# StanceXplore: Visualization for the Interactive Exploration of Stance in Social Media

R. M. Martins*
Linnaeus University
Växjö, Sweden

V. Simaki†
Linnaeus University
Växjö, Sweden

K. Kucher‡
Linnaeus University
Växjö, Sweden

C. Paradis§
Lund University
Lund, Sweden

A. Kerren¶
Linnaeus University
Växjö, Sweden

## Abstract

The use of interactive visualization techniques in Digital Humanities research can be a useful addition when traditional automated machine learning techniques face difficulties, as is often the case with the exploration of large volumes of dynamic—and in many cases, noisy and conflicting—textual data from social media. Recently, the field of stance analysis has been moving from a predominantly binary approach—either *pro* or *con*—to a multifaceted one, where each unit of text may be classified as one (or more) of multiple possible stance categories. This change adds more layers of complexity to an already hard problem, but also opens up new opportunities for obtaining richer and more relevant results from the analysis of stance-taking in social media. In this paper we propose StanceXplore, a new visualization for the interactive exploration of stance in social media. Our goal is to offer DH researchers the chance to explore stance-classified text corpora from different perspectives at the same time, using coordinated multiple views including user-defined topics, content similarity and dissimilarity, and geographical and temporal distribution. As a case study, we explore the activity of Twitter users in Sweden, analyzing their behavior in terms of topics discussed and the stances taken. Each textual unit (tweet) is labeled with one of eleven stance categories from a cognitive-functional stance framework based on recent work. We illustrate how StanceXplore can be used effectively to investigate multidimensional patterns and trends in stance-taking related to cultural events, their geographical distribution, and the confidence of the stance classifier.

## 1 Introduction

In Digital Humanities (DH) [28], the combination of text mining and visualization methods has resulted in tools that exploit modern or contemporary text corpora, extract linguistic patterns from various language resources, and provide the scholars with new and enriched digitalized educational material (e.g. [3, 6, 32]). The availability of large-scale, user-generated textual content from social media, such as reviews, opinions and comments on politics and news, raised interest to the areas of sentiment analysis and opinion mining [20]. Techniques from these areas approach text analysis by extracting opinions and sentiments with the goal of aiding in the comprehension of how people feel about something, how these feelings are expressed, and how they spread [24].

Among the many related fields, one that has attracted attention lately is stance identification in discourse [21, 23, 30]. Stance taking is the way speakers position themselves in relation to their own or other people's beliefs, opinions, and statements in ongoing communicative interaction with others. Interesting findings about the attitude of people can be derived by looking at their stance regarding cultural, educational, social, and political events [10, 38].

In this paper we present StanceXplore, a visualization for the interactive exploration of stance-taking in social media. Stance analysis of content from social media is usually met with unique challenges due to the highly dynamic and heterogeneous language forms and constructional patterns in discourse, which can vary considerably depending on geography, time, and user identities/roles. All of these factors (or dimensions) of the data are relevant and must be considered together when exploring trends within a corpus, as such trends may be spread over different dimensions due to, e.g., specific reactions to relevant events (time), the effect of different cultural backgrounds (space), and previously unknown similarities between the writing of different groups. Our proposed visualization aids the exploration of stance in social media with a coordinated multiple views approach, where each of these dimensions can be explored separately, while, at the same time, all views react to brushing and filtering. We aim to help DH researchers discover stance-taking patterns in social media corpora by moving interactively from a general overview of the data's features into subsets defined by different combinations of filters for each dimension.

We demonstrate our visualization with a case study on the use of the English language by Twitter users from Sweden. By exploring Twitter's hashtag functionality, which allows users to specify topics that thematically orient their tweets, we show how our tool can support tasks such as: (a) identifying the stance distribution on the most frequent hashtags, (b) grouping these hashtags into broad thematic fields by similarity of content, (c) understanding the geographical distribution of stance-taking trends in the corpus, (d) finding important events during a certain time period and check how Twitter users have positioned themselves in relation to these events. We conclude that StanceXplore offers DH researchers the opportunity to obtain insights into the corpus that are not readily available without interactive exploration, are multidimensional by nature (i.e. are simultaneously based on independent aspects such as time, space, and language use), and are relevant to the comprehension of the dynamics of stance-taking in this specific Twitter user base.

