Scalable Visualisation of Sentiment and Stance

Jon Chamberlain[1], Udo Kruschwitz[1], Orland Hoeber[2]
[1]University of Essex, Wivenhoe Park, Colchester CO4 3SQ, UK
[2]University of Regina, 3737 Wascana Pkwy, Regina, SK S4S 0A2, Canada
{jchamb,udo}@essex.ac.uk, orland.hoeber@uregina.ca

Abstract

Natural language processing systems have the ability to analyse not only the sentiment of human language, but also the stance of the speaker. Representing this information visually from unevenly distributed and potentially sparse datasets is challenging, in particular when trying to facilitate exploration and knowledge discovery. We present work on a novel visualisation approach for scalable visualisation of sentiment and stance and provide a language resource of e-government public engagement of 9,278 user comments with stance explicitly declared by the author.

Keywords: sentiment, stance, information visualisation, opinion mining, e-government, language resource

1. Introduction

The ever growing amount of user generated content online presents a variety of challenges, one of them being how to summarise large collections of user comments in online discussion forums and social networks, capturing the gist of what has been said and reflecting the different view points on a range of topics. Natural language processing systems have the ability to analyse not only the sentiment of this communication, but also the stance of the speaker.

Online participation is increasing at an exponential rate and the desire for consumption of such data has driven innovations in communication platforms, in particular on social media platforms such as Facebook[1] and Twitter[2]; however, similar scenarios can exist at much smaller, local scales such as comments on online newspaper reports and e-government consultation schemes.

Representing information visually from these unevenly distributed and potentially sparse datasets is problematic, in particular when trying to facilitate exploration and knowledge discovery. Traditional linear scaling will result in large values dominating smaller ones; logarithmic scaling addresses this problem, but is not intuitive to casual users.

This paper addresses these challenges by discussing related work in the area of sentiment and stance analysis, as well as information visualisation relevant to this field (Section 2.). We then propose a novel approach to scalable visualisation of sentiment and stance (Section 3.). In Section 4. we outline a case study of how this approach can be used for visualising user participation on an e-government portal, followed by further details of how the language resource was acquired and how it will be shared with the community (Section 5.). In Section 6. we compare our approach to other visualisation techniques and, in conclusion, we discuss the implications of this approach and its relevance to the NLP researchers (Section 7.).

2. Related Work

Summarising and visualising online discussions has become ever more important for users to understand the complexities of multi-faceted issues in modern society. There are many approaches for visualising sentiment or stance as time series data, including timelines (Kucher et al., 2014), dense pixel displays (Hao et al., 2011), summaries of online conversations (Riccardi et al., 2016) and summaries of Twitter data (Mohammad et al., 2016a). Websites such as CreateDebate[3] and Kialo[4] attempt to organise discussion into supporting and refuting statements; the latter providing users with interactive overviews and maps of the discussion. These attempts to "empower reason" go some way towards helping users; however, it remains a challenge to present numerous discussions points in a relevant and unbiased way.

Some approaches have developed methods for dealing with topically organised text (Hoque and Carenini, 2016); however, dealing with potentially extreme differences in the amount of data, whilst still supporting cross-topic comparisons, remains problematic. If the data are unevenly distributed or sparse, a large number of data points for a particular topic can make it difficult to visually convey the information in the smaller topics. Furthermore, if there is a desire to evaluate the sentiment of the human language against the formal stance taken by the author, care must be taken to ensure that the visual encodings are comparable.

Adding interactivity enables the user to engage in information seeking among the textual data, using the sentiment and stance visualisation as a source of "information scent" (Pirolli and Card, 1999). While much progress has been made in searching such collections, e.g. via paradigms like faceted search (Russell-Rose and Tate, 2013), exploration and navigation have traditionally attracted less attention. Integrating natural language processing, information visualisation, and interactive information retrieval holds great value for enabling people to discover meaningful information from within complex information repositories (Hoeber, 2014). This research presents an approach that enables the visual analysis and comparison of sentiment and stance over a potentially large number of topics (either represented explicitly or derived from the data).

