Temporal Sentiment Analysis of Learners: Public Versus Private Social Media Communication Channels in a Women-in-Tech Conversion Course

Jialin Yu
Department of Computer Science
Durham University
Durham, UK
jialin.yu@durham.ac.uk

Olanrewaju Tahir Aduragba
Department of Computer Science
Durham University
Durham, UK
olanrewaju.m.aduragba@durham.ac.uk

Zhongtian Sun
Department of Computer Science
Durham University
Durham, UK
zhongtian.sun@durham.ac.uk

Sue Black
Department of Computer Science
Durham University
Durham, UK
sue.black@durham.ac.uk

Craig Stewart
Department of Computer Science
Durham University
Durham, UK
craig.d.stewart@durham.ac.uk

Lei Shi
Department of Computer Science
Durham University
Durham, UK
lei.shi@durham.ac.uk

Alexandra Cristea
Department of Computer Science
Durham University
Durham, UK
alexandra.i.cristea@durham.ac.uk

***Abstract*—Social media is ubiquitous, a continuous part of our daily lives; it offers new ways of communication. This is especially crucial in education, where various online systems make use of *(perceived) public or private communication, as a means to support the learning process*, often in *real-time*. However, not much research has been carried out in analysing and comparing such channels and the way participants use them. Thus, this paper analyses a course offering both public and private types of communication to its participants. Participants communicate via two social media channels (beyond traditional email etc.): Twitter (open to the public) and Microsoft Teams (for internal communication). In this paper, we specifically analyse the communication patterns of learners, focusing on the *temporal analysis of their sentiments on the public versus the private platform*. The comparison shows that, as possibly expected, there exist similarities between expressed sentiment in public and private channels. Interestingly however, the private platform is more likely to be used for negative utterances. It also shows that sentiment can be clearly connected to events in the course (e.g., the residentials increase both volume and positivity of comments). Finally, we propose new measures for sentiment analysis to better express the nature of change and speed of change of the sentiment in the two channels used by our learners during their learning process.**

***Index Terms*—Private and Public, Temporal Sentiment Analysis, TechUPWomen, Deep Learning, Social Communication Pattern, Natural Language Processing**

I. Introduction

Social media has for some time been serving as a tool to study real-world phenomena, such as brand popularity [1], silver-screen box office returns [2] and election outcomes [3]. Most existing studies mainly use publicly available data from social media channels, which everyone is allowed to get involved; however, to date, there is no comparison between the same event timeline reflected on *public channels* (open to the general public) versus restricted, *private channels* (which limit the group of users who can access it via a private social network).

In this paper, we have tracked data from a publicly promoted Women-in-Tech retraining course with data from public and private social media platform and used sentiment analysis to understand the public and private expressiveness over the social media channels. The original data sets collected through social media platforms are unlabelled, we used transfer learning technique to handle this problem [4]. Through the analysis, we aim at answering the following two research questions:

RQ1. Do people have different levels of sentiment expressiveness in public and private communication channels?

RQ2. Can we infer the sentiment within a private communication channel based on a publicly accessed social media channel such as Twitter?

The contributions of our study include: 1) we identified a research gap within social media research and analysed the sentiment information in both public and private channels using an educational conversion course as a case study, to identify the *patterns of sentiment over public and private channels*. 2) We explore the influence of sentiment over public and private channels on the course progress of an educational programme 3) We discovered, for the first time, that *learner* *behaviour is better demonstrated on the private channel than the public channel*, and discuss reasons for, and implications of this fact.

II. Related Work

A. Public versus Private Social Media User Community Analytics

Social media is used daily for public (often professional) and private (often personal) purposes, including contacting friends, family members and colleagues, as well as expressing and sharing opinions across a wide variety of subjects. Lange [5] defined two types of user behaviour: 1) "publicly private", the actions to post limited accessed content by known identities; and 2) "privately public", the actions to share public content by limited accessed identities. In this paper, we define the characteristic of social media channels as public and private and we use the term: social media channel, to signify the level of access granted to different social network communities (i.e., private social media channel means for this community only; public social media channel means for everyone who have access to the platform).

