A lightweight algorithm for the emotional classification of crowdsourced venue reviews

Panayiotis Kolokythas, Andreas Komninos, Lydia Marini, John Garofalakis
Computer Engineering & Informatics Department
University of Patars, Rio 26504
Greece
[kolokytp, akomninos, lmarini, garofala]@ceid.upatras.gr

ABSTRACT

Finding emotions in text is an area of research with wide-ranging applications. Analysis of sentiment in text can help determine the opinions and affective intent of writers, as well as their attitudes, evaluations and inclinations with respect to various topics. Previous work in sentiment analysis has been done on a variety of text genres, including product and movie reviews, news stories, editorials and opinion articles, or blogs. We describe a lightweight emotion annotation algorithm for identifying emotion category & intensity in reviews written by social media (Foursquare) users. The algorithm is evaluated against human subject performance and is found to compare favourably. This work opens up opportunities for solving the problem of helping user navigate through the plethora of venue reviews in mobile and desktop applications.

CCS CONCEPTS

• **Information systems → Sentiment analysis;**
• **Information systems → Multilingual and cross-lingual retrieval;** • *Information systems → Information extraction*

KEYWORDS

Sentiment polarity, Venue tips, Social Networks

ACM Reference format:

P. Kolokythas, A. Komninos, L. Marini and J. Garofalakis. 2017. A lightweight algorithm for the emotional classification of crowdsourced venue reviews. *In Proceedings of the 21st Panhellenic Conference on Informatics, Larisa, Greece, September 2017,* 6 pages.
https://doi.org/ 10.1145/3139367.3139422

PCI 2017, September 28–30, 2017, Larissa, Greece

ACM ISBN 978-1-4503-5355-7/17/09...$15.00
https://doi.org/10.1145/3139367.3139422

1 INTRODUCTION

The advent of Web 2.0 (also termed the participatory web) has empowered users with the ability to quickly and easily contribute information that can be shared via platforms and applications with other users. One very successful example of this concept is the generation of tips and reviews about venues, for the benefit of other users. Large companies like TripAdvisor, Amazon, Booking.com and Google have leveraged this ability to provide users with impartial information about venues, services and products. The downside, however, is that popular items of interest are accompanied by hundreds, if not thousands of user-generated comments and it is, of course, impractical for the average user to read through all of them, in order to form an informed opinion. The problem is particularly pronounced during the use of mobile applications, given the limitations posed by the available screen real-estate and also the sporadic and short-term use of mobiles, especially when a user is on the move. To resolve the issue, platforms typically also ask the user to provide a summary of their opinion in a quantifiable manner (e.g. to provide a score out of 10, or rate an item using stars, typically up to 5). These summarized opinions can then be aggregated to form a quantified overview of the item which a user can rely on to form a first impression, without having to read all the comments. However, this summary erases all the qualitative aspects of an opinion, which may be important to the individual user's context. For example, in the hotel booking website Booking.com, a venue might have an overall rating of 8.0/10, which is rather high. However, this rating can emerge from a range of subjective factors (e.g. location, price, cleanliness, noise). The user has to then resort to reading individual factor ratings (if the platform supports this), or to read other users' comments to form an impression which might be a top priority for the individual user (e.g. cleanliness).

Reading other users' comments can provide useful insights not reflected in scores. However, given the hundreds or thousands of comments associated with an item, the question remains of how to prioritise this information so that the user can form a reasonable opinion about the item, without having to read the entirety of the comments. One possible solution might be to limit the number of comments to the most recent ones, but this can result in missing out important information, or a list of low-quality, uninformative comments. Some platforms allow users to rate comments for usefulness, however, this solution also relies on the active participation of users and an opinion which may not be reliable until a user has actually had experience with an item and can assess the utility of a comment objectively. A further possible solution is to employ sentiment analysis on the comments in order to find positive and negative ones, and thus present an appropriate mix to users.

A further problem is that in many countries, comments are left by multilingual users (e.g., in Greek and English) and thus require translation before they can be used. The use of Latin alphabets to write comments in a non-Latin language (e.g. writing Greek using a Latin alphabet – also known as writing in "greeklish") further compounds the problem.

In this paper we present a lightweight algorithm for addressing the problem of emotional classification of user generated comments for venues in Greece, addressing simultaneously the problem of translating and overcoming the "greeklish" writing problem. Our algorithm considers also the use of emoticons in comments as well as colloquial and casual writing style, e.g. using multiple punctuation marks (e.g. "it's perfect!!!!!", "soooo good!").