## 2 Background and Related Work

While no universally accepted definition of DH exists, Schreibman et al. state that the discipline of DH "includes not only the computational modeling and analysis of humanities information, but also the cultural study of digital technologies, their creative possibilities, and their social impact" [28, p. XVII]. DH research on literary studies commonly use techniques developed under the umbrella of information visualization (InfoVis) and visual analytics (VA), more specifically, text visualization [18]. Important examples include the *literature fingerprinting* by Keim and Oelke [15] and VarifocalReader by Koch et al. [16]. Sínclair and Rockwell [32] introduce computational methods for text analysis to the DH audience and discuss their software suite called Voyant Tools, which includes several visual representations of text analysis results. The authors argue that such tools facilitate the exploration of the data and can lead to interesting discoveries. In general, these techniques focus on close and distant reading tasks, as described by Jänicke et al. [14] in a

*e-mail: rafael.martins@lnu.se
†e-mail: vasiliki.simaki@lnu.se
‡e-mail: kostiantyn.kucher@lnu.se
§e-mail: carita.paradis@englund.lu.se
¶e-mail: andreas.kerren@lnu.se

systematic overview of text visualization techniques for DH studies. Other recent examples are related to the analysis of text variants [3], named entities such as fictional characters [36], or arbitrary concepts and relationships within a large text document [5]. One common feature for most of the techniques is their orientation towards works of literature as the input data. In this work, however, we focus on data originating in social media rather than literary fiction. Chen et al. [7] provide an overview of the existing analysis and visualization methods for social media data, concluding that the most popular analytical approaches for such texts include extraction of keywords, detection of topics, and sentiment analysis.

Sentiment analysis usually involves automatic detection of positive, neutral, and negative content in texts [24]. In a recent survey, Kucher et al. [20] discuss the corresponding sentiment visualization techniques developed both inside and outside the InfoVis/VA community, concluding that the majority of such techniques use social media data rather than customer reviews, editorial media data (e.g., news reports), or literature. Such techniques have been used to provide an overview of a Twitter corpus or a monitoring interface for a stream of text posts (tweets), usually with an option to drill down to the underlying texts on demand—which arguably also mirrors the distant and close reading tasks in DH discussed above. With regard to application scenarios, Diakopoulos et al. [8] and Marcus et al. [22] use their respective systems Vox Civitas and TwitInfo for digital journalism; Cao et al. [4] apply their system Whisper for the analysis of emergency events; and Humayoun et al. [12] analyze the public response to Brexit using their recent system TExVis.

Besides the analysis and visualization of positive and negative sentiments, emotion, or similar affective categories, social media data also provide interesting opportunities for the analysis and visualization of *stance*. Stance classification studies usually address stance-taking as a binary issue of the *pro* or *con* positioning of the speaker towards a fact/event/idea. In most cases, the data are extracted from online debates, where controversial opinions and stance-taking are observed, and they are automatically annotated [10, 38]. The classification accuracy achieved in these studies varied from 69 to 88%, and various different feature sets were used: lexicons, n-grams, cue words, post information, punctuation, and POS tags. More recent studies include other categories of subjectivity such as agreement and disagreement [34], condition and contrast [33], or prediction and uncertainty [30, 35]. The existing work in stance visualization includes the works by Almutairi [2] and El-Assady et al. [9], which focus on works of literature and transcripts of debates, respectively. Textual data from social media have been used for stance visualization by Kucher et al. [21] in their system uVSAT; however, Twitter is not supported as a data source, and their typical input documents are much larger/longer than tweets. Mohammad et al. [23] provide a dashboard visualization of a stance-annotated Twitter corpus, and Kucher et al. [19] support visual analysis of the stance annotation process for utterances (sentences) with their system ALVA. In contrast to these approaches, the focus of this work is to provide an interactive stance visualization of a Twitter corpus with support for the temporal, geospatial, and topic perspectives—similar to TwitInfo [22], Whisper [4], or TExVis [12], but supporting stance analysis rather than the usual task of sentiment analysis.

## 3 STANCEXPLORE: DESCRIPTION & METHODOLOGY

We propose to approach the challenge of interactively exploring stances in social media by using coordinated multiple views, where each view shows a different perspective of the data, i.e., a window into a specific aspect of the corpus under analysis. The focus of StanceXplore is the interactive brushing and filtering supported by visualization in such a way that each view can be explored independently, but, at the same time, the whole set of views adapts to users' actions. This design is inspired by Shneiderman's well-known visual information-seeking mantra [29]—"Overview first, zoom and filter, then details-on-demand"—and the implementation of the *distant reading* concept in visualization tools, as described in [14]. These related concepts can, when combined, be used effectively to direct readers to specific subsets of text that are relevant to the task at hand.