Social media networks such as Twitter and Facebook offer a massive amount of data and more than 80% of this data can be used for analytics purposes [6]. Predictive insights can be gained from the data in topics such as finance, marketing and consumer growth [7]. Additionally, real-time events tracking and prediction through social media can also be realised [8], [9]. However, these social media analytics are mainly based on publicly available information collected from Twitter and Facebook, which related to the public social media channel defined above and do not consider data from private social media channels. Additionally, opinions may be expressed in different demeanours, e.g., (perceived) private ones may be more informal and potentially express more sentiments as opposed to those expressed on public channels., depending on their (perceived) public or private status. Hence, it would be interesting to explore the differences in level of expressiveness of sentiment between public and private social media channels. Importantly, to the best of our knowledge, there is no prior work on sentiment analysis and comparison between public and private social media channels for the same topic/event. Addressing this research gap, we applied sentiment analysis to examine the differences in data generated from public and private communities through social media platforms (Twitter and Microsoft Teams discussion forum) for the TechUpWomen course [1].

B. Measure Event with Temporal Sentiment Analysis

Sentiment analysis refers to the task of information identification and extraction through a series of methods, including text analysis and natural language processing from vast amounts of data [10]. An individual's opinions concerning specific topics and events can be measured and evaluated through sentiment analysis. With easy access to the large and open datasets from social media platforms such as Twitter, web search engines have become popular data source tools in sentiment analysis for trend capturing and event measurement [11]. Sentiment analysis can be divided into two categories prediction and 'nowcasting'. Nowcasting utilises online social media data for real-time event assessing [12]. It has been successfully applied in quantifying and monitoring real-world phenomena [13], emotion analysis [14], real-time mortality rate [15], influenza outbreaks [16], price and sales performance of products [17] and voting intentions during political election [18]. This paper mainly focuses on nowcasting the evolution of temporal sentiment information in both the public and private channels of the TechUPWommen course that ran from July 2019 to January 2020.

C. Transfer Learning in Natural Language Processing

Transfer learning aims to train a well-performed learner to perform different tasks using data from one domain to a different domain [19]. During this process, knowledge learnt from the previous tasks will be transferred to the new task by leveraging labelled data either in the source domain or in the target domain. The paper by Long [4] has shown that transfer learning allows models to learn representations and improves classification accuracy significantly even with unlabelled data in one of the domains. With such benefits, transfer learning has been applied to various natural language processing tasks such as translation [20], [21], speech recognition [22], event detections [23], semantic segmentation [24], and sentiment analysis [25].

III. Methodology

This paper investigates the transfer learning techniques defined by Ruder [26] and uses it with the state-of-the-art pre-trained language modelling model, Bidirectional Encoder Representations from Transformers(BERT), for sentiment analysis tasks on two different data sources. The two datasets are collected from the same event in public (Twitter) and private (Microsoft Teams) social media channels separately.

A. Data Collection

In this study, data is collected from both a public social media channel (Twitter) and a private social media channel (Microsoft Teams) from July 2019 (program start) till January 2020 (program end). This covers the span of the TechUP-Women program for 28 weeks, total number of data points are provided in Table I with a detailed explanation of the program structure in Figure 1.

Twitter data is collected based on pre-defined rules, including keywords e.g. 'Techup', 'TechUp', 'Techupwomen', 'TechUpwomen', hashtags such as #techupwomen, #tuw and a selection of official Twitter accounts. Chats in Microsoft Teams are collected from three channels which are intended for three terms of the course (see Figure 1). In the analysis, we combine the data from these three different channels to perform the analysis. During the data collection progress, we paid particular attention to the private exposition of the users

