Dynamic Emotions of Supporters and Opponents of Anti-racism Movement from George Floyd Protests

Jaihyun Park
University of Illinois Urbana-Champaign
jaihyun2@illinois.edu

Abstract

Social media empowers citizens to raise the voice and expressed civil outrage leads to collective action to change the society. Since social media welcomes anyone regardless of the political ideology or perspectives, social media is where the supporters and opponents of specific issue discuss. This study attempts to empirically examine a recent anti-racism movement initiated by the death of George Floyd with the lens of stance prediction and aspect-based sentiment analysis (ABSA). First, this study found the stance of the tweet and users do change over the course of the protest. Furthermore, there are more users who shifted the stance compared to those who maintained the stance. Second, both supporters and opponents expressed negative sentiment more on nine extracted aspects. This indicates that there was no significant difference of sentiment among supporters and opponents and raise a caution in predicting stance based on the sentiment. The contribution of the study is two-fold. First, ABSA was explored in the context of computational social science and second, stance prediction was first attempted at scale.

1 Introduction

Social media is often used to promote social movement and exhort bystanders to join the social movement. For example, the success of Arab's Spring movement is often ascribed to deeply interconnected relationship with social media (Lotan et al., 2011). How supporters of movement mobilize people by starting the discourse on social media is indispensable to understand the birth of social movements and the development of social movements. In this sense, an empirical analysis on a recent anti-racism social movement initiated by the death of George Floyd on Twitter is crucial in understanding social media as a medium of spreading sentiments and their own belief. Amid grievance of his death, the protest got violent, followed by looting and arson in some cities (Fields and Shaw, 2020). Given the nature of social movements, a political hot potato, it is apparent that there are supporters and opponents of social movements. People may support social movements no matter how violent the protesters are due to their deep sympathy while some may change their stance and emotion after violent civil unrest which had caused chaos in the cities. Therefore, it needs our attention to 1) identify the stance of Twitter users if they posted anything about George Floyd social movements, 2) identify the aspects relevant to the protest, 3) with regard to the aspects, identify the sentiments of the aspects when users discuss about it. Focusing on three perspectives, this study forms two research questions:

- RQ 1. Does the stance toward anti-racism movement change over time?
- RQ 2. How does the sentiment toward anti-racism movement of the supporters and opponents differ?

This study suggests that the stance of the protest experience changes in accordance with the rapidly changing situation of the protest. For instance, the number of tweets that support the protest gradually decreased over the course of the protest. The number of tweets of opposing the protest increased before the protested entered the Day 4. After the Day 4, the number of opposing tweets decreased and never reached the highest point. On Day 3, the National Guard is deployed to protect properties of the civil society. This may alludes that the escalation of violence has led Twitter user to spread information that does not belong to any stance (high volume of neutral stance) and also infuriated real-life looting and arson might have thwarted the opponents of the the protest on social media. Also, regarding various aspects of the protest, supporters and opponents did not show significant sentiment differences. Both sides expressed similar magnitude of sentiment toward aspects except *murder*. This finding may suggest that distinguishing the stance by the sentiment of the text do not reflect the real stance of the text.

This research contributes in understanding of the landscape of social movement and social media. The stance analysis and sentiment analysis will shed a light on cultivating peaceful and organized social movement to bring gradual change to the society while not impairing the integrity of the society. The code and data used for the study is available[1].

2 Previous works

Van Stekelenburg et al. (2011) explain that emotional grievance is at the heart of every protest and coupled with emotional grievance, group-based anger is a motivational thrust to protesters to participate the protest (van Cranenburgh, 2018). In relation to anger, the feeling of being treated unfairly also motivates protesters to join the protest (Cass and Walker, 2009). However, emotion is not created in a vacuum according to Goodwin and Pfaff (2001). It is a product of social construction, which bases on cultural, historical, and some aspects of reality.

Social media has become a vent of expressing frustration or anger towards government and policy. Min and Yun (2019) argued that social media can provide networks where individuals who don't know each other can come together to leverage collective action. Although anger can be considered as negative and far from constructive, (Wahl-Jorgensen, 2018) distinguishes irrational and illegitimate anger and rational and legitimate anger appear in political emotion. According to Wahl-Jorgensen (2018), the feeling of care and passionate can attract more people to join the protest.