2 RELATED WORK

2.1 Literature review

Sentiment analysis of social network comments has been demonstrated to have diverse and useful applications. In [4], emotional classification of tweets was used to predict significant events during the 2012 British Olympics (e.g. medal wins). Tweet sentiment analysis was used in [7] to detect user opinion on the UX encountered during use of that platform, as an alternative to UX research. In [13] it was found that tweets that are more emotionally charged spread further and more quickly in a social network, which is useful guidance for marketers and influencers. Sentiment analysis of hotel reviews [1] and movie reviews [11] have been found to be good predictors for assigned user scores and can thus help filter out bad contributions or improve recommendations. Finally, a geographic visualization of emotionally analysed content (e.g. [2, 3]) can help users form a better opinion of how "nice" an area might be, and by analyzing a user's own tips left for venues can improve the recommendations given to this user, compared to using check-ins or ratings alone [16].

Most work in classifying social network text has been done with Twitter, using a variety of approaches to classify texts. These approaches are either based on lexical analysis based on dictionaries (e.g. [1, 14]) and detection of "main phrases" in text [15], or machine learning approaches, using a range of algorithms including naïve Bayes, random forests, SVMs and neural networks (e.g. [5, 6, 15]). There is no clear overall advantage for any of these techniques, as their performance is dependent on the domain of application, nature of the text, parameters employed by the researchers (of which we could find no systematic investigation) and preprocessing of the text to be classified.

The pre-processing of text is a crucial step in determining the success of sentiment classification. In [1], it is recognized that colloquial language, grammar mistakes and neutral statements pose problems during analysis. Researchers like [6] propose a thorough "clean up" of text, removing mentions, hashtags, newlines, certain emoticons, repeated letters) as a pre-processing step. However, other evidence exists that elements like hashtags can benefit the performance of classifiers when they are used to label text [8, 10], that emoticons often correlate well with the overall sentiment of text [12] and that slang is a strong indicator of emotion which should be considered [9].

In conclusion it appears that there exist no "magical" solutions to the problem of sentimental classification of social network text. However, approaches that are based on some pre-processing of information and use of emotional dictionaries seem to be dominant in literature. Another problem entirely missing in literature and which we aim to address in this work, is the analysis of text when it is produced by multilingual users or written in a certain language but using the alphabet of another (e.g. Greek text in Latin characters).

2.2 Additional motivation and findings

For the purposes of a different project we conducted a user survey on trip planning behaviour before and during trips to a new destination, relating to the use of information technology as a tool to prepare and gather visitor information. We present some results from this survey here, because they are pertinent to the discussion about the motivation behind sentiment polarity classification of venue tips and comments.

We distributed an e-survey by inviting people to participate through posting in various on-line forums and social networks (Facebook). We collected 284 responses (50,4% males, 49,6% females). Participants were all from Greece and ages were mostly in the categories of 18-25 years old (68.3%) and 26-30 years old (20.4%). Of these participants, 89,9% uses a smarthphone. In our question of whether they use social network apps for tourism purposes (Facebook, TripAdvisor, FourSquare, Twitter, Google+), 30% mentioned none of the above, while the most popular was Facebook (51.4%) and FourSquare amounted to 10%.

Out of all participants, 81.1% mentioned they do read other visitors' comments for venues that they plan to visit. When asking respondents about the number of comments they feel they should read in order to form a reliable opinion on a venue, 66.4% stated that based on their experience, they should read 10 or more comments, while 28.2% between 5-9 comments. However, participant actual behaviour differs from this reported ideal. From the body of respondents who mentioned they do read comments, the majority (39.6%) reads only the first 5-10 comments (3 first only: 9.8%, 10 or more: 17.5%, all comments: 7.7%, only the most popular-liked comments: 24.4%). These findings are of particular interest – it's clear that the sheer number of comments left for venues is overwhelming and thus not read by users, and that users look for either a "smart" way to reduce the volume of comments to read by sorting them by popularity, where this function is available, or default to reading the 5-10 most recent ones.

This behaviour leads to reduced confidence in the validity of comments. Only 44% of respondents stated that they felt that the amount of comments they actually read is enough to help them reliably form an opinion about venues.