In order to be used with StanceXplore, a corpus must contain the full text of all tweets, be geolocalized and timestamped (these are related specifically to views (e), (c) and (d) on Fig. 1, respectively). User information is not necessary, as the tweets are anonymized (every reference using @ is changed to @*User*). Each tweet is classified according to its stance using a Support Vector Machine (SVM) [37] classifier, previously trained on data extracted from political blogs and manually annotated by two linguistic experts. The ten stance categories are based in a cognitive-functional approach introduced recently [30, 31, 35]. AGREEMENT/DISAGREEMENT expresses a similar or different opinion (e.g., *Ok then, I'll do that*), CERTAINTY expresses the speaker's confidence to its sayings (e.g., *Of course it is true*), CONTRARIETY expresses a compromising or contrastive opinion (e.g., *The result is fairly good, but it could be better*), HYPOTHETICALITY expresses a potential consequence of a condition (e.g., *If it's nice tomorrow, we will go*), NECESSITY expresses a request, recommendation, instruction, or obligation (e.g., *I must hand back all the books by tomorrow*), PREDICTION expresses a guess/conjecture about a future event (e.g., *I believe that he will do it for you*), SOURCE OF KNOWLEDGE expresses the origin of the speaker's sayings (e.g., *I saw Mary talking to Elena yesterday*), TACT/RUDENESS expresses pleasantries/unpleasantries (e.g., *You lazy bastard. Get lost*), UNCERTAINTY expresses doubt towards the speaker's sayings (e.g., *I don't know if that is the case, actually*), and VOLITION expresses wishes or refusals (e.g., *I wish I could join you next summer*). If no stance is detected, the tweet is NEUTRAL.

The total number of tweets per stance can be seen in the *Stances* view (Fig. 1a), also encoded in the lengths of the bars. This view also functions as a color legend; the color assigned to each stance category in this view is used in most other views during the interactive exploration process. By clicking on the stances in this view, the user can choose to filter all the other views to include only tweets classified with the selected stances (in the example of Fig. 1a, all stances are active except NEUTRAL).

The *Hashtags* view (Fig. 1b) shows the hashtags of the corpus in two interchangeable panels: the *Table*, in descending order of frequency, and the *Grid*, where they are grouped and distributed according to content similarity. These two panels offer two distinct but complementary views, and can be switched by the user as desired. When a hashtag is selected it is always shown on top of the table, while the rest of the hashtags are sorted in descending order by their *string* similarity to the selected one, as computed with the Sørensen-Dice coefficient [13]. This sorting highlights similar hashtags only by their name, e.g. `#Eurovision` and `#Eurovision2016`. The distribution of hashtags in the 2-D hexagon grid is obtained with a Self-Organizing Map (SOM) [17] by extracting the best-matching units for each hashtag. In order to train the SOM, features are extracted from each hashtag $h$ by first generating a vector space model representation $v(h)$ [27] that includes the content of every tweet $\{t \mid h \in t\}$, then computing the TF-IDF of $v(h)$ [26]. Essentially, the interpretation of the hexagon grid layout is simple: hashtags that occupy nearby hexagons are similar in *content*, with *content* referring to the aggregation of the text of all the tweets that include those hashtags. The visual encoding of the grid's hexagon units is further augmented with color, representing the single most frequent stance present on the hashtags of the unit, and size, representing the total sum of tweets in the hashtags that are included in the unit. Again, interacting with either of these two views will change the filtering on all the others, which in this case means that only tweets that contain any of the selected hashtags will be visible after a selection.

With the Twitter API's geo-search function [1] it is possible to estimate the location of each tweet within different administrative