Empirical study on `Gezi Park Protest` in Turkey demonstrated that the sentiment toward the protest do change over time (Dincelli et al., 2016). Dincelli et al. (2016) adopted a simple heuristic approach (sentiment polarity) to understand the opinion toward the protest. In other words, if the sentiment of the tweet is positive, then the tweet is considered sympathetic to the protest. Nonetheless, this approach lacks the target which is being considered positive or negative. For instance, the tweet might be explaining positive sentiment towards the government, not toward the protesters. As suggested in the study (Jasper, 1998), social movements are affected by transitory context-specific emotions. Depending on where the context situates the protest-goers and their associated emotion, the protest could move further beyond. Addressing the importance of context-specific emotion, Aspect-based sentiment analysis (ABSA) (Pontiki et al., 2014) can be leveraged to understand the context-specific emotion. Even though the text can be talking about the same topic, the aspect or the context that the text is covering might be different. For instance, two reviews of the camera might be talking about two different aspects: the price and the lens. Therefore, ABSA gained attention from researchers in natural language processing to better understand where the sentiment is pointing at. Now ABSA is being explored in a variety of language (Pontiki et al., 2016). However, ABSA has not been applied to the domain of computational social science to understand the phenomenon in social issues yet.

[1] `https://github.com/91jpark19/LING506_FA20`

3 Development of anti-racism movement

The death of George Floyd was first known to the public when eight minutes, 46 seconds of short video that recorded the last moment of George Floyd was posted on social media. An unarmed black man's last cry, `I can't breathe` reminded a systemic racism prevailed in policing and the society in general. The protest was started in Minneapolis. At first, the protest did not involve violence. After the protest entered Day 2, the protest spread throughout the country, including Los Angeles and St.Louis. In St.Louis, the first looting and arson was reported (Taylor). On Day 3, the governor of Minnesota activated The National Guard to protect civil society from vandalism and violence. Although, peaceful demonstration and violence are hard to separate as peaceful protest prolonged after looting started, the violent protest changed the nature of social movement and brought negative views on the movement.

4 Data

Tweets were collected with the search term "George Floyd Protest" from May 26th to June

Since the death of George Floyd	Date	Number of Tweets
Day 2	May 26th	1,242
Day 3	May 27th	6,208
Day 4	May 28th	16,647
Day 5	May 29th	30,104
Day 6	May 30th	43,170
Day 7	May 31th	48,520
Day 8	June 1st	54,077

Table 1: The number of tweets collected

1st using Brandwatch (5,789 tweets) and Twint (199,969 tweets). The geographical area was restricted to have tweets posted in the United States and only tweets in English were chosen. The preprocessing step followed tokenization, lowercasing, stopwords filtering and lemmatization. For the tokenization stage, the data was tokenized using `Ekphrasis` tokenizer (Baziotis et al., 2017), which is useful for spell correction such as informal words and elongated words, which often appears on social media. With an help of `Ekphrasis`, hashtags has been considered as words and split if it needs to be split. For instance, the hashtag *#GeorgeFloyd* was separated into *Geroge* and Floyd to be counted as plain text. For normalization process, the NLTK stopwords list and Porter stemmer from NLTK was used. Table 1 shows a brief description of collected data.

In total, 129,540 users are included in the dataset. One user posted as many as 858 times, who is not affiliated with news media.

5 Methods

5.1 Stance labeling

In order to identify the stance of the tweet, 200 tweets were sampled and either of three categories are labeled: 'Support', 'Oppose', 'None'. For the tweets that are labeled 'None' contains factual information, instead of expressing opinion toward anti-racism movement. For instance, *Protests demanding justice for George Floyd disperse across Denver* *https://www.denverpost.com/2020/05/28/george-floyd-death-colorado-protest* is delivering news about the progress of George Floyd protest in a plain and neutral style of language. Therefore, most of the time, tweets from news media handle were labeled as 'None'. Otherwise, the stance was labeled either 'Support' or 'Oppose'. The example tweet of support includes *Nothing else we can do to let our voices be heard': Protesters say violent riots the only way to get George Floyd justice #USA #protests*, which expresses that the violence is the mean to bring justice to resolve pervasive racism in the United States.

On the other hand, labeling 'Oppose' stance requires more sophisticated approach. Since George Floyd protest escalation, the protest had evolved to involve arson, looting, and violence. The violence raised question to George Floyd protest and the tweets that expressed the protesters should stop violence were labeled as 'Oppose'. For instance, *Thank you so much, FINALLY a decent comment on what's going on! I'm quite upset to see how so many people seem to be ok with the looting and violent protests. What happened to George Floyd was a terrible crime and protesting is understandable, but doing it violently is NOT ok.* was labeled as oppose.

There are two ground truth dataset being used to find out of which sampled ground truth dataset performs the best in predicting the stance. The first round of sampling returned 52 support tweets, 25 oppose tweets, and 123 none tweets. In order to make the ground truth data have less disproportionate, another sampling of 200 tweets was followed. The second round of labeling returned 33 tweets of support, 42 tweets of oppose, and 125 tweets of none.

