

Alternate ACM SIG Proceedings Paper in LaTeX Format*

[Extended Abstract][†]

Ben Trovato[‡]
Institute for Clarity in
Documentation
1932 Wallamaloo Lane
Wallamaloo, New Zealand
trovato@corporation.com

G.K.M. Tobin[§]
Institute for Clarity in
Documentation
P.O. Box 1212
Dublin, Ohio 43017-6221
webmaster@marysville-
ohio.com

Lars Thørvæld[¶]
The Thørvæld Group
1 Thørvæld Circle
Hekla, Iceland
larst@affiliation.org

Lawrence P. Leipuner
Brookhaven Laboratories
Brookhaven National Lab
P.O. Box 5000
lleipuner@researchlabs.org

Sean Fogarty
NASA Ames Research Center
Moffett Field
California 94035
fogartys@amesres.org

Charles Palmer
Palmer Research Laboratories
8600 Datapoint Drive
San Antonio, Texas 78229
cpalmer@prl.com

ABSTRACT

todo

CCS Concepts

•Computer systems organization → Embedded systems; Redundancy; Robotics; •Networks → Network reliability;

Keywords

ACM proceedings; L^AT_EX; text tagging

1. INTRODUCTION

Nowadays, the World Wide Web has transformed from a large, static library that people only browse into a vast and dynamic information resource. Relying on this, social networks is a very popular and powerful tool for expressing opinions, broadcasting news, and simply communicating

with friends. People using them for commenting on significant events in real time, with several hundred micro-blogs posted each second.

The most popular micro-blogging service is Twitter. The popularity of Twitter stems from its availability on a number of different electronic devices (web and cell phones. There is a prevalence of a subculture in Twitter that encourages users to acquire a large friend pool, as well as send tweets on a wide variety of subjects, typically several times a day.

Monitoring and analysing this rich and continuous flow of user-generated content can yield unprecedentedly valuable information, which would not have been available from traditional media outlets. Tweets can be seen as a dynamic source of information enabling individuals, corporations, and government organizations to stay informed of what is happening now. For instance, people would be interested in getting advice, opinions, facts, or updates on news or events. Companies are increasingly using Twitter to advertise and recommend products, brands, and services; to build and maintain reputations; to analyse users' sentiment regarding their products (or those of their competitors); to respond to customers' complaints; and to improve decision making and business intelligence. Twitter has also emerged as a fast communication channel for gathering and spreading breaking news, for predicting election results, and for sharing political events and conversations. It has also become an important analytical tool for crime prediction and monitoring terrorist activities.

Twitter promotes an attractive style stating breaking news, as there is very little lag between the time that an event happens or is first reported in the news media and the time at which it is the subject of a posting on Twitter. Twitter can be characterized as an endless database, which collects millions of real-time short text messages every second. Tweets also have a mechanism by which the user can link to other objects on the web such as articles, images or videos which is typically used to link tweets to related material on the Internet. Thereafter, the first result is that the size of information is multiplied and the variety of references is bigger, as well. These messages are not only just data, but they can

*(Produces the permission block, and copyright information). For use with SIG-ALTERNATE.CLS. Supported by ACM.

[†]A full version of this paper is available as *Author's Guide to Preparing ACM SIG Proceedings Using L^AT_EX_{2_ε} and BibT_EX* at www.acm.org/eaddress.htm

[‡]Dr. Trovato insisted his name be first.

[§]The secretary disavows any knowledge of this author's actions.

[¶]This author is the one who did all the really hard work.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

WOODSTOCK '97 El Paso, Texas USA

© 2017 ACM. ISBN 123-4567-24-567/08/06...\$15.00

DOI: 10.475/123.4

be manipulated efficiently. One well-timed subject of research is to use those messages for event detection. In other words, the tweets is a source of inventing which topics are more seasonable. Event detection has also instant impact on the world, through the quick transmission of the news and necessary briefing in some cases.

With the passage of time and the effect of more and more users the topic acquire much popularity. Through this phenomenon we can form a general summarization of the event. This process is called event summarization. The massive crowd keeps close pace with the development of trending topics and provide the timely updated information. Twitter has shown its powerful ability in information delivery in many events, like the wildfires in San Diego and the earthquake in Japan. In response to searches for ongoing events, today's major search engines simply find tweets that match the query terms, and present the most recent ones. This approach has the advantage of leveraging existing query matching technologies, and for simple one-shot events such as earthquakes it works well. However, for events that have "structure" or are long-running, and where users are likely to want a summary of all occurrences so far, this approach is often unsatisfactory.