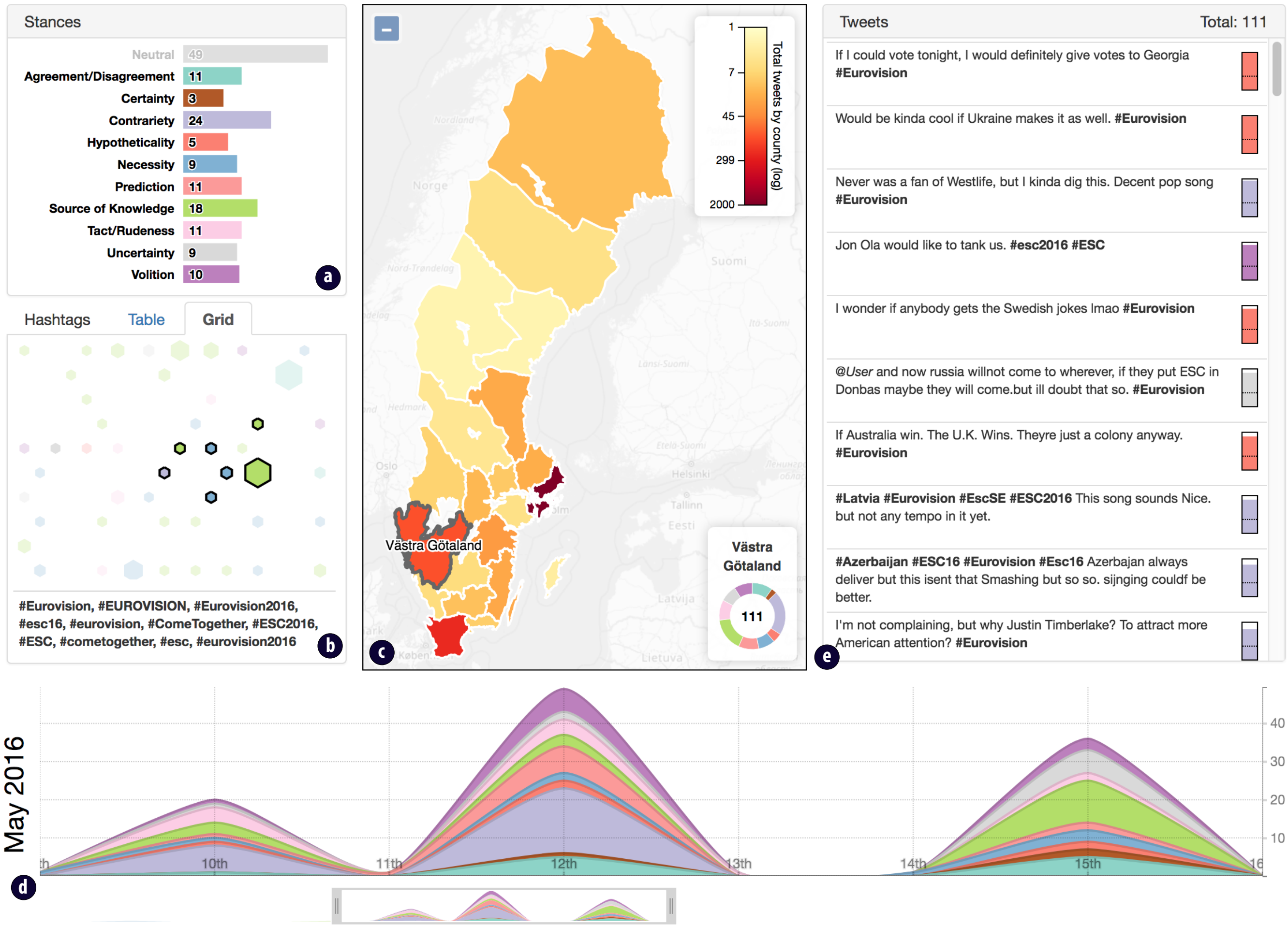


Figure 1: Overview of StanceXplore, showing English tweets from Sweden during May 2016 (case study from Sect. 4). The following filters are applied according to each view: (a) non-NEUTRAL tweets; (b) hashtags related to `#Eurovision`, manually selected by the user using the hexagon grid; (c) tweets originating from the county of Västra Götaland; and (d) from 9th to 16th of May 2016. Close reading of the tweets (e) shows the users' diverse opinions, their stances, and the classifier's confidence (using Platt scaling [25]).

regions such as cities, counties, or states. This information is shown in the *Map* view (Fig. 1c), along with a color encoding of the total (possibly filtered) number of tweets of each region. In the example from Fig. 1c, a log scale is used to improve the visibility of the values, since the difference in the total number of tweets between main and peripheral regions is very large. By interacting with the map, the user can explore the specific stance distribution within each region (Fig. 1c, bottom-right), switch between different administrative levels of granularity (e.g. cities *vs.* counties), and filter the data by limiting tweets to specific regions.

The temporal aspect of the corpus can be seen in the *Timeline* view (Fig. 1d) as a stacked area graph that shows the number of tweets per day for each color-coded stance. The used visual encoding is similar to *ThemeRiver* [11], but we decided to use a fixed time axis as it increased the legibility of the view. An interactive filter is located below the timeline and allows the setting of a specific time range for the analysis (in the example, the time range is between days 8 and 17 of May 2016).

