Analysing Sentiments Expressed on Twitter by UK Energy Company Consumers

Victoria Ikoro[1], Maria Sharmina[2], Khaleel Malik[3] and Riza Batista-Navarro[1]
[1]*School of Computer Science*, [2]*Alliance Manchester Business School*, [3]*Tyndall Centre for Climate Change Research*
University of Manchester, Manchester, United Kingdom
Email: {victoria.ikoro | maria.sharmina | khaleel.malik | riza.batista}@manchester.ac.uk

***Abstract*—Automatic sentiment analysis provides an effective way to gauge public opinion on any topic of interest. However, most sentiment analysis tools require a general sentiment lexicon to automatically classify sentiments or opinion in a text. One of the challenges presented by using a general sentiment lexicon is that it is insensitive to the domain since the scores assigned to the words are fixed. As a result, while one general sentiment lexicon might perform well in one domain, the same lexicon might perform poorly in another domain. Most sentiment lexica will need to be adjusted to suit the specific domain to which it is applied. In this paper, we present results of sentiment analysis expressed on Twitter by UK energy consumers. We optimised the accuracy of the sentiment analysis results by combining functions from two sentiment lexica. We used the first lexicon to extract the sentiment-bearing terms and negative sentiments since it performed well in detecting these. We then used a second lexicon to classify the rest of the data. Experimental results show that this method improved the accuracy of the results compared to the common practice of using only one lexicon.**

***Index Terms*—Social media analytics, Sentiment analysis, Sentiment lexicon, UK energy sector.**

I. Introduction

There are concerns that UK consumers remain with their old energy suppliers despite being kept on unfavourable tariffs. It is important to investigate which aspects of energy companies' service customers find positive, in order to encourage switching. Sentiment analysis is increasingly receiving a lot of attention from researchers working on natural language processing, from businesses wanting to monitor the opinions of customers on their services and products, and from the general public for opinion retrieval on topics of interest [1-5]. In this work, we present a novel application of sentiment analysis on the interactions between UK energy consumers and the energy providers using data from Twitter. We compare sentiments of consumers patronising the UK's largest and oldest suppliers of gas and electricity known as the Big Six energy companies versus three new entrants. While the Big Six are well established and currently hold a market share of about 80 percent for gas and electricity in the UK, the new entrants are seeing a significant growth in customers partly due to their commitment to renewable energy.

This work is funded by The University of Manchester Research Institute.

II. Related Work

There are three main approaches to sentiment classification: machine learning, lexicon-based methods, and hybrid methods combining the use of machine learning and lexica to optimise the accuracy of sentiment classification. In this study, we focus on optimising a lexicon-based approach because we do not have sufficient training data to conduct supervised learning. Hasan Saif et al. [11] proposed a lexicon-based approach for sentiment analysis on Twitter called SentiCircles. This approach received much attention due to its ability to take into account the co-occurrence patterns of words in different contexts in tweets to capture their semantics and update their pre-assigned strength and polarity in sentiment lexica accordingly. In other work [12], a sentiment analysis model called SMARTA was developed based on a hybrid lexicon that improved a general lexicon for sentiment analysis, based on domain knowledge. Meanwhile, in their work on creating a domain-specific lexicon, Asghar et al. [13] proposed a unified framework which integrates information theory concepts and revised term weighting measures for predicting and assigning modified scores to domain specific words. They evaluated the system on data sets focussed on three subject areas (i.e., drugs, cars and hotels) and achieved promising results. The aforementioned techniques attempt to improve on general-knowledge sentiment lexica and have the advantage of being relatively robust, while discerning domain-specific words and assigning accurate polarity scores.

III. Data Collection

Twitter timelines of the energy companies were extracted, then using the "in reply to status ID" (RSID) metadata field, we filtered only those posts, i.e., tweets, that were sent in response to a customer's message. Using the RSID with the Twitter application programming interface (API), we retrieved the original message that was sent by the customer to the energy companies. We then combined the original messages from the consumers and the replies from the companies to retrieve a conversation thread. To account for tweets sent to the energy companies that may have been ignored, we used information from Twitter metadata to retrieve the timeline of the customer and filtered all tweets sent by the customer to the energy company including those that were not replied to. One of the advantages of using this approach to retrieve the data for sentiment analysis was that we were able to retrieve a conversation thread between the consumers and the energy suppliers within a specific time frame. In total, we collected over 60,000 tweets split over nine energy companies. In this paper we refer to the Big Six as Company 1-6, and to the new entrants as New Entrant Company 1-3.