[1] https://www.facebook.com
[2] https://twitter.com
[3] http://www.createdebate.com
[4] https://www.kialo.com

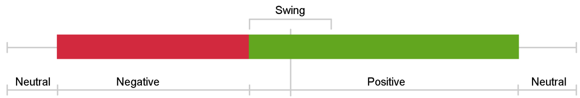

Figure 1: A basic representation of how a single bar is calculated using the percentages of total responses (positive, negative, and neutral).

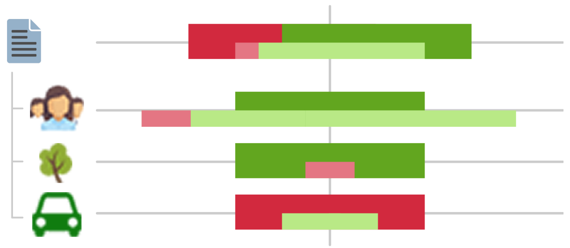

Figure 2: Representation of an expanded (by topic) double bar showing stance and sentiment simultaneously.

3. Approach

The goal of our approach is to visualise both sentiment and stance simultaneously, scaling the representation to allow for sets of different sizes to be shown and compared, and highlighting the polarisation of opinion.

Figure 1 shows how a single bar (stance or sentiment) is calculated. The full width of the bar represents 100% of the comments received, at either end of the bar are the proportion of neutral comments. Positive and negative comments are in the centre of the bar, with swing represented by deviation from the centre line. Figure 2 shows how these bar representations can be combined (stance embedded within sentiment), and used within a topic hierarchy.

This representation gives both overview and detail, displaying hierarchically organised sentiment and stance, and supporting sensemaking for analysis and synthesis of information. Such topical organisation can be also be considered an instance of faceted browsing (Tunkelang, 2009; Russell-Rose and Tate, 2013).

This approach is scalable to unevenly distributed datasets where most of the nodes have only a few data points but some have comparatively very large amounts. Linear representations do not scale for this type of data and logarithmic transformation is not intuitive to the user.

With the data organised based on a topical hierarchy, the visualisation enables topics to be compared to their parents and to one another and, within a given topic, the sentiment and stance can also be compared.

While doing so hides the absolute value of the number of comments made for each of the sentiment and stance classes, it enables a visual comparison of the relative swing across each topic. Following Shneiderman's *Information Seeking Mantra* ("overview first, zoom and filter, details on demand") (Shneiderman, 1996), this approach enables the user to interactively explore the information in a flexible manner. The default view of the sentiment and stance provides an overview of general opinion expressed within the data. The hierarchical topics can be expanded and collapsed (e.g., zoomed), topics can be removed from the view (e.g., filtered), and specific sentiment and stance selections can be made in order to retrieve the associated comments (e.g., details on demand), see Figure 3.

More importantly, the visualisation provides a clear depiction of situations where there is significant swing in the sentiment or stance, and when the sentiment and stance are inconsistent with one another. These are important conditions since they represent potential issues that may need further study and analysis.

Figure 3: User exploration is supported through interactivity of the graphs on mouse-over. A fly-out box shows more detail of how the chart is constructed by displaying an abridged comment, sentiment and stance.

Figure 4: Visualisations of explicit stance for three planning applications: #131452 has a total of 167 comments (94 object, 73 support, 0 neutral); #150239 has 336 comments (75 support, 252 object, 9 neutral); and #146223 has 4 comments (2 object, 1 support, 1 neutral).

4. Case Study

It is common for Community Question Answering (cQA) systems to include methods for users to make comments, as well as to make upvotes or likes on comments (for example, StackOverflow[5] or Yahoo!Answers[6]) but it is less usual for the stance of the comment to be explicitly entered unless the platform is specifically for debate (e.g. CreateDebate and Kialo). Another example of where this does occur is in the commenting of planning applications.

