can help by detecting co-occurrent hashtags starting even from a single high-frequency hashtag.

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