[1] https://techupwomen.org/

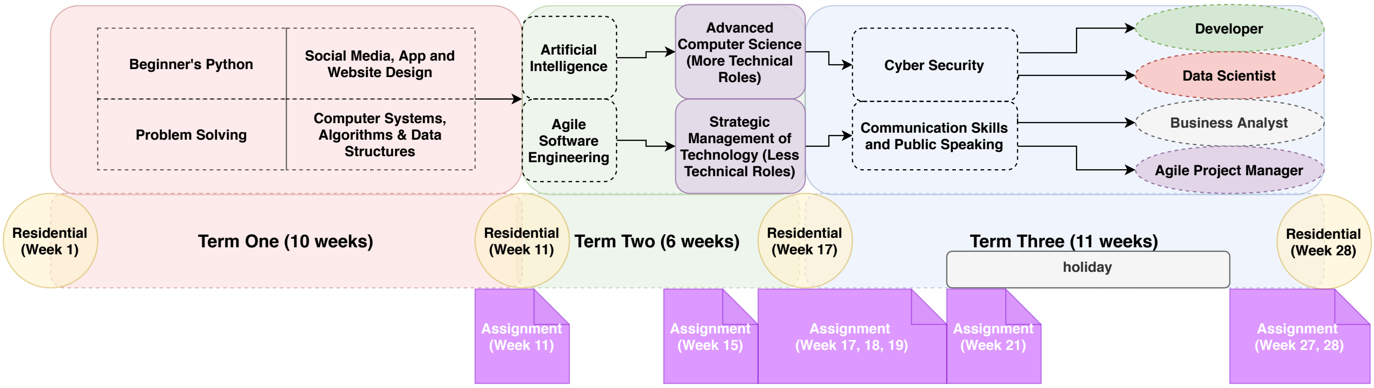

Fig. 1. Module structure, residential weekends of the TechUPWomen programme

data and any data related to personal information was removed according to data protection regulation.

TABLE I
GENERAL INFORMATION OF THE DATA COLLECTED

Dataset	Size
Twitter	10957
Microsoft Teams Topic 1	1039
Microsoft Teams Topic 2	246
Microsoft Teams Topic 3	176

B. *Transfer Learning for Natural Language Processing*

Transfer learning is defined based on the concept of "**domain**" and "**task**": a domain D refers to a dataset which is generated from a feature space $X \in \mathbb{R}^d$ and owns a probability distribution of $\mathbb{P}(X)$ defined over the feature space X, where $X = x_1, \ldots, x_n \in \mathbb{R}^d$. Given the domain $D = \{X, \mathbb{P}(X)\}$, a task T is defined on a label space $Y \in \mathbb{R}^k$ with a probability distribution $\mathbb{P}(Y)$. There are mainly two transfer learning problems: *inductive* and *transductive* transfer learning [26] that are focused on 'task' and 'domain' respectively.

The inductive transfer learning aims to solve the problem where the tasks from the source domain and target domain are different, they are defined based on different data sources. Since the differences exist both in task and data, inductive transfer learning requires a knowledge transfer process, known as fine-tuning, with the target domain data.

The transductive transfer learning aims to solve the problem where the tasks in both source domain and target domain are the same but are defined based on different data sources. For transductive transfer learning, we directly apply the model trained on the source domain task and data to the target domain data.

In this study, both transfer learning techniques were applied on our unlabelled data. We used the smallest version of BERT, named BERT-Base Uncased model [27] and a public data set with polarised labels [28]. For the sentiment analysis task, inductive transfer learning was applied on the public Twitter data set and transductive transfer learning was applied on the private discussion forum data.

C. *Measuring sentiment over public and private channels*

We perform sentiment analysis based on the previous two approaches. To address the research questions, we define a measure for the change of sentiment, given the sentiment information from the beginning to the end of the considered period $x_1, .., x_n$. As the number of public and private information communications may not be on the same scale (as in our case, see Figures 5,6), we define the *smooth sentiment information* based on the ratio of change in the amount of sentiment given as follows:

$$Sm_n = \frac{(x_n + 1) - (x_{n-1} + 1)}{(x_{n-1} + 1)} = \frac{x_n - x_{n-1}}{(x_{n-1} + 1)} \quad (1)$$