Event detection is a growing domain of research. Many different species of algorithms have been detected regarding this sector. A common approach are techniques that are based on text categorization. In addition, there are some methods that reclaim the display frequency of each term.

The computational treatment of sentiment has recently attracted a great deal of attention, in part because of its potential applications. One of the main reasons for sentiment analysis is the aforementioned increase of user-generated content on the Web which has resulted in a wealth of information that is potentially of vital importance to institutions and companies. Typically, document-based sentiment analysis processes operate at a particular level, i.e. at the word or sentence level, for extracting a document's sentiment. In machine learning, the most popular approach for sentiment analysis, the selection of appropriate features for representing a document is crucial. In sentiment identification at the word level different types of features have been introduced, which are either sentiment-based (e.g. words which express a specific sentiment), syntactic-based (e.g. part-of-speech and n-grams), or semantic-based (e.g. semantic word vector spaces which capture the meaning of each word).

Document-level polarity classification is not a special case of text categorization with sentiment -rather than topic-based categories. Hence, standard machine learning classification techniques, such as support vector machines (SVMs), can be applied to the entire documents themselves. Nevertheless, some researches presented a technique that it is easy to improve the accuracy, by integrating sentence-level subjectivity detection with document-level sentiment polarity.

As we know, in the machine learning approach, each classifier is trained using a collection of representative data. In contrast, the semantic-orientation approach does not require prior training; instead, it measures a word containing positive or negative sentiment. Each approach has its own benefits and drawbacks. For example, the machine learning approach tends to be more accurate, but the semantic-orientation approach has better generality. Recently, a new lexicon-enhanced method was accrued to generate a set of sentiment words based on a sentiment lexicon as a new fea-

ture dimension. It combines these sentiment features with content-free and content-specific features used in the existing machine-learning approach. In the evaluation stage, they showed that adding the new set of sentiment features can increase sentiment-classification performance.

The Internet and other communication technologies play a potentially disruptive role on the constraints imposed on social networks. These technologies reduce the overhead and cost for being introduced to new people regardless of geography, and help us stay in touch with those we know. Some have even gone so far as to call this "the end of geography," where the process of relationship formation becomes disentangled from distance altogether.

However, geography still plays an important role. The reason is because of the strong relationship between event detection and geographical location each user belongs. Twitter is a social networking website, which means that users need not be viewed in isolation, but instead can be viewed as part of a large network of other users, user groups, and user cliques. Moreover, users have some meta-data information, such as description, source location, friends, which means that the social network structure in Twitter can aid in finding users that are most likely to tweet about news belonging to a particular geographic location or region.

The rise of micro-blogging services spurred various applications to mine the data coming from those services. Many such applications could benefit from information about the location of users, but unfortunately location information is currently very sparse. The main problem is that less than 1 per cent of tweets are geo-tagged and information available from the location field in users' profiles is unreliable at best. The benefits of mining those data promises new personalized information services, including local news summarized from tweets of nearby Twitter users, the targeting of regional advertisements, spreading business information to local customers, and novel location-based applications (e.g., Twitter-based earthquake detection, which can be faster than through traditional official channels).

There is a great number of geoinference using social networks. One direction has produced approaches that claim to accurately locate the majority of posts within tens of kilometres of their true locations. Another method predicts the location of an individual from a sparse set of located users with performance that exceeds IP-based geolocation. On the side, there is also a technique that predicts locations of Twitter users at different granularities, such as city, state, or time zone, using the content of their tweets and their tweeting behaviour.

Getting started the first section of this survey is the presentation of some techniques that aim to event detection. The survey detects both algorithms that are based on text categorization and frequency display methods. The second chapter deals with techniques of sentiment analysis. We give more weight on techniques that use machine learning. The last chapter unfolds methods for location identification.

2. EVENT DETECTION

Given a series of twitter posts, the goal of event detection is to extract a particular event by analysing the text or hashtag of a tweet. The process of event detection is not a lenient task as tweets stream in huge volumes and the level of noise is kept high [24]. On the other hand, the huge volume of the stream allows the use of streaming algorithms,

thus making event detection an accomplishable task [24].

The conventional approach for this problem is to represent the documents as term frequency vectors [24]. When a new document arrives, it is compared to all previous ones, and if its similarity to a specific document called "centroid" is below a threshold, the new document is registered as a new event [24]. Unfortunately, this simple approach doesn't perform well as the dimensionality of the data expands.