A 5-Fold cross validation with a linear SVM model was used to validate the performance of which ground truth dataset performs the best in predicting the stance. Setting a 5-fold cross validation, the first ground truth dataset returned 0.675 of accuracy while the second ground truth dataset returned (0.685). Therefore, for the stance prediction, the second ground truth dataset was used. For the classifier, the same approach for validation process was chosen: a linear SVM model, which is the best performing method according to (Mohammad et al., 2016).

5.2 Topic modeling

In order to understand the aspects relevant to the protest, Non-matrix factorization (NMF) topic modeling (Lee and Seung, 2000) available in Python `sklearn` was used. NMF extracts relevant topical words that is helpful in representing the overall topics covered in corpus. Given that NMF performs better than LDA topic modeling (Chen et al., 2019) especially for short argumentative text, this study adopted NMF topic model-

Topic	Topical Words
Murder	peopl ***murder*** cop like kill polic think say riot fuck peac start make know bad
BLM	***black*** live matter safe stay white commun everyon justic man mater stand pleas mani peopl
Safe	need stop pleas chang justic ***peac*** riot stay safe say help home polic racism famili
Destroy	***loot*** destroy burn busi riot death steal store citi properti peac excus build noth use
Justice	want ***justic*** minneapoli restaur burn build peac famili serv let deserv citi bring commun support
Violence	***violenc*** peac destruct support answer incit violent messag memori honor famili caus group way say
Happening	***happen*** right wrong riot chang think peac know understand noth thing agre disgust countri support
White People	***white*** definit someth vandal peopl wonkett supremacist black privileg dept hous minnesota strang truth area
Antifa	***antifa*** group far extremist left blame barr like war civil right terrorist tactic organ trump

Table 2: The result of NMF Topics and topical words. The bolded words are used for ABSA

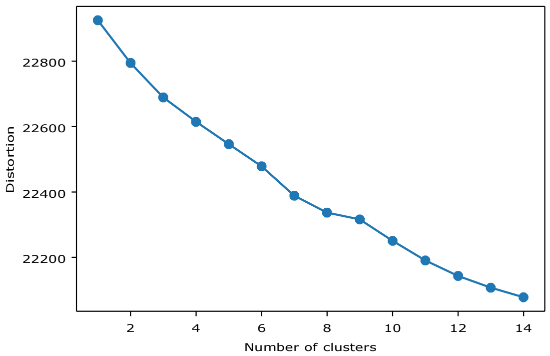

Figure 1: The depreciation of distortion rate

ing. The number of topic was chosen after running K-mean clustering available in `sklearn`. Figure 1 illustrates the depreciation of topic distortion. Adopting elbow method, optimal number of cluster is decided where the slope of distortion rate meets the smallest drop for the first time (Madhulatha, 2012). Therefore, 9 topics with 15 words (9 X 15) are extracted. The detail of the extracted topics and words are presented in table 2

After the topic modeling, the words that the author think they are important for individual topic as aspects. Using the chosen words, aspect-based sentiment analysis was followed in order to understand corresponding sentiment toward each aspect.

5.3 Aspect-based sentiment analysis

Aspect-based sentiment analysis (ABSA) is conducive to understanding the sentiment of the text toward specific aspects (features) of the target. Therefore, ABSA is often used in product reviews (Pontiki et al., 2014, 2016). For instance, LDA-based feature extraction and sentiment analysis on electorinc devices form Amazon and restaurant review from Yelp were experimented (Jo and Oh, 2011). To enhance the model performance, fine-tuned BERT was used in many researches and demonstrated its usefulness in identifying the targeting the aspect and sentiment toward the target (Sun et al., 2019; Rietzler et al., 2019; Li et al., 2019). Reflecting that BERT in ABSA is competitive, this study also used `Aspect-based-sentiment-analysis` package that implemented BERT [2]. This BERT-base ABSA returns three predicted labels (Neutral, Negative, and Positive) and polarity of the each label. Taking the result of NMF topic modeling, one word that the author of this study think important for each topic was considered as an aspect of the protest. Representative one word was written in bold and italic in table 2. BERT-base ABSA was conducted focusing on the chosen nine aspects.