This allows us to measure the change of sentiment over time without worrying about the scale and missing values from data. In this paper, we consider the temporal changes in sentiment as time series. Hence, we use the hinge loss version of the sentiment for positive and negative communications as the *absolute smooth sentiment*:

$$AbsS_n = max(0, Sm_n) \quad (2)$$

This allows us to study the aggregation of sentiment in a time window, given a window size m and a decreasing factor σ (where $0 < \sigma \leq 1$), define as the *total sentiment information accumulated across a given time period*; this is specifically useful for nowcasting and offers a wide view on sentiment change:

$$AggS_n = \sum_{i=0}^{m} AbsS_{n-i} \times \sigma^i \quad (3)$$

IV. EXPERIMENTS

As described in the methodology section, we have applied both inductive and transductive transfer learning techniques as shown in figure 2. We use pre-trained BERT model maintained by HuggingFace [29] and use one single layer architecture to learn the nonlinear relationship between the transformation in source task and target task. As shown in figure 2, special text tokens are padded on the original text: [CLS] tokens are attached at the beginning of each sentence and [SEP] tokens are added in between two different sentence followed by the original order. After padding of these special tokens, each sentence is fed into the pre-trained BERT model with randomly generated masks placed on the sentence.The experiment setup for the fine-tuning training process uses a dropout of 0.5 on dropout layer which helps to reduce over-fitting and improve generalisation performance [30]; the cross-entropy loss as the objective function and the Adam optimizer [31], following the suggested setting used in previous studies [32]. We tested the model performance with different hyperparameters and selected the learning rate of 2e-05 and set weight decays equal to 0.01 for our model in this experiment. After the fine-tuning the model, sentiment analysis is performed on both public and private channel data and the results are presented in a polarised format on a weekly basis.

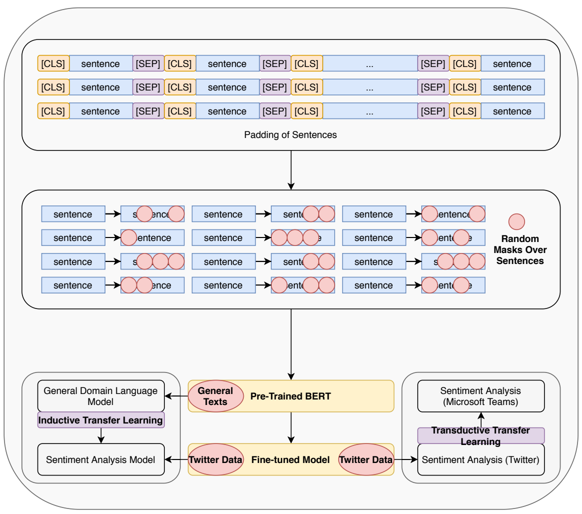

Fig. 2. Detailed explanation of the experiments for both inductive and transductive transfer learning applied over public and private channel data

V. Results and Discussion

A. Polarised Sentiment Time-Series Analysis

We first investigate the sentiments by calculating the *smooth sentiment information*, as defined in the methodology section above, for positive and negative sentiments. The depiction of this smooth sentiment, illustrated in Figure 3, shows that the positive and negative sentiment information generally share the same trend in both the public and the private channels. Another interesting result is that the negative changes tend to outperform positive changes in both public and private channels (5 out of 6 times). The public channel holds information on the events (residential weekends) in week 11, 17 and 28 and the private channel reflects sentiment increase in week 11, 17 and 19 which related to learner activities (assignments).

B. Aggregate Polarised Sentiment Time Series Analysis

Next, we consider the aggregation effect of sentiment information given a specific window size and we exclude the holiday period from the analysis. As defined previously in the methodology section: first, we analyse the sentiment information given various window sizes; as the total length of overall period analysed is of 20 weeks (excluding holiday weeks), we compare the window sizes of 2, 4 and 8; and the results are shown respectively in Figure 4.