Finally, the *Tweets* view (Fig. 1e) shows the full text of every tweet that satisfies all the filters defined interactively. Besides each tweet's text, a small bar shows the stance category assigned to the tweet (color) and the confidence of the classifier (size, computed with Platt scaling [25]), with the minimum size (lowest possible confidence) indicated by a dashed line.

## 4 Case Study

In this section we illustrate the features of StanceXplore with a case study on the use of the English language by Twitter users in Sweden. The corpus was extracted using Twitter's REST API [1] with filters by language (English), country (Sweden), and time (May 2016). The aim of this case study is to highlight the ability of StanceXplore to support (i) free exploration of stance-classified data from social media, (ii) detection of patterns and trends in stance-taking in social media along temporal and geospatial dimensions, and (iii) the iterative and dynamic testing of hypotheses with responsive interaction and feedback from filtering. [1]

We begin with the *Stances* view (Fig. 1a). It shows that NEUTRAL is the most frequent result of the classification process. One explanation for this is that the classifier's training set was extracted from political blogs, with no size restrictions. Tweets, on the other hand, can be considered as fragmented discourse because of the limited character size of the text (it can be hard to formulate complete sentences within 140 characters) and the intervention of metacomments. As a result, the classifier sometimes cannot decide with strong confidence for a stance, and when no stances are detected the tweet is classified as NEUTRAL. Another reason is the fact that stance is

[1] To better understand the dynamics of the user interaction, the reader is encouraged to watch the video at: `https://vimeo.com/230334496`.

a very subtle concept that can be difficult to identify, and even in the original manual annotations the NEUTRAL utterances were very frequent. In order to neutralize the effect of NEUTRAL as the most dominant stance and allow for the exploration of different patterns, we disable this category by shift-clicking on it. From now on only non-NEUTRAL tweets will show up on all the coordinated views.

Investigation of cultural events. We next look at the *Hashtags* grid and notice that the largest hexagon unit (with 1,916 tweets) contains only one hashtag: `#Eurovision`. The Eurovision Song Contest (ESC) is a traditional TV song competition that takes place every year between (mainly) European countries. Clicking on this hexagon unit lets us focus solely on tweets that include the hashtag `#Eurovision`. A quick session of close reading of the tweets indicates that ESC was held in Stockholm that month, which made it a hot topic of Twitter in Sweden. However, maybe the biggest change after this new filtering is in the timeline: the vast majority of tweets were posted between 10 and 15 of May 2016, with almost zero mentions outside that range. Indeed, ESC took place on 10, 12, and 14 of May 2016. But while the dates in which the contest took place may be clear, the stance distribution is not, since too much space is wasted on empty days. To improve this situation, we zoom in (using the timeline slider) into the desired time range, which then allows the relevant tweets and stances to occupy most of the space allocated to the timeline. A few trends on the stance-taking regarding ESC are now observable: SOURCE OF KNOWLEDGE (which sets the color of the hexagon), NECESSITY and CONTRARIETY are regularly strong throughout the period; VOLITION shows a peak of representation in the second day of the contest; and UNCERTAINTY is the strongest stance after the final day.

One natural way to proceed with the exploration is to go back to the *Hashtags* grid and browse through the hexagon units near the selected one; these are the ones that are similar in content to the current focus, so they might be relevant to enrich the results. This leads to an interesting insight into the corpus: many different hashtags were used to refer to the same event. While some might be easy to locate with conventional string-comparison methods, such as those with different capitalizations (`#eurovision`, `#EUROVISION`) and suffixes (`#Eurovision2016`), others might be more challenging to detect without the content-based similarity visualization, such as abbreviations (`#ESC`, `#esc16`) and specific themes (`#ComeTogether`). However, two other nearby hashtag groups prove to be even more interesting and insightful. The first one, `#AUS`, is related to the fact that Australia participated in ESC 2016 even though it is not an European country. By investigating the stances and close reading of the tweets including this hashtag, it is possible to see that the Australian performance was well-liked and received positive feedback, specially on the second day of the contest. The second interesting nearby hashtag group includes both `#Ukraine`—the winner of ESC 2016—and `#Russia`. Again, by investigating the stances and close reading of the tweets after filtering by this hashtag group, we can infer that a fierce dispute took place between the two countries during the contest, with tweets moving from predominantly PREDICTION in the first days to a small surge of AGREEMENT/DISAGREEMENT and UNCERTAINTY after the final results.