In the past, opinions on a planning applications would have been submitted in writing to the planning office to support or object; however, this process has now moved online. Users can now access the details of an application through an online portal, leave text comments, upload files and are also explicitly asked whether they are writing to support or object to an application, or whether they are making a

[5] https://stackoverflow.com
[6] https://uk.answers.yahoo.com

general observation (i.e. a neutral stance). Our case study analyses data from such a portal[7], operated by Colchester Borough Council (CBC), based in Essex, UK.

The portal is used for conducting public consultation and to gain local insight regarding planning applications. The comments are then used alongside existing planning policy to shape decisions. Planning officers and local government officials have a gauge of public opinion regarding proposed applications, as well as a way of capturing knowledge from the community that planning officers may have missed.

One of the most important roles of the planning officer is to summarise the planning documents and comments submitted from the public in a planning document that goes before a committee to decide whether the planning application is approved, requires more information or is rejected. Online comments are not searched by planning officers but each is given due consideration, making a summary visualisation important in their workflow. In this particular case the user (planning officer) is not so interested in the quantity of opinions, rather whether so-called Material Planning Considerations[8] have been raised: matters that will influence the decision of the application such as parking, traffic, conservation, safety, etc. In this case the scalable visualisation ignores comment quantity and instead represents the balance between support, object and neutral opinions (see Figure 4). Further hierarchical decomposition and representations of the data would allow such issues to be located quickly (e.g. the last bar in Figure 2).

The comments vary in size from a single word (e.g. "object!") to hundreds of paragraphs covering numerous topics that provide evidence for the stance. Topic clustering may prove useful to break the long comments down; however, sentence-based analysis has been successful in analysing stance in online article comments (Riccardi et al., 2016). Examples (from the corpus) of straightforward stance include support (Example 1) and objection (Example 2); however, neutral stance (or general observations) can be more ambiguous (Example 3 and 4).

(1) Fantastic to bring new jobs to the town and boost the local economy.

(2) The local infrastructure cannot cope, especially in light with the proposed development of land currently occupied by the MoD.

(3) West Mersea Town Council are unable to comment, more detailed information required.

(4) Councillors have discussed this application and have no objections.

Within the corpus many additional ambiguous statements exist, inline with previous findings in Twitter data (Mohammad et al., 2016a). Despite being a formal system for members of the public to submit comments to a planning consultation, authors are often ambiguous in their meaning, with the use of sarcasm (Example 5), emotional responses (Example 6) and rhetorical questions (Example 7).

(5) People say it will kill the town centre, but our Council has already done that.

(6) Essential community services are being cut - is this fair?

(7) Why do we need these built when a large portion of green space in the local area is being bulldozed for mass housing?

The planning officer will be most interested in finding material considerations, in particular information that was not previously known (Example 8).

(8) I have seen great crested newts at the lower end of this project nearer the train station!

Table 1: Distribution of explicit, stance-labeled online text comments per planning application.

n(2,840)	**Min**	**Max**	**Mean**	**SD**
Total	1	435	3.5	15.4
Negative	0	420	1.8	12.0
Positive	0	252	1.0	7.3
Neutral	0	9	0.4	0.8
Swing	-417	203	-0.8	13.0

5. Language Resource

Planning application data, comments and associated metadata from 2008-16 was accessed from the CBC portal on 8 Feb 2017 (a total of 15,703 applications and 9,278 online text comments).

CBC receive an average 1,745 sd(271) planning applications per year of which the majority (67.5%) get conditional approval but 10.0% are refused (the remaining applications can be assigned 18 other statuses such as withdrawn, observations only, etc).

2,840 (18.1%) of the planning applications had at least one online comment (see Table 1) and some applications attract considerable interest. Nine applications had over 100 comments (the maximum being 435), 144 applications had over 10 comments and 349 applications had over five comments. This highlights the problem of scalability the planning team face when attempting to summarise this data.