Finally, we asked participants to state whether the comments they read should contain positive, negative or a mix of both in order to help them form a reliable opinion for a venue. The vast majority (84.2%) stated that only a mixture of positive and negative comments would help them form a reliable opinion, while just 5.1% stated they would rely on positive comments only (10.7% negative only).

These findings highlight a set of important findings that support the need for sentiment polarity classification of user-generated venue tips: To help users form a reliable opinion about a venue, designers of mobile tourism services should not display more than 10 comments and also these displayed comments have to contain a mixture of positive and negative ones in order to help users form a reliable opinion on the venue. While in some services (e.g. TripAdvisor) the comments are often accompanied by a user rating of the venue, in other services like FourSquare or Facebook, these are often disjointed and viewed separately. Even when the comments are accompanied by a rating, it is not enough to rely on the rating since a high rating might be accompanied by a negative comment about a minor issue (which of course might be very important to someone else). Hence the automatic detection of sentiment polarity of venue comments can be used to provide a smarter way to restrict the information space for users and help mobile tourism application designers deliver a better experience, especially when combined with other metrics such as tip popularity (helpfulness), recency etc.

3 DESCRIPTION OF OUR APPROACH

3.1 System architecture

For our implementation we adopted a bag-of-words approach, which separates text in tokens (words). These words are then processed and emotionally classified using pre-compiled dictionaries. As a corpus, we extracted user tips left in the Foursquare service, which is not limited to the 140 character limit that exists on Twitter.

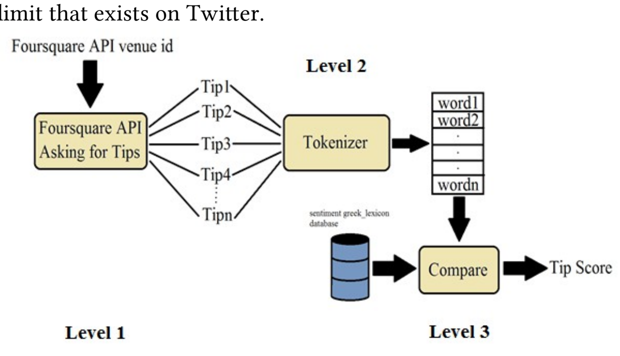

Figure 1: Overall system architecture

The architecture is split in 3 levels: Level 1 retrieves the tips left at a venue through the FourSquare API. Level 2 is the tokenizer that splits the tip into a bag of words. Level 3 performs the pre-processing and sentiment classification of each word. The final polarity of the tip (positive or negative) is computed as a function of the polarities of all words in a tip.

3.2 Handling Greek and English text

Greek text is handled through the use of the Greek Sentiment Lexicon which contains approximately 3000 words, marked for objectivity (subjective, strictly subjective, objective) and polarity (positive, negative, neutral, both). Objectivity has four measures (one for each possible use of the word as a noun, verb or adjective). To calculate the polarity of a text, we compute the frequency of positive, negative or neutral words. Then each frequency is multiplied by the average subjectivity rating of the text. This is computed for each word by summing the four subjectivity ratings attached to it, assigning a score of 0.2 to strictly subjective rating, 0.225 to subjective ratings and 0.25 to objective ratings. This yields for each word a minimum of 4*0.2=0.8 weight if it is fully strictly subjective and a maximum of 4*0.25=1 weight if its fully objective. By computing the average subjectivity score for the entire text, we multiply each polarity frequency with this figure to derive 3 scores for the text, so if a text contains 60% positive words, 30% negative and 10% neutral with an overall subjectivity score of 0.9, its final three scores are [pos: 0.6*0.9 = 0.54, neg: 0.3*0.9=0.27, neu: 0.1*0.9=0.09] and the text is classified as positive with a score of 0.54.

For the handling of English text, we used the API of a service called twinword sentiment analysis2. The API returns a word-by-word scoring for the text, as well as an overall scoring, which ranges from [-1, 1] (strongly negative, fully positive).

Because our research applied to venues in Greece, we considered a weighting of the emotional classification of tips based on the language that they are written in. As such, we apply a slightly larger weight to the tips written in Greek (w=0.6) than in English (w=0.4) because it is logical to consider that local users will have greater ability to assess the services of a venue compared to tourists. Thus overall, the emotional polarity of a venue is

Rp = 0.6 * Pg(p) + 0.4 * Pe(p), where Rp is the polarity score for [positive, neutral, negative] tip frequencies, Pg(p) is the average score of Greek tips for that polarity and Pe(p) is the average score of English tips for that polarity. Thereby for each venue we compute 3 scores, and determine its final polarity according to which score is greatest.