The aggregated sentiment across weeks shows a similar trend as in Figure 3. However, the aggregated sentiments are smoother and have more momentum to keep extreme changes of sentiments over the previous weeks. The larger the window size chosen, the more momentum gets magnified. The drop in positive sentiment on the private platform after Week 9 (and the subsequent rise in negative sentiment) is much clearer for smaller window size, such as $m = 2$. For larger ones, the cumulative effect lasts longer, as a result the drop in negative sentiment in week 17 becomes preponderant (corresponding to the third residential).

Next, we analyse how the decreasing factor influences the sentiment. For a fair comparison, we use the same window size of 4 with a variety of decreasing factors, ranging between 0.8, 0.5 and 0.3 (selected from range 0 to 1). Figure 5 displays this comparison and also suggest faster changes, in general, the negative sentiment, with the fastest changes are more clearly occurring in weeks 9 and 19. Also, the higher the decay, the closer the speed is to the actual speed of change.

C. Sentiment Comparison for Public and Private Channels

As shown in Figure 6, the general trend for sentiment expressiveness in terms of positive and negative communications across public and private channel is similar. However, if we focus on sudden variations across positive and negative sentiment information, the positive sentiment is equally expressed over the public channel (Twitter, 3 out of 6) and private channel (Microsoft Teams, 3 out of 6); while the negative sentiment is more likely to be expressed through the private channels (Microsoft Teams, 5 our of 7). In general, we could conclude that both sentiments, positive and negative, are expressed more on the private channel. The expressiveness level on the public channel was lower than that in the private channel, possibly due to the fact that people are more likely to express their feelings, especially negative emotions, when they are closer in relationship to their audience. The private channel created a closed-loop community, where participants were more likely to connect than in a public social channel.

D. Discussion

Revisiting our research question, we can say that for educational campaigns such as TechUPWomen, sentiment analysis can be a power tool to preform *nowcasting*; i.e., to track the ongoing progress of the program and understand learner behaviours - importantly, it allows us to better understand the usage of private versus public channels. Our results suggest that the sentiment expressed over the public channel can be better used for event tracking. However, it may not provide too much information about learners' behaviour, which we believe is more related to private channels.

VI. Limitations and Future Work

First, as the transfer learning was based on public (Twitter) data, this might result in the model more accurately when

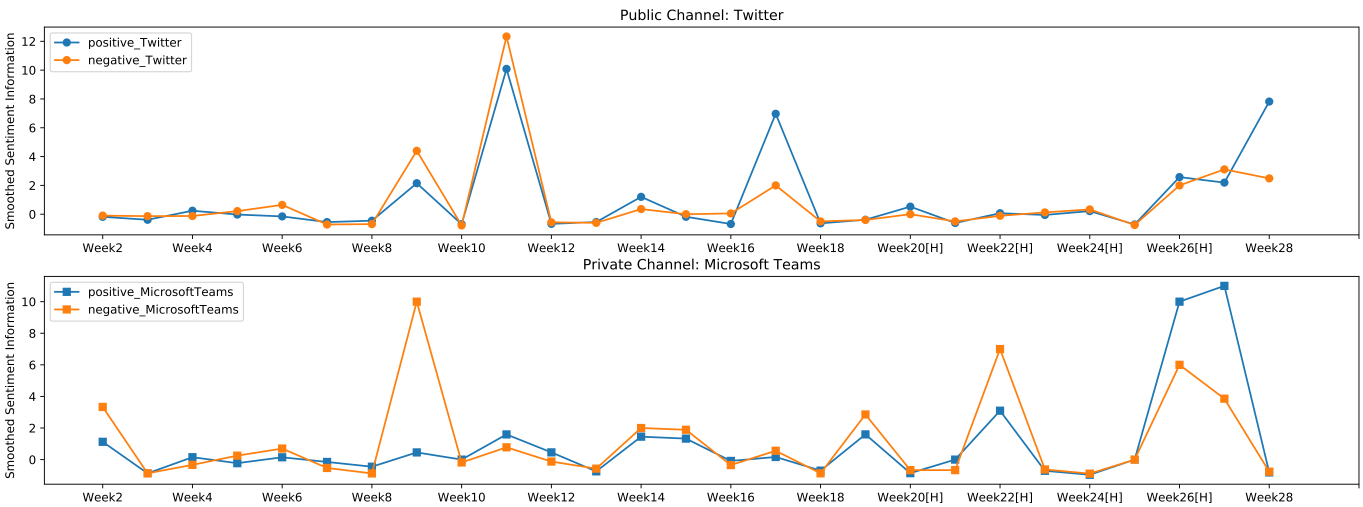

Fig. 3. Polarised Smoothed Sentiment Information (positive and negative) for public and private channel(compared within the same channel)