Aspects of geographical distribution. With all the filters reset, one look at the *Map* view shows clearly that the geographical distribution of English tweets in Sweden is not balanced among all counties. In fact, only three areas contain the vast majority of English tweets: Stockholm, with 55,712 tweets; Västra Götaland, with 16,029 tweets; and Skåne, with 14,295 tweets. Not surprisingly, these counties include, in this same order, the three largest cities in Sweden—Stockholm, Gothenburg and Malmö. The counties with the most tweets are consistently located in the southern part of Sweden; as we move towards the northern parts of the country, the numbers decrease significantly. This is compatible with the fact that the northern regions of Sweden, known for their increasingly harsh weather, are more sparsely populated than the south. Considering the characteristics of this distribution, an analysis of the busiest areas of the country might be the most common approach. In this section, however, we decided to take a different path and explore a less obvious question: *what are people tweeting about (in English) outside the main areas, and what are their attitudes regarding their chosen topics?*

For this, we first turn to the *Map* view and filter only tweets that come from Norrbotten—the northest county in Sweden—totalling 717 tweets distributed in all stances. NEUTRAL is the most frequent stance, representing almost half of the subset of tweets with 353 tweets, followed by SOURCE OF KNOWLEDGE (75 tweets) and NECESSITY (71 tweets). Close inspecting of the tweets classified as SOURCE OF KNOWLEDGE shows that average confidence is low, while the opposite is true for NECESSITY. For the rest of the analysis, we again disable NEUTRAL and focus on the rest of the stances.

Looking next at the *Hashtags* grid, we notice that, apart from `#Eurovision`, two other hexagon units are salient (due to their size), including hashtags such as `#Jobs`, `#CareerArc`, and `#Hiring`. The time distribution of these posts shows a periodical pattern throughout the whole month, with tweets being made every few days (with periods of inactivity between them). Close reading of the filtered tweets shows that they are all very similar job advertisements; the strong use of Twitter for job advertisements in this area may be related to a possible difficulty of attracting personnel due to their remote location. However, one interesting observation is that the classifier has achieved low confidence with these tweets, assigning diverse stances such as CONTRARIETY and SOURCE OF KNOWLEDGE. Repeating the same analysis steps with Västerbotten, a neighboring county immediately to the south of Norrbotten, we notice an especially salient hexagon marked with AGREEMENT/DISAGREEMENT. It contains sports-related tags such as `#Endomondo` and `#endorphins`. Close reading of the tweets after filtering shows that all (but one) have the same structure and almost the same text: a report on the completion of a sports activity. These are known to be generated automatically by health-monitoring applications, and are not supposed to express any specific stance. From this investigation with StanceXplore we can notice, however, that the classifier did not assign the expected NEUTRAL stance, but used AGREEMENT/DISAGREEMENT with low confidence. This insight could be useful to help DH researchers in finding flaws in the stance classification system and improve it with more training data and better examples.

## 5 Conclusion

In this paper we proposed StanceXplore, a visualization aimed at supporting DH researchers in the interactive exploration of stance-annotated textual content originated from social media. The proposed visualization uses coordinated multiple views to simultaneously show different aspects of the corpus under analysis, in a way that allows the user to explore each view independently and to interactively apply filters that affect the outcome of all the views. With a case study of the use of English by Twitter users from Sweden, we demonstrated how StanceXplore can be used to support a progressive exploration process, starting from a general overview of the data (distant reading) and moving step-by-step into more specific subsets of the corpus (close reading) that exhibit different stance-taking patterns and trends, defined by multiple aspects (or dimensions) of the data such as time, space, and similarities/dissimilarities in the use of the English language.


## Acknowledgments

The authors wish to thank Jonas Lundberg for providing the data used in the case study. This research was funded by the Swedish Research Council, framework grant "The Digitized Society—Past, Present, and Future" (StaViCTA), No. 2012-5659.

## References


[1] Twitter's REST API. https://dev.twitter.com/rest. Access: July 2017.