Some applications will be simple and take very little time to process; others will take considerably longer and be more complex in the summary. Each comment also contains the explicitly entered stance of the author regarding the application (object, support or neutral) and by summing these stance values we can calculate the swing.

The highest object swing was 417 from 435 total comments and the highest support swing was 203 from 246 total comments. The average swing for the entire dataset was 0.8 sd(13.0) object, an indication that users are more likely to use the portal to post comments objecting to proposals.

[7] `http://www.colchester.gov.uk/article/13483/Search-Applications-Online`, accessed 1 Feb 2018

[8] `http://www.colchester.gov.uk/article/13488/Commenting-on-a-Planning-application`, accessed 1 Feb 2018

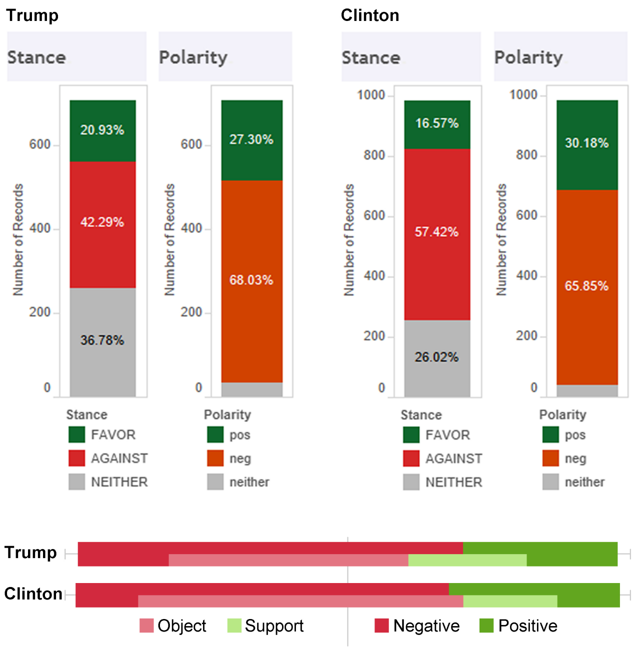

Figure 5: Visualisation of the SemEval dataset, comparing the detailed view (top) of SemEval for stance and sentiment (polarity) with the compact view of our approach (bottom) on two targets: Donald Trump and Hillary Clinton.

The comments are publicly available online via the portal and the distribution of the anonymised language resource for research purposes has been agreed with CBC.

6. Comparison to SemEval

Stance and opinion datasets for popular social media such as Twitter have started to emerge (Mohammad et al., 2016a), and have found their way into academic competitions such as SemEval (Mohammad et al., 2016b). Here we compare our proposed visualisation approach with that used for the visualisation of the SemEval dataset. Figure 6 compares the SemEval visualisation with our compact visualisation for two targets: Donald Trump and Hillary Clinton. Whilst lacking the details of the SemEval approach, our approach still visualises the similarity between sentiment (also called polarity) distribution and the differences between stance of the two targets. Comparing three or more targets would become increasing more difficult for the SemEval approach, whereas our approach would scale to the amount required.

7. Discussion

The impact of scalable visualisation of sentiment and stance can be seen within the workflow of planning applications. Planning officers have a legal obligation to consider all material issues raised during the consultation period of planning. Should considerations be missed or ignored and the planning decision challenged, the council would be liable for any compensation due to the decision being changed. Therefore, the laborious and meticulous process of analysing each comment is required; however, the benefit of support through summarisation and visualisation techniques would increase the efficiency of dataflow through the organisation and identify potential risk areas.

Analysis of the data from the case study supports the notion that negative motivations are more powerful than positive ones for those participating in online forums i.e., people are more likely to complain or object than they are to agree or support but it is not surprising to see this bias in official channels of communication.