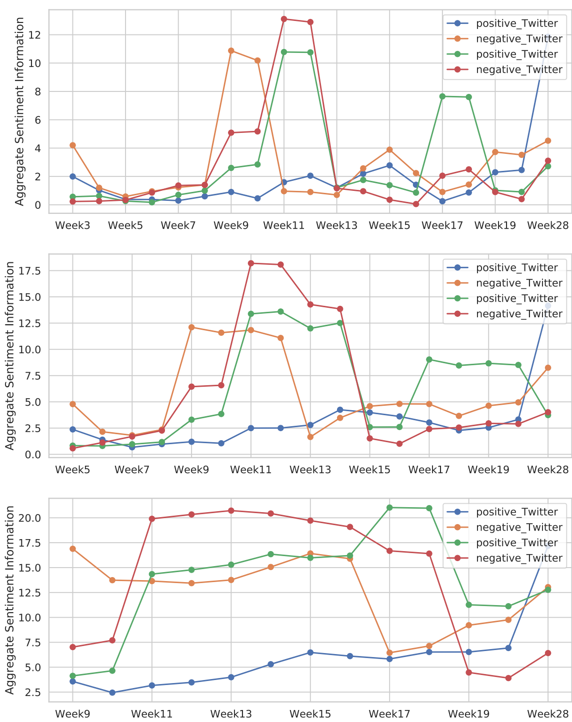

Fig. 4. Aggregate Sentiment Time-Series for window sizes of $m = 2, 4, 8$ and decreasing factor $\sigma = 1$ from top to bottom

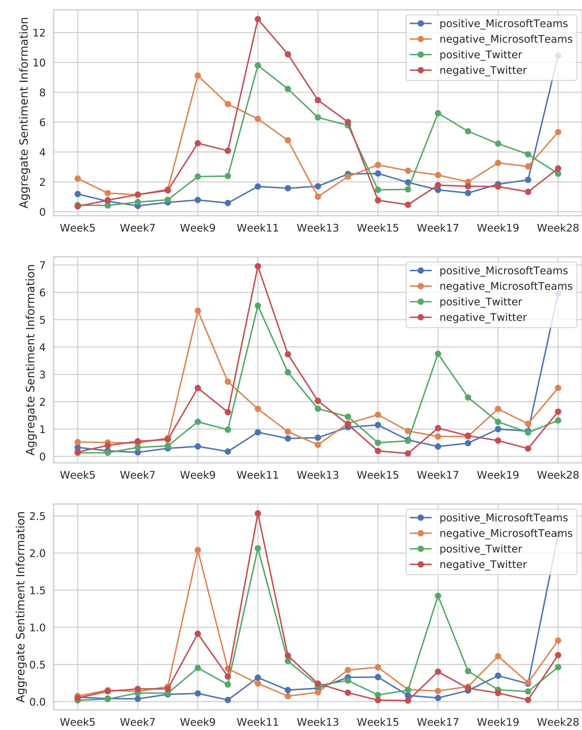

Fig. 5. Aggregate Sentiment Time-Series for the window size $m = 4$ and various decreasing factors $\sigma = 0.8, 0.5, 0.3$ from top to bottom

estimating sentiments of tweets, as opposed to chats from Microsoft Teams. However, the overall trends were very similar in both public and private channel over the event per week, with data generated from the same event, and therefore our results are plausible. Second, as only polarised labels were provided from the public dataset, it only allowed the classifier to categorise either positive or negative sentiment, without the intermediate state of 'neutral'. This might have affected the results of our analysis; we expect that many of the comments labelled as negative might have been neutral. Nevertheless, the analysis was limited to sentiment analysis only - we could potentially use other natural language processing methods to provide more insights about the TechUpWomen programme.