[2] B. A. A. Almutairi. Visualizing patterns of appraisal in texts and corpora. *Text & Talk*, 33(4–5):691–723, 2013. doi: 10.1515/text-2013-0031

[3] B. Asokarajan, R. Etemadpour, J. Abbas, S. Huskey, and C. Weaver. Visualization of Latin textual variants using a pixel-based text analysis tool. In *Proceedings of the International EuroVis Workshop on Visual Analytics*, EuroVA '16. The Eurographics Association, 2016. doi: 10.2312/eurova.20161119

[4] N. Cao, Y.-R. Lin, X. Sun, D. Lazer, S. Liu, and H. Qu. Whisper: Tracing the spatiotemporal process of information diffusion in real time. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2649–2658, Dec. 2012. doi: 10.1109/TVCG.2012.291

[5] S. Chandrasegaran, S. K. Badam, L. Kisselburgh, K. Ramani, and N. Elmqvist. Integrating visual analytics support for grounded theory practice in qualitative text analysis. *Computer Graphics Forum*, 36(3):201–212, 2017. doi: 10.1111/cgf.13180

[6] A. T. Chen, J. Martell, and P. Lach. Supporting discovery through contextual representation: Developing a tool for visually exploring slave narratives. In *Proceedings of the Workshop on Visualization for the Digital Humanities*, VIS4DH '16, 2016.

[7] S. Chen, L. Lin, and X. Yuan. Social media visual analytics. *Computer Graphics Forum*, 36(3):563–587, 2017. doi: 10.1111/cgf.13211

[8] N. Diakopoulos, M. Naaman, and F. Kivran-Swaine. Diamonds in the rough: Social media visual analytics for journalistic inquiry. In *Proceedings of the IEEE Symposium on Visual Analytics Science and Technology*, VAST '10, pp. 115–122. IEEE, 2010. doi: 10.1109/VAST.2010.5652922

[9] M. El-Assady, R. Sevastjanova, B. Gipp, D. Keim, and C. Collins. NERεx: Named-entity relationship exploration in multi-party conversations. *Computer Graphics Forum*, 36(3):213–225, 2017. doi: 10.1111/cgf.13181

[10] K. S. Hasan and V. Ng. Why are you taking this stance? Identifying and classifying reasons in ideological debates. In *Proceedings of the 2012 Conference on Empirical Methods on Natural Language Processing*, vol. 14 of *EMNLP 2014*, pp. 751–762. Association for Computational Linguistics, 2014.

[11] S. Havre, E. Hetzler, P. Whitney, and L. Nowell. ThemeRiver: Visualizing thematic changes in large document collections. *IEEE Transactions on Visualization and Computer Graphics*, 8(1):9–20, 2002. doi: 10.1109/2945.981848

[12] S. R. Humayoun, S. Ardalan, R. AlTarawneh, and A. Ebert. TExVis: An interactive visual tool to explore Twitter data. In *Proceedings of the EG/VGTC Conference on Visualization — Short Papers*, EuroVis '17. The Eurographics Association, 2017. doi: 10.2312/eurovisshort.20171149

[13] D. A. Jackson, K. M. Somers, and H. H. Harvey. Similarity coefficients: measures of co-occurrence and association or simply measures of occurrence? *The American Naturalist*, 133(3):436–453, 1989.

[14] S. Jänicke, G. Franzini, M. F. Cheema, and G. Scheuermann. On close and distant reading in digital humanities: A survey and future challenges. In *Proceedings of the EG/VGTC Conference on Visualization — STARs*, EuroVis '15. The Eurographics Association, 2015. doi: 10.2312/eurovisstar.20151113

[15] D. A. Keim and D. Oelke. Literature fingerprinting: A new method for visual literary analysis. In *Proceedings of the IEEE Symposium on Visual Analytics Science and Technology*, VAST '07, pp. 115–122, 2007. doi: 10.1109/VAST.2007.4389004

[16] S. Koch, M. John, M. Wörner, A. Müller, and T. Ertl. VarifocalReader — in-depth visual analysis of large text documents. *IEEE Transactions on Visualization and Computer Graphics*, 20(12):1723–1732, Dec. 2014. doi: 10.1109/TVCG.2014.2346677

[17] T. Kohonen. The self-organizing map. *Neurocomputing*, 21(1):1–6, 1998. doi: 10.1016/S0925-2312(98)00030-7

[18] K. Kucher and A. Kerren. Text visualization techniques: Taxonomy, visual survey, and community insights. In *Proceedings of the 8th IEEE Pacific Visualization Symposium*, PacificVis '15, pp. 117–121. IEEE, 2015. doi: 10.1109/PACIFICVIS.2015.7156366

[19] K. Kucher, A. Kerren, C. Paradis, and M. Sahlgren. Visual analysis of text annotations for stance classification with ALVA. In *Poster Abstracts of the EG/VGTC Conference on Visualization*, EuroVis '16, pp. 49–51. The Eurographics Association, 2016. doi: 10.2312/eurp.20161139