In a wider application, this type of visualisation would be helpful for the general public to view complex data sources, in particular those that have been subject to manipulation through fake news and reporter bias. An example is within the voting records of politicians (their recorded stance) compared to the words they use during speeches and interviews (their observed sentiment and stance). This avenue of research is being actively explored and may yield interesting insights into voting participation and behaviour relevant for NLP involvement in future e-government engagement initiatives.

Previous research (Mohammad et al., 2016a) has highlighted that, whilst reasonably accurate to classify using machine learning algorithms, sentiment analysis is not sufficient to understand human responses in the form of comments or discussion, and additionally that stance is a complex concept to analyse and visualise. Determining targets of opinion vs targets of interest (i.e. targets being mentioned vs targets that are not) make the task even more difficult, hence our desire to make available a dataset with stance explicitly mentioned.

In order to assist planning officers to identify and make sense of the application comments, this visualisation will be implemented and evaluated on their data to inform the development of a new platform (see Figure 6). Work to extend the approach to support information seeking strategies is ongoing.

8. Conclusion

In this paper we present an approach to scalable visualisation of sentiment and stance to enable analysis and exploration of complex large-scale data. This approach has been implemented on a case study of e-government planning consultation data where participants explicitly declare their stance to an application as well as write a comment. This work has the potential to provide impact in terms of cost savings and efficiency in the long term for e-government engagement and wider applications. The language resource used in this research will be made available to practitioners in this field.

9. Acknowledgements

We acknowledge support from grant number ES/L011859/1, from The Business and Local Government Data Research Centre, funded by the Economic and Social Research Council to provide researchers and analysts with secure data services. Thanks to Sally Harrington and Andrew Tyrrell from CBC for advising on the case study.