IV. METHODOLOGY

One of the challenges in sentiment analysis is the lack of annotated data sets that can be used to train a model capable of adjusting to differences in multiple domains [6]. In this case study, for example, we are not aware of any annotated data sets for training a model that can accurately classify tweets related to the experiences of gas and electricity consumers. Hence, we have used sentiment lexica for our analysis. There are some domain-specific lexica that take into account the variations in the use of words and the context or community in which a word is being assessed for polarity. This is especially needed in domains with much non-standard English, such as in finance [7]. However, creating a domain-specific dictionary can be very expensive and time-consuming [8]. For the energy-sector domain studied in this paper, there are many words whose usage in standard English (Table 1) is different from that in other domains. We optimised the accuracy of sentiment analysis by combining functions from two sentiment lexica namely Sentimentr and the Hu & Liu opinion lexicon. Sentimentr was used because it includes valence shifters (negators, amplifiers, de-amplifiers, and adversative conjunctions) while still maintaining speed [9]. We observed that for the domain under study, the Sentimentr package performed well at detecting negative sentiments, however, it struggled to discriminate between positive and the neutral tweets. This could partly be because the lexicon combines many dictionaries, and upon manual inspection, we noted that most of the tweets that were assigned a positive polarity were neutral. To circumvent this issue, we used the Sentimentr package to retrieve negative tweets. Upon analysing the polarity being assigned to words, we masked some high-frequency words for which the lexicon gave misleading polarity. For example, we replaced the words "smart" with "smartm" and "compliant" with "compliantt" since they were high-frequency words and had a wrong polarity. Masking them allowed the software to then treat them as neutral (which is their domain-specific polarity) rather than positive. We passed the remaining data through the Hu & Liu opinion lexicon [10] which was better at detecting the positive and neutral tweets and combined the results from both lexica. Figure 1 shows the workflow used for our sentiment analysis.

TABLE I: Some domain-specific words and their polarity.

Word	General Sentiment Polarity	Domain- Specific Polarity
"smart"	positive	neutral
"compliant"	positive	neutral
"power"	positive	neutral
"energy"	positive	neutral
"credit"	positive	neutral

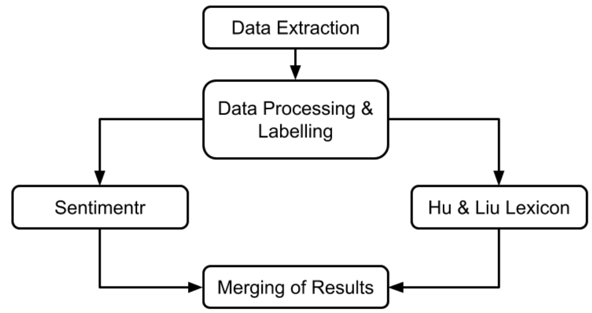
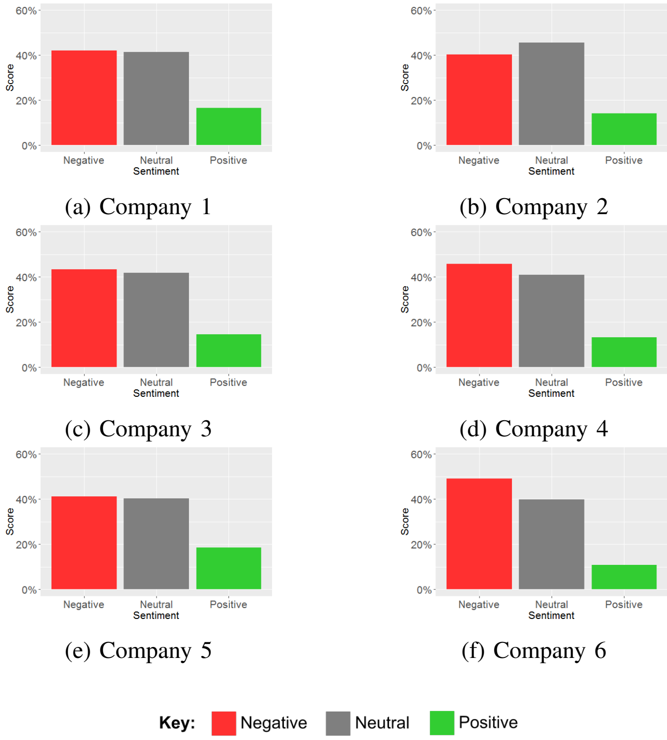