VII. Conclusions

In this paper, we have applied temporal analysis of sentiments in public and private social media communication channels for the TechUPWomen training programme. We con-

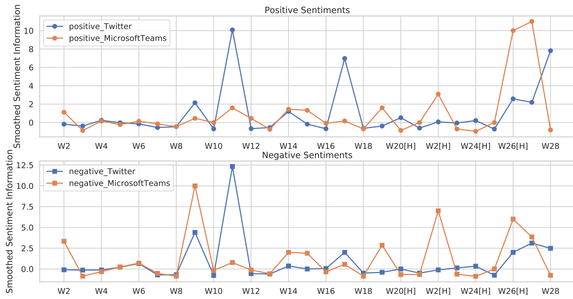

Fig. 6. Polarised Smoothed Sentiment Information (positive and negative) for public and private channel(compared between channels)

sidered the number of (positive or negative) communications in both channels as time series and analysed the changes, additionally, we introduced time window and decreasing factor to study the aggregate variations over long time framework. The results for temporal analyses of sentiments in both the communication channel help us to summarize the events based on sentiment and time and offer different insight into the sentimental landscape of private versus public communication around the course. The results suggest that sentiment expressions on a public social media platform are strongly associated to the ongoing event and the structure of the training programme and sentiment expressions are linked to learner behaviours (coursework assignments) in the private social channel. When comparing these two results, however, the level of expressiveness for negative sentiment is much higher on the private channel than on the public channel - here, related to stress over assignment deadlines. We also argue in this paper that it is possible to infer the sentiment on a private channel based on a publicly accessible social media platform.

References

[1] L. De Vries, S. Gensler, and P. S. Leeflang, "Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing," *Journal of interactive marketing*, vol. 26, no. 2, pp. 83–91, 2012.

[2] S. Asur and B. A. Huberman, "Predicting the future with social media," in *2010 IEEE/WIC/ACM international conference on web intelligence and intelligent agent technology*, vol. 1. IEEE, 2010, pp. 492–499.

[3] B. O'Connor, R. Balasubramanyan, B. R. Routledge, and N. A. Smith, "From tweets to polls: Linking text sentiment to public opinion time series," in *Fourth international AAAI conference on weblogs and social media*, 2010.

[4] M. Long, J. Wang, G. Ding, J. Sun, and P. S. Yu, "Transfer feature learning with joint distribution adaptation," in *Proceedings of the IEEE international conference on computer vision*, 2013, pp. 2200–2207.

[5] P. G. Lange, "Publicly private and privately public: Social networking on youtube," *Journal of computer-mediated communication*, vol. 13, no. 1, pp. 361–380, 2007.

[6] P. Tyagi, S. Chakraborty, R. Tripathi, and T. Choudhury, "Literature review of sentiment analysis techniques for microblogging site," *Available at SSRN 3403968*, 2019.

[7] W. Fan and M. D. Gordon, "The power of social media analytics," *Communications of the ACM*, vol. 57, no. 6, pp. 74–81, 2014.

[8] N. Elgendy and A. Elragal, "Big data analytics: a literature review paper," in *Industrial Conference on Data Mining*. Springer, 2014, pp. 214–227.

[9] H. Isah, P. Trundle, and D. Neagu, "Social media analysis for product safety using text mining and sentiment analysis," in *2014 14th UK workshop on computational intelligence (UKCI)*. IEEE, 2014, pp. 1–7.

[10] B. Batrinca and P. C. Treleaven, "Social media analytics: a survey of techniques, tools and platforms," *Ai & Society*, vol. 30, no. 1, pp. 89–116, 2015.

[11] M. V. Mäntylä, D. Graziotin, and M. Kuutila, "The evolution of sentiment analysis—a review of research topics, venues, and top cited papers," *Computer Science Review*, vol. 27, pp. 16–32, 2018.