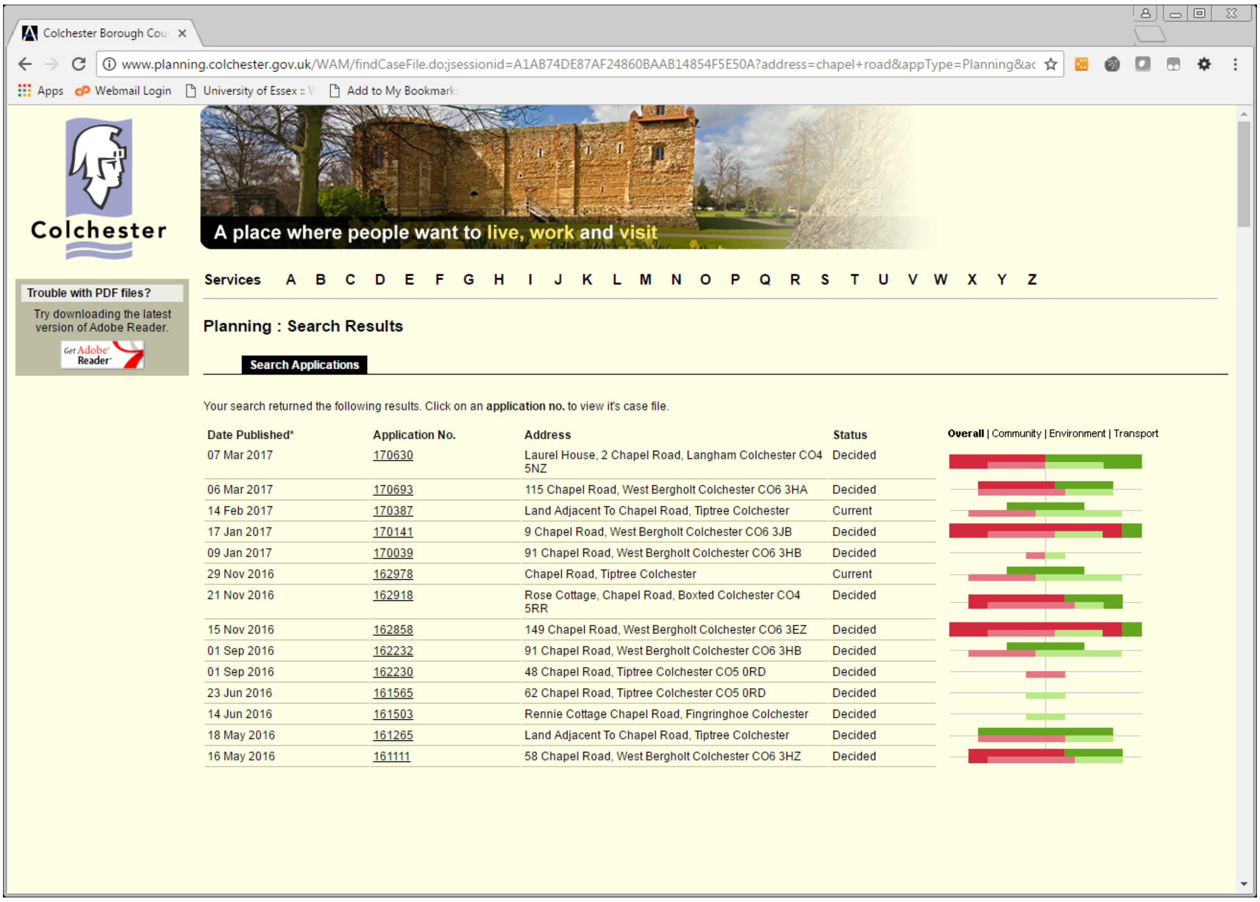

Figure 6: A screenshot showing how the visualistion can be applied to the existing portal to enhance understanding and prioritisation of planning applications.

10. Bibliographical References

Hao, M., Rohrdantz, C., Janetzko, H., Dayal, U., Keim, D. A., Haug, L. E., and Hsu, M. C. (2011). Visual sentiment analysis on Twitter data streams. In *Proceedings of the IEEE Conference on Visual Analytics Science and Technology*, pages 277–278.

Hoeber, O. (2014). Visual search analytics: Combining machine learning and interactive visualization to support human-centred search. In *Proceedings of Beyond Single-Shot Text Queries: Bridging the Gap(s) Between Research Communities Workshop*, pages 37–43.

Hoque, E. and Carenini, G. (2016). MultiConVis: A visual text analytics system for exploring a collection of online conversations. In *In Proceedings of the International Conference on Intelligent User Interfaces*, pages 96–107.

Kucher, K., Kerren, A., Paradis, C., and Sahlgren, M. (2014). Visual analysis of stance markers in online social media. In *Proceedings of the IEEE Conference on Visual Analytics Science and Technology*, pages 259–260.

Mohammad, S., Kiritchenko, S., Sobhani, P., Zhu, X., and Cherry, C. (2016a). A dataset for detecting stance in tweets. In Nicoletta Calzolari (Conference Chair), et al., editors, *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC 2016)*, Paris, France, may. European Language Resources Association (ELRA).

Mohammad, S. M., Kiritchenko, S., Sobhani, P., Zhu, X., and Cherry, C. (2016b). Semeval-2016 task 6: Detecting stance in tweets. In *Proceedings of the International Workshop on Semantic Evaluation*, SemEval '16, San Diego, California, June.

Pirolli, P. and Card, S. (1999). Information Foraging. *Psychological Review*, 106(4):643–675.

Riccardi, G., Béchet, F., Danieli, M., Favre, B., Gaizauskas, R. J., Kruschwitz, U., and Poesio, M. (2016). The SENSEI project: Making sense of human conversations. In *Proceedings of the First International Workshop on Future and Emergent Trends in Language Technology*, pages 10–33.

Russell-Rose, T. and Tate, T. (2013). *Designing the Search Experience: The Information Architecture of Discovery*. Elsevier (Morgan Kaufmann).

Shneiderman, B. (1996). The eyes have it: A task by data type taxonomy for information visualizations. In *Proceedings of the IEEE Symposium on Visual Languages*, pages 336–343.

Tunkelang, D. J. (2009). *Faceted search*. Morgan & Claypool Publishers.