Fig. 1: Sentiment analysis workflow

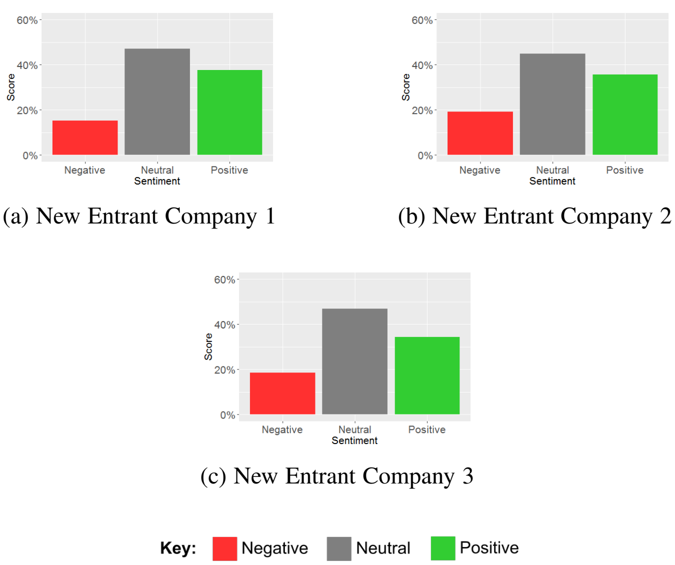
V. RESULTS

We manually inspected the results of about 7% of the total data. Our approach performed well against the common practice of using only one sentiment package. It is notable from Figures 2 and 3 that the measured sentiments from the interactions between the new entrant energy companies and their consumers were overall more positive than interactions between the Big Six and their customers. On average about 45% of the tweets from customers of the Big Six energy companies were negative, 40% were neutral and 15% were positive. Meanwhile, on average about 19% of the tweets from the customers of the new entrant energy providers were negative, 47% was neutral and 34% were positive. To gain insight into what topics the tweets from customers were focussed on, we used Latent Dirichlet Allocation (LDA) for topic modelling. LDA is an unsupervised model which can be used to identify probable topics (group of words) from a collection of large text. In LDA, once the initial data has been preprocessed, every word is assigned a probability of belonging to a number of generated topics. The number of topics n to be generated from a corpus is set by the user and for this work we found that the most coherent topics are generated when n is between 20 and 25. The words with the highest probability in each group of words were selected to represent the topic for a particular group. The frequency axes in Fig. 4 and Fig. 5 represent the number of tweets that contribute to a particular topic. However, this number is not exclusive which means that a single tweet can contribute to one or more topics. From Fig. 4 and Fig. 5 we see some common themes that appear in the Big Six companies as well as in the New Entrants. Common themes include topics relating to the company's customer service, smart meters, engineering services, payments of bills, waiting times and gas and electricity supply. However, it can be observed that some of the topics that are unique to the tweets from new entrant company customers pertain to renewable and green energy.



(a) Company 1
(b) Company 2
(c) Company 3
(d) Company 4
(e) Company 5
(f) Company 6

Fig. 2: Sentiment analysis results on the tweets of customers of the Big Six



(a) New Entrant Company 1
(b) New Entrant Company 2
(c) New Entrant Company 3

Fig. 3: Sentiment analysis results on the tweets of customers of the new entrant energy companies

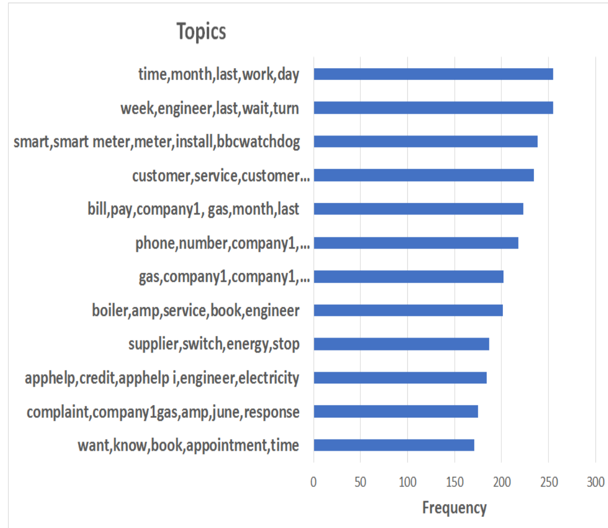


Fig. 4: Twelve most frequently discussed topics detected from tweets of customers of one of the Big Six energy companies.