3.3 Handling special cases in text

Prior to assessing a tip's text polarity, we performed some pre-processing to handle special cases in text, as outlined below.

The first type of problem text is spelling mistakes. Due to our reliance on dictionaries for polarity detection, a misspelled word cannot be categorised. To handle this problem we use the Levenshtein string distance metric between a tip word and

[2] https://www.twinword.com/api/sentiment-analysis.php

words in a standard dictionary. We set a threshold to replace a tip word that cannot be found in our dictionary with one that exists in it, only if the string distance between them is 1. So for example, the misspelled word «τέλοια» will be replaced with the word «τέλεια» which has a string distance of 1 and can be found in our dictionary. For English text, we ran the text past a simple

To handle the occurrence of emoticons we replaced the emoticons with their description word as defined in the Unicode emoji table and also created a set of commonly used emoticon ASCII representations (smile, laugh, sad, wink, tongue, surprise, annoyed, cry), and created appropriate regular expressions to detect their occurrence [for example, we used the word "laugh" for the following ASCII representations ">:D", ":-D", ":D", "8-D", "x-D", "X-D", "=-D", "=D", "=-3", "8-)"].

Finally, for Greek text written in Latin alphabet, we wrote a function to detect such cases and convert this to its proper Greek alphabet form by substituting the characters with their relevant Greek spelling. This represented a significant issue because Greeklish text can take many forms, depending on the user, for example «τύχη» can be written as "tyxi, tuxi, tyxh, tuxh". We tried to fuzzily disambiguate what the author intended to write but since this is a first approach, the process can be greatly improved.

4 EXPERIMENTAL EVALUATION

4.1 Experiment setup

To assess the efficiency of this approach, we performed a classification experiment to compare the performance of our algorithm against human evaluators. For this we run the classier on a total of over 24,000 comments from approximately 3,000 venues in FourSquare, found for the city of Patras, Greece. From these comments we selected a random pool of 90 comments based on their automatically detected polarity (positive, neutral, negative) and language (Greek, English), selecting 15 comments for each of the six possible variable combinations. We limited the comments to a minimum of 10 characters and maximum of 300, in order to obtain a representative sample of shorter and longer comments.

Table 1: Text lengths per tip category

Polarity	avg length	min length	max length	std. deviation
Neg	77.70	11	271	63.75
Neu	43.20	12	100	23.97
Pos	73.37	18	228	49.57

We then invited participants to join a laboratory session, where we asked them to classify a number of tips for polarity. The test took place in front of a computer, using a web-based environment to present and record the participants' classification. For each participant, our system selected a random choice of 4 comments from each category, which we presented to them and asked them to perform an assessment of the polarity of the comments, without disclosing the system-derived polarity. The comments were presented in a totally random order. As such, each participant classified a total of 24 comments.

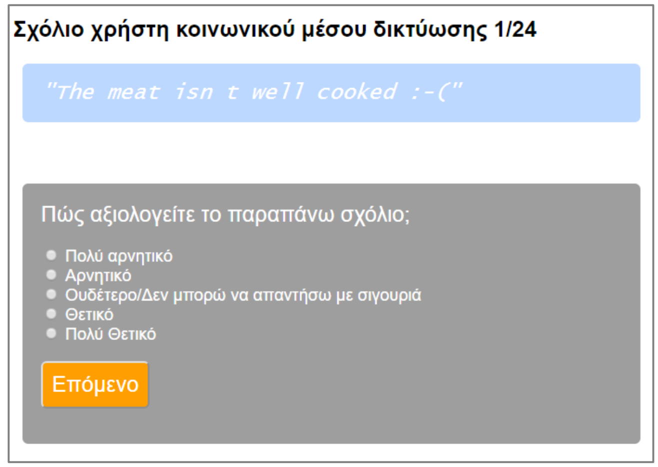

Figure 2: Example of the web-based environment of the classification task. A tip is presented in the blue background section. The user then is asked to rate the comment in a 5-point likert scale [-2=strongly negative, 0=neutral/can't tell, 1=strongly positive] and then proceed to the next tip.