Merikoi users postaroun sixna news. Oi followers sinithos einai akiroi. -> Ara psaxnw to "Most common set of followers among them", me th logiki oti xrhstes pou endiaferontai gia nea, pithano na kanoun follow parapanw apo 1 atoma pou postaroun nea. ref2

3. CONCLUSIONS

This paragraph will end the body of this sample document. Remember that you might still have Acknowledgments or Appendices; brief samples of these follow. There is still the Bibliography to deal with; and we will make a disclaimer about that here: with the exception of the reference to the L^AT_EX book, the citations in this paper are to articles which have nothing to do with the present subject and are used as examples only.

4. ACKNOWLEDGMENTS

This section is optional; it is a location for you to acknowledge grants, funding, editing assistance and what have you. In the present case, for example, the authors would like to thank Gerald Murray of ACM for his help in codifying this *Author's Guide* and the .cls and .tex files that it describes.

5. ADDITIONAL AUTHORS

Additional authors: John Smith (The Thørväld Group, email: jsmith@affiliation.org) and Julius P. Kumquat (The Kumquat Consortium, email: jpkumquat@consortium.net).

6. REFERENCES

- [1] H. Abdelhaq, C. Sengstock, and M. Gertz. Eventtweet: Online localized event detection from twitter. *Proceedings of the VLDB Endowment*, 6(12):1326–1329, 2013.
- [2] L. Backstrom, E. Sun, and C. Marlow. Find me if you can: improving geographical prediction with social and spatial proximity. In *Proceedings of the 19th international conference on World wide web*, pages 61–70. ACM, 2010.
- [3] C. Budak, D. Agrawal, and A. El Abbadi. Structural trend analysis for online social networks. *Proceedings of the VLDB Endowment*, 4(10):646–656, 2011.
- [4] M. Cataldi, L. D. Caro, and C. Schifanella. Personalized emerging topic detection based on a term aging model. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 5(1):7, 2013.
- [5] D. Chatzakou, V. Koutsonikola, A. Vakali, and K. Kafetsios. Micro-blogging content analysis via emotionally-driven clustering. In *Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on*, pages 375–380. IEEE, 2013.
- [6] D. Chatzakou, N. Passalis, and A. Vakali. Multispot: Spotting sentiments with semantic aware multilevel cascaded analysis. In *International Conference on Big Data Analytics and Knowledge Discovery*, pages 337–350. Springer, 2015.
- [7] Z. Cheng, J. Caverlee, and K. Lee. You are where you tweet: a content-based approach to geo-locating twitter users. In *Proceedings of the 19th ACM international conference on Information and knowledge management*, pages 759–768. ACM, 2010.
- [8] R. Compton, D. Jurgens, and D. Allen. Geotagging one hundred million twitter accounts with total variation minimization. In *Big Data (Big Data), 2014 IEEE International Conference on*, pages 393–401. IEEE, 2014.
- [9] Y. Dang, Y. Zhang, and H. Chen. A lexicon-enhanced method for sentiment classification: An experiment on online product reviews. *IEEE Intelligent Systems*, 25(4):46–53, 2010.
- [10] M. Desai and M. A. Mehta. Techniques for sentiment analysis of twitter data: A comprehensive survey. In *Computing, Communication and Automation (ICCCA), 2016 International Conference on*, pages 149–154. IEEE, 2016.
- [11] C. N. Dos Santos and M. Gatti. Deep convolutional neural networks for sentiment analysis of short texts. In *COLING*, pages 69–78, 2014.
- [12] D. Gao, W. Li, and R. Zhang. Sequential summarization: A new application for timely updated twitter trending topics. In *ACL (2)*, pages 567–571. Citeseer, 2013.
- [13] A. Giachanou and F. Crestani. Like it or not: A survey of twitter sentiment analysis methods. *ACM Computing Surveys (CSUR)*, 49(2):28, 2016.
- [14] T. Hua, F. Chen, L. Zhao, C.-T. Lu, and N. Ramakrishnan. Sted: Semi-supervised targeted event detection. *KDD'13*, pages 11–14, 2013.
- [15] D. Jurgens, T. Finethy, J. McCorriston, Y. T. Xu, and D. Ruths. Geolocation prediction in twitter using social networks: A critical analysis and review of current practice. In *ICWSM*, pages 188–197, 2015.
- [16] V. Kharde, P. Sonawane, et al. Sentiment analysis of twitter data: A survey of techniques. *arXiv preprint arXiv:1601.06971*, 2016.
- [17] L. Kong, Z. Liu, and Y. Huang. Spot: Locating social media users based on social network context. *Proceedings of the VLDB Endowment*, 7(13):1681–1684, 2014.
- [18] C. Li, J. Weng, Q. He, Y. Yao, A. Datta, A. Sun, and B.-S. Lee. Twiner: named entity recognition in targeted twitter stream. In *Proceedings of the 35th international ACM SIGIR conference on Research and development in information retrieval*, pages 721–730. ACM, 2012.
- [19] J. Mahmud, J. Nichols, and C. Drews. Where is this tweet from? inferring home locations of twitter users. *ICWSM*, 12:511–514, 2012.
- [20] K. R. McKelvey and F. Menczer. Truthy: Enabling the study of online social networks. In *Proceedings of the 2013 conference on Computer supported cooperative work companion*, pages 23–26. ACM, 2013.
- [21] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean. Distributed representations of words and phrases and their compositionality. In *Advances in*