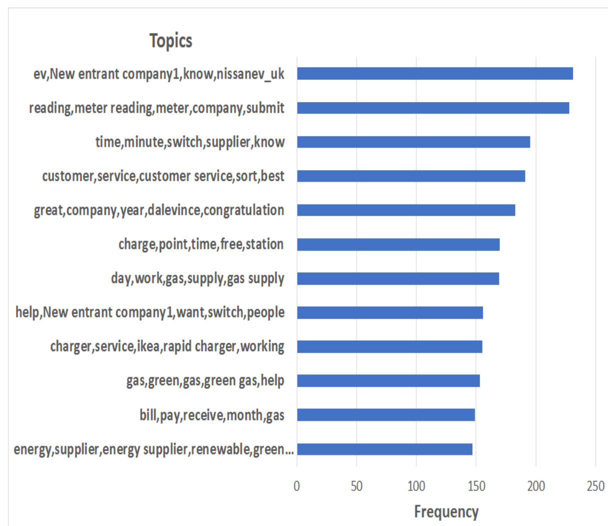


Fig. 5: Twelve most frequently discussed topics detected from tweets from customers of one of the new entrant energy companies.

VI. CONCLUSION

We present a novel application of social media analysis by harvesting tweets sent from energy consumers to their energy providers. We compare the results of sentiment analysis on consumer tweets interacting with the Big Six (Britain's largest and oldest gas and electricity suppliers) versus three new entrant energy providers. Our results show that in general the sentiments from the new entrant energy consumers are more positive than those coming from consumers of the Big Six. Topic modelling shows that there is substantial difference in terms of topics being discussed in the tweets revolving around the use of renewable energy.

References

[1] A. Collomb, C. Costea, D. Joyeux, O. Hasan, and L. Brunie. A Study and Comparison of Sentiment Analysis Methods for Reputation Evaluation. Technical Report RR-LIRIS-2014-002, March 2014.

[2] [2] M. Daiyan, S. K. Tiwari, M. Kumar, and M. Aftab Alam. A Literature Review on Opinion Mining and Sentiment Analysis. International Journal of Emerging Technology and Advanced Engineering, 5(4):262-280, 2015.

[3] A. N. Jebaseeli and E. Kirubakaran. A Survey on Sentiment Analysis of (Product) Reviews. International Journal of Computer Applications, 47(11):36-39, Jun 2012.

[4] B. Liu. Sentiment Analysis and Opinion Mining. Synthesis Lectures on Human Language Technologies. Morgan and Claypool Publishers, 2012.

[5] W. Medhat, A. Hassan, and H. Korashy. Sentiment analysis algorithms and applications: A survey. Ain Shams Engineering Journal, 5(4):1093-1113, 2014.

[6] T. Al-Moslmi, N. Omar, S. Abdullah, and M. Albared, Approaches to cross-domain sentiment analysis: A systematic literature review, IEEE Access, vol. 5, pp. 16173-16192, 2017.

[7] T. Loughran and B. McDonald. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. The Journal of Finance. 2011;66(1):35-65.

[8] L. Hamilton, K. Clark, J. Leskovec, D. Jurafsky. Inducing Domain-Specific Sentiment Lexicons from Unlabeled Corpora. Proceedings of EMNLP 2016, 595-605.

[9] T.Rinker, (n.d.). Package 'sentimentr'. Retrieved from https://cran.rproject.org/.pdf

[10] M. Hu and B. Liu. KDD. 2004 Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining.

[11] Hassan Saif, Yulan He, Miriam Fernandez and Harith Alani. Contextual Semantics for Sentiment Analysis of Twitter, Information Processing and Management, Vol 52, Issue 1, 2016, pp.5-19.

[12] Muhammad A, Wiratunga N, Lothian R. Contextual sentiment analysis for social media genres. Knowledge-Based Systems. 2016; 108:92-101

[13] Asghar MZ, Khan A, Ahmad S, Khan IA, Kundi FM. A unified framework for creating domain dependent polarity lexicons from user generated reviews. PLoS One. 2015.