We recruited a total of 95 participants (42 female), all native Greek speakers. The participants' age mean was 30.2 years old (sd=10.13) while our youngest participant was 16 and oldest was 68. Participants did not receive compensation for their time. Twenty-eight participants were secondary education graduates, 53 had a university degree and 14 had a postgraduate degree. Asking about their level of expertise in English, 11 mentioned a "basic knowledge" level, 43 a "good" knowledge (equivalent to the Cambridge Lower certificate) and 41 "excellent" (equivalent to the Cambridge Proficiency certificate). Finally, thirty-one participants were not familiar with participatory social network applications such as FourSquare, a further 33 where "somewhat familiar" and the final 31 were "very familiar" with such applications.

4.2 Results

We begin our analysis by showing the manner in which participants classified the displayed tips. One interesting observation is that our participants believed that the comments in both languages positively or negatively polarised comments where respectively more than the neutral comments (English: 33.14% negative, 30.10% neutral, 36.77% positive; Greek: 35.24% negative, 28.39% neutral, 36.36% positive). However, the differentiation from the algorithm's polarity classification (33% in each category) was not large.

A further observation shows the time taken on average to come to a conclusion for the classification of polarity. Here it is interesting to observe that participants needed a considerable amount of time to come to conclusions, requiring several seconds to process each one. On average, participants took 6.36sec (sd=13.6sec) to classify comments in English, and 6.04sec (sd=11.42) to classify comments in Greek. This highlights why browsing lengthy lists of tips is a hindrance to users.

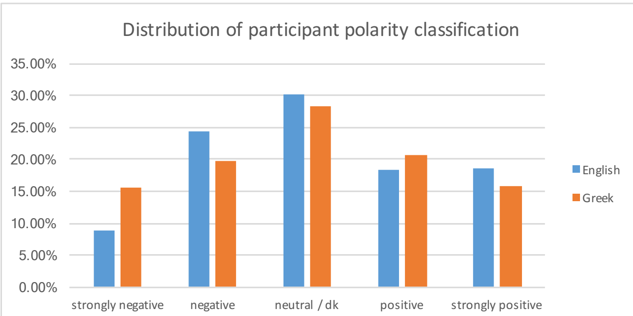

Figure 3: Distribution of subjective polarity assessments by participants.

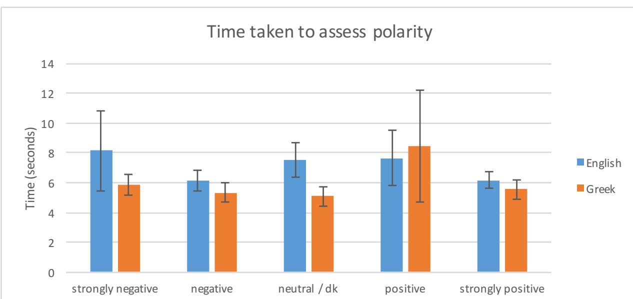

Figure 4: Distribution of time taken to make polarity assessments by participants (error bars at 95%c.i.).

Further to this, we plotted the time taken to assess a comment versus the length of the comment, to see if there are any correlations between these two measures (Figures 5 & 6 show averages time by comment length). Due to the distribution of raw data for English and Greek comments, we performed a Spearman's Rho correlation test. The test is not statistically significant for neither English nor Greek ($R=0.39$, $p>0.05$ & $R=0.20$, $p>0.05$ respectively). This is a surprising finding as we would have expected that longer text must require more time for participants to classify. A plausible explanation is that participants adopt a behaviour which scans the text for keywords that might aid classification. Due to the similarity in times taken to actually derive the classification, it appears that our participants spent most of their time deciding on how to classify the text based on these rapidly discovered keywords, rather than finding the keywords themselves.

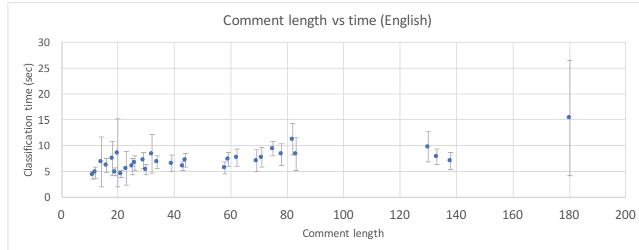

Figure 5: Average time taken to classify an English tip compared to tip length (error bars at 95%c.i.).