[12] D. Giannone, L. Reichlin, and D. Small, "Nowcasting: The real-time informational content of macroeconomic data," *Journal of Monetary Economics*, vol. 55, no. 4, pp. 665–676, 2008.

[13] M. Mendoza, B. Poblete, and I. Valderrama, "Nowcasting earthquake damages with twitter," *EPJ Data Science*, vol. 8, no. 1, p. 3, 2019.

[14] T. Lansdall-Welfare, V. Lampos, and N. Cristianini, "Nowcasting the mood of the nation," *Significance*, vol. 9, no. 4, pp. 26–28, 2012.

[15] H. K. Green, N. J. Andrews, G. Bickler, and R. G. Pebody, "Rapid estimation of excess mortality: nowcasting during the heatwave alert in england and wales in june 2011," *J Epidemiol Community Health*, vol. 66, no. 10, pp. 866–868, 2012.

[16] M. A. Johansson, A. M. Powers, N. Pesik, N. J. Cohen, and J. E. Staples, "Nowcasting the spread of chikungunya virus in the americas," *PloS one*, vol. 9, no. 8, 2014.

[17] E. W. See-To and E. W. Ngai, "Customer reviews for demand distribution and sales nowcasting: a big data approach," *Annals of Operations Research*, vol. 270, no. 1-2, pp. 415–431, 2018.

[18] V. Lampos, "On voting intentions inference from twitter content: a case study on uk 2010 general election," *arXiv preprint arXiv:1204.0423*, 2012.

[19] K. Weiss, T. M. Khoshgoftaar, and D. Wang, "A survey of transfer learning," *Journal of Big data*, vol. 3, no. 1, p. 9, 2016.

[20] Y. Zhu, Y. Chen, Z. Lu, S. J. Pan, G.-R. Xue, Y. Yu, and Q. Yang, "Heterogeneous transfer learning for image classification," in *Twenty-Fifth AAAI Conference on Artificial Intelligence*, 2011.

[21] Z. Murez, S. Kolouri, D. Kriegman, R. Ramamoorthi, and K. Kim, "Image to image translation for domain adaptation," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 4500–4509.

[22] D. Wang and T. F. Zheng, "Transfer learning for speech and language processing," in *2015 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA)*. IEEE, 2015, pp. 1225–1237.

[23] W. Huang, T. Wang, W. Chen, and Y. Wang, "Category-level transfer learning from knowledge base to microblog stream for accurate event detection," in *International Conference on Database Systems for Advanced Applications*. Springer, 2017, pp. 50–67.

[24] S. Sankaranarayanan, Y. Balaji, A. Jain, S. Nam Lim, and R. Chellappa, "Learning from synthetic data: Addressing domain shift for semantic segmentation," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 3752–3761.

[25] B. Sun, L. Yang, P. Dong, W. Zhang, J. Dong, and C. Young, "Super characters: A conversion from sentiment classification to image classification," *arXiv preprint arXiv:1810.07653*, 2018.

[26] S. Ruder, "Neural transfer learning for natural language processing," Ph.D. dissertation, NUI Galway, 2019.

[27] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," *arXiv preprint arXiv:1810.04805*, 2018.

[28] A. Go, R. Bhayani, and L. Huang, "Twitter sentiment classification using distant supervision," *CS224N project report, Stanford*, vol. 1, no. 12, p. 2009, 2009.

[29] T. Wolf, L. Debut, V. Sanh, J. Chaumond, C. Delangue, A. Moi, P. Cistac, T. Rault, R. Louf, M. Funtowicz *et al.*, "Huggingface's transformers: State-of-the-art natural language processing," *ArXiv, abs/1910.03771*, 2019.

[30] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: a simple way to prevent neural networks from overfitting," *The journal of machine learning research*, vol. 15, no. 1, pp. 1929–1958, 2014.

[31] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.

[32] I. Beltagy, K. Lo, and A. Cohan, "Scibert: A pretrained language model for scientific text," in *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, 2019, pp. 3606–3611.