[20] K. Kucher, C. Paradis, and A. Kerren. The state of the art in sentiment visualization. *Computer Graphics Forum*, 2017. Published electronically before print. doi: 10.1111/cgf.13217

[21] K. Kucher, T. Schamp-Bjerede, A. Kerren, C. Paradis, and M. Sahlgren. Visual analysis of online social media to open up the investigation of stance phenomena. *Information Visualization*, 15(2):93–116, 2016. doi: 10.1177/1473871615575079

[22] A. Marcus, M. S. Bernstein, O. Badar, D. R. Karger, S. Madden, and R. C. Miller. TwitInfo: Aggregating and visualizing microblogs for event exploration. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '11, pp. 227–236. ACM, 2011. doi: 10.1145/1978942.1978975

[23] S. M. Mohammad, S. Kiritchenko, P. Sobhani, X. Zhu, and C. Cherry. SemEval-2016 task 6: Detecting stance in tweets. In *Proceedings of the International Workshop on Semantic Evaluation*, SemEval '16, 2016.

[24] B. Pang and L. Lee. Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval*, 2(1–2):1–135, 2008. doi: 10.1561/1500000011

[25] J. Platt. Probabilistic outputs for support vector machines and comparisons to regularized likelihood methods. *Advances in Large Margin Classifiers*, 10(3):61–74, 1999.

[26] G. Salton and C. Buckley. Term-weighting approaches in automatic text retrieval. *Information processing & management*, 24(5):513–523, 1988.

[27] G. Salton, A. Wong, and C.-S. Yang. A vector space model for automatic indexing. *Communications of the ACM*, 18(11):613–620, 1975.

[28] S. Schreibman, R. Siemens, and J. Unsworth. *A New Companion to Digital Humanities*. John Wiley & Sons, 2016.

[29] B. Shneiderman. The eyes have it: a task by data type taxonomy for information visualizations. In *Proceedings of the IEEE Symposium on Visual Languages*, VL '96, pp. 336–343, 1996. doi: 10.1109/VL.1996.545307

[30] V. Simaki, C. Paradis, and A. Kerren. Stance classification in texts from blogs on the 2016 British referendum. In *Proceedings of the International Conference on Speech and Computer*, SPECOM '17. Springer, 2017. To appear.

[31] V. Simaki, C. Paradis, M. Skeppstedt, M. Sahlgren, K. Kucher, and A. Kerren. Annotating speaker stance in discourse: the Brexit Blog Corpus. *Corpus Linguistics and Linguistic Theory*, 2017. To appear.

[32] S. Sinclair and G. Rockwell. Text analysis and visualization. In S. Schreibman, R. Siemens, and J. Unsworth, eds., *A New Companion to Digital Humanities*, pp. 274–290. John Wiley & Sons, 2016.

[33] M. Skeppstedt, M. Sahlgren, C. Paradis, and A. Kerren. Active learning for detection of stance components. In *Proceedings of the Workshop on Computational Modeling of People's Opinions, Personality, and Emotions in Social Media at COLING '16*, PEOPLES '16, pp. 50–59. Association for Computational Linguistics, 2016.

[34] M. Skeppstedt, M. Sahlgren, C. Paradis, and A. Kerren. Unshared task: (Dis)agreement in online debates. In *Proceedings of the 3rd Workshop on Argument Mining at ACL '16, short papers track*, ArgMining '16, pp. 154–159. Association for Computational Linguistics, 2016.

[35] M. Skeppstedt, V. Simaki, C. Paradis, and A. Kerren. Detection of stance and sentiment modifiers in political blogs. In *Proceedings of the International Conference on Speech and Computer*, SPECOM '17. Springer, 2017. To appear.

[36] F. Stoffel, W. Jentner, M. Behrisch, J. Fuchs, and D. Keim. Interactive ambiguity resolution of named entities in fictional literature. *Computer Graphics Forum*, 36(3):189–200, 2017. doi: 10.1111/cgf.13179

[37] S. Tong and D. Koller. Support vector machine active learning with applications to text classification. *Journal of Machine Learning Research*, 2(Nov):45–66, 2001. doi: 10.1162/153244302760185243

[38] M. A. Walker, P. Anand, R. Abbott, J. E. F. Tree, C. Martell, and J. King. That is your evidence?: Classifying stance in online political debate. *Decision Support Systems*, 53(4):719–729, 2012. doi: 10.1016/j.dss.2012.05.032