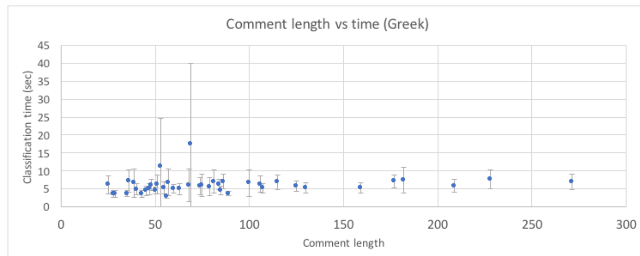

Figure 5: Average time taken to classify a Greek tip compared to tip length (error bars at 95%c.i.).

Next, we present our system's performance, using the human-classified tips as a baseline. As can be seen in Figures 7 & 8, both precision and recall are at very high levels, for both languages, as compared with the classification of human users that was our baseline.

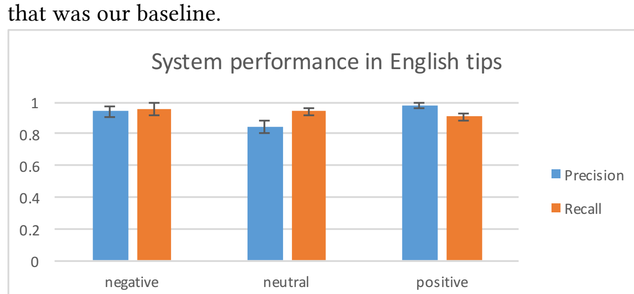

Figure 7: Precision and recall averages in English tips (error bars at 95%c.i.)

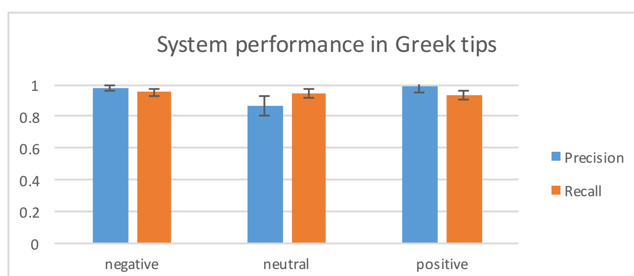

Figure 8: Precision and recall averages in Greek tips (error bars at 95%c.i.)

CONCLUSION AND DISCUSSION

As discussed previously, there is a clear case for the use of sentiment polarity classification in the user-generated comments and tips left for venues in various social networking applications used for tourism. We found that users are overwhelmed by the amount of such information that is available to them and resort to limiting their reading of comments to just a few. Further support for the veracity of this behaviour comes from the finding of reading times of comments from our experiment participants, where we found that they need an average of 6 seconds approximately to read and classify a comment for polarity, resulting in long interaction times in order to form an opinion about a venue. We also found that to form a reliable opinion users need to view both positive and negative comments, a process which may require a long time of discovery and reading, especially in venues with large amounts of comments.

Our algorithm for the classification of comments based on polarity performs very well, compared to human evaluators. In both English and Greek cases, the adopted approach led to high levels of precision and recall, showing that a lightweight approach to classification for venue comments is viable and possibly preferable to more complex approaches based on machine learning or other heavyweight mining algorithms.

In summary, our work shows that designers of tourism mobile applications should limit the number of comments shown to users to about 10, taking care to include an appropriate mixture of positive and negative polarity comments in the result set. This can be achieved through the application of our lightweight classification algorithm and supplemented with additional metrics to reduce the result set such as comment recency, self-reported usefulness and others. Our findings show that users spend an almost equal amount of time processing comments, regardless of their length. A plausible explanation of this might be that users look for specific keywords in the text to determine polarity (and thus whether it should be more carefully read), hence designers might also consider implementing a view of such polarity-related keywords as “tags” (e.g. hashtags) before the comment body, in order to reduce users’ cognitive load.

In the future, we would like to explore the implementation of this approach in the automatic selection and presentation of venue comments to users, in order to assess the effect on the user experience and the subjective and objective assessment of the confidence of users in the process of forming an opinion about venues they intend to visit.