neural information processing systems, pages 3111–3119, 2013.

- [22] G. Paltoglou and M. Thelwall. Twitter, myspace, digg: Unsupervised sentiment analysis in social media. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 3(4):66, 2012.
- [23] B. Pang and L. Lee. A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts. In *Proceedings of the 42nd annual meeting on Association for Computational Linguistics*, page 271. Association for Computational Linguistics, 2004.
- [24] S. Petrović, M. Osborne, and V. Lavrenko. Streaming first story detection with application to twitter. In *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*, pages 181–189. Association for Computational Linguistics, 2010.
- [25] J. Sankaranarayanan, H. Samet, B. E. Teitler, M. D. Lieberman, and J. Sperling. Twitterstand: news in tweets. In *GIS*, 2009.
- [26] H. Sayyadi and L. Rschid. A graph analytical approach for fast topic detection.
- [27] A. Severyn and A. Moschitti. Unitn: Training deep convolutional neural network for twitter sentiment classification. In *Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015)*, Association for Computational Linguistics, Denver, Colorado, pages 464–469, 2015.
- [28] R. Socher, J. Pennington, E. H. Huang, A. Y. Ng, and C. D. Manning. Semi-supervised recursive autoencoders for predicting sentiment distributions. In *Proceedings of the conference on empirical methods in natural language processing*, pages 151–161. Association for Computational Linguistics, 2011.
- [29] C. Suen, S. Huang, C. Eksombatchai, R. Soric, and J. Leskovec. Nifty: a system for large scale information flow tracking and clustering. In *Proceedings of the 22nd international conference on World Wide Web*, pages 1237–1248. ACM, 2013.
- [30] D. Tang, F. Wei, N. Yang, M. Zhou, T. Liu, and B. Qin. Learning sentiment-specific word embedding for twitter sentiment classification. In *ACL (1)*, pages 1555–1565, 2014.
- [31] J. Weng and B.-S. Lee. Event detection in twitter. *ICWSM*, 11:401–408, 2011.

APPENDIX

A. HEADINGS IN APPENDICES

The rules about hierarchical headings discussed above for the body of the article are different in the appendices. In the **appendix** environment, the command **section** is used to indicate the start of each Appendix, with alphabetic order designation (i.e. the first is A, the second B, etc.) and a title (if you include one). So, if you need hierarchical structure *within* an Appendix, start with **subsection** as the highest level. Here is an outline of the body of this document in Appendix-appropriate form:

A.1 Introduction

A.2 The Body of the Paper

A.2.1 Type Changes and Special Characters

A.2.2 Math Equations

Inline (In-text) Equations.

Display Equations.

A.2.3 Citations

A.2.4 Tables

A.2.5 Figures

A.2.6 Theorem-like Constructs

A Caveat for the T_EX Expert

A.3 Conclusions

A.4 Acknowledgments

A.5 Additional Authors

This section is inserted by L^AT_EX; you do not insert it. You just add the names and information in the `\additionalauthors` command at the start of the document.

A.6 References

Generated by bibtex from your .bib file. Run latex, then bibtex, then latex twice (to resolve references) to create the .bbl file. Insert that .bbl file into the .tex source file and comment out the command `\thebibliography`.

B. MORE HELP FOR THE HARDY

The sig-alternate.cls file itself is chock-full of succinct and helpful comments. If you consider yourself a moderately experienced to expert user of L^AT_EX, you may find reading it useful but please remember not to change it.