REFERENCES

[1] Jorge Carrillo de Albornoz, Laura Plaza, Pablo Gervás, and Alberto Díaz. 2011. A Joint Model of Feature Mining and Sentiment Analysis for Product Review Rating. In *Advances in Information Retrieval*, 55–66. https://doi.org/10.1007/978-3-642-20161-5_8

[2] J. Bernabé-Moreno, A. Tejeda-Lorente, C. Porcel, H. Fujita, and E. Herrera-Viedma. 2015. Emotional Profiling of Locations Based on Social Media. *Procedia Computer Science* 55: 960–969. https://doi.org/10.1016/j.procs.2015.07.107

[3] Eivind Bjørkelund, Thomas H. Burnett, and Kjetil Nørv\a ag. 2012. A Study of Opinion Mining and Visualization of Hotel Reviews. In *Proceedings of the 14th International Conference on Information Integration and Web-based Applications & Services* (IIWAS ’12), 229–238. https://doi.org/10.1145/2428736.2428773

[4] Jan Chołoniewski, Julian Sienkiewicz, Janusz A. Hołyst, and Mike Thelwall. 2014. The role of emotional variables in the classification and prediction of collective social dynamics. *arXiv:1412.7184 [physics]*. Retrieved from http://arxiv.org/abs/1412.7184

[5] Shenghua Liu, Fuxin Li, Fangtao Li, Xueqi Cheng, and Huawei Shen. 2013. Adaptive Co-training SVM for Sentiment Classification on Tweets. In *Proceedings of the 22Nd ACM International Conference on Information & Knowledge Management* (CIKM ’13), 2079–2088. https://doi.org/10.1145/2505515.2505569

[6] Eugenio Martínez-Cámara, M. Teresa Martín-Valdivia, L. Alfonso Ureña-López, and Ruslan Mitkov. 2015. Polarity classification for Spanish tweets using the COST corpus. *Journal of Information Science* 41, 3: 263–272. https://doi.org/10.1177/0165551514566564

[7] Marília S. Mendes, Elizabeth Furtado, Vasco Furtado, and Miguel F. de Castro. 2014. How Do Users Express Their Emotions Regarding the Social System in Use? A Classification of Their Postings by Using the Emotional Analysis of Norman. In *Social Computing and Social Media*, 229–241. https://doi.org/10.1007/978-3-319-07632-4_22

[8] Saif M. Mohammad. 2012. #Emotional Tweets. In *Proceedings of the First Joint Conference on Lexical and Computational Semantics - Volume 1: Proceedings of the Main Conference and the Shared Task, and Volume 2: Proceedings of the Sixth International Workshop on Semantic Evaluation* (SemEval ’12), 246–255. Retrieved from http://dl.acm.org/citation.cfm?id=2387636.2387676

[9] M. S. Neethu and R. Rajasree. 2013. Sentiment analysis in twitter using machine learning techniques. In *2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT)*, 1–5. https://doi.org/10.1109/ICCCNT.2013.6726818

[10] Qadir, Ashekul and Riloff, Ellen. 2014. Learning Emotion Indicators from Tweets: Hashtags, Hashtag Patterns, and Phrases. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP 2014)*.

[11] T. P. Sahu and S. Ahuja. 2016. Sentiment analysis of movie reviews: A study on feature selection classification algorithms. In *2016 International Conference on Microelectronics, Computing and Communications (MicroCom)*, 1–6. https://doi.org/10.1109/MicroCom.2016.7522583

[12] K. Soranaka and M. Matsushita. 2012. Relationship between Emotional Words and Emoticons in Tweets. In *2012 Conference on Technologies and Applications of Artificial Intelligence*, 262–265. https://doi.org/10.1109/TAAI.2012.30

[13] Stefan Stieglitz and Linh Dang-Xuan. 2013. Emotions and Information Diffusion in Social Media—Sentiment of Microblogs and Sharing Behavior. *Journal of Management Information Systems* 29, 4: 217–248. https://doi.org/10.2753/MIS0742-1222290408

[14] Katerina Tsagkalidou, Vassiliki Koutsonikola, Athena Vakali, and Konstantinos Kafetsios. 2011. Emotional Aware Clustering on Micro-blogging Sources. In *Affective Computing and Intelligent Interaction*, 387–396. https://doi.org/10.1007/978-3-642-24600-5_42

[15] V. Wijaya, A. Erwin, M. Galinium, and W. Muliady. 2013. Automatic mood classification of Indonesian tweets using linguistic approach. In *2013 International Conference on Information Technology and Electrical Engineering (ICITEE)*, 41–46. https://doi.org/10.1109/ICITEED.2013.6676208

[16] Dingqi Yang, Daqing Zhang, Zhiyong Yu, and Zhu Wang. 2013. A Sentiment-enhanced Personalized Location Recommendation System. In *Proceedings of the 24th ACM Conference on Hypertext and Social Media* (HT ’13), 119–128. https://doi.org/10.1145/2481492.2481505