6 Validation

In order to examine the validity of the linear SVM classifier, this section presents the tweets and its predicted stance. *George Floyd was the last straw in this. People attacked Kaep for peaceful protest. Perhaps if people had listened rather than attacked, we wouldn't be at this point.* This tweet was predicted as oppose. Depending on how we read the tweet, it can be controversial to decide if this tweet is expressing in favor of the protest or not. However, I believe the use of *wouldn't be at this point* expresses the user's disappointment that the protest has gone to violent. Another example of oppose stance says *I thought this protest was about George Floyd? I don't think any AMERICAN would want this sickening riot to happen.* and *Rioting, Looting Arson are Not "Protests"...They're CRIMES! The thugs destroying their own neighborhoods putting Thousands more people out of work, are Exploiting George Floyd's murder in an attempt to try to justify it all!???? Even his mother asked people*

[2]https://pypi.org/project/aspect-based-sentiment-analysis/

to Not act this way! Contrary to the first tweets, two tweets express the concern about escalating violence in the protest scenes.

However, due to low accuracy of the classifier, there exists false positives. *My grandmother just told me that she worries about me going to the protest for GeorgeFloyd Sunday, but she completely understands why I have to go!!* was classified as oppose stance, though the user explained that the user needed to participate the protest. *Second night of curfew in Milwaukee. Helicopters circling above and police everywhere. Just heard distant gunshots too. This protest 100% needs to happen because change 100% needs to happen. #GeorgeFloyd was murdered. pic.twitter.com/rdBQNtOflg* is another case of false positive where the user justified the violence in the protest scene.

The classifier predicted the correct support stance to the tweets: *If you're blasting the methods people are using to protest George Floyd's murder, unkindly shut the fuck up. People are angry and fed up. People have reached their boiling point because black lives continue to be unjustly taken and our system continues to protect their murderers.* and *If they want to stop protests they need to arrest and prosecute all 4 police that participated in George Floyd's death and the good cops need to stand up against these bad cops* were classified as support as the first tweet implied the use of violence is justifiable because the protesters had no choice but to use it. The second tweet also showed the protest needs to go on.

However, the classifier predicted following false positive for support stance. *We will not be heard by destroying. We need to create laws; we need to lobby the government to fix our system. The protest is a protest, but looting doesn't solve the issue at hand. GeorgeFloyd protests2020 BlackLivesMatter be safe out there!* This tweet expressed the concern about looting and the protest should follow the due process. The sampled tweets for the validation showed that the classifier was troubled in understanding the negation since the negations were filtered out because of the stopwords. This may be inherent problem of lexicon-based classification.

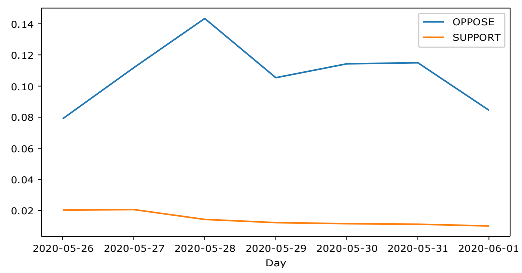

Figure 2: The ratio of predicted oppose tweets and support tweets

7 Results

7.1 RQ 1. Does stance toward anti-racism movement change over time?

Tweets that support the anti-racism movement were 2,307 tweets while opposing anti-racism movement were 21,428. The tweets do not show any stance consisted 176,233 tweets. This study operationalized the 'supporters' the user who consistently showed in favor of George Floyd protest, the 'opponents' the users who consistently posted tweets against to the protest. For those who did not support nor oppose the protest were considered as 'neutralers'. For those who posted multiple tweets contradicting one another are considered 'ambivalence'. This study found 1,761 supporters, 16,319 opponents, 107,784 neutralers, and 127,779 ambivalence.

From the macroscopic analysis, the tweets with opposing stance and supporting stance change over time. In figure 2, the percentage of tweets taking against to the protest peaked to 0.14 on Day 4. The proportion of oppose stance tweets went down after Day 4. On Day 4, similarly, the proportion of support stance tweets went down. Afterwards, the support tweets did not increase.

From the user-level analysis, users who kept the original stance remained marginal to ambivalent users. Even though the majority of tweets did not take any stance, there were more users who shifted their stance [3]

[3]There are more than six cases of ambivalence. The basic cases of ambivalence are: supporter to opponent, supporter to neutraler, opponent to supporter, opponent to neutraler, neutraler to supporter, neutraler to opponent. However, there may be a case that the user changed the stance multiple times. Such as opponent to neutraler to supporter then neutraler.

7.2 RQ 2. How does the sentiment toward anti-racism movement of the supporters and opponents differ?

Among 15 topical words, the author of this study chose one important aspect, which is representing each topic in table 2. Using 9 aspect words, aspect-based sentiment analysis was explored on supporters of the protest and opponents of the protest. 1,761 supporters posted 1,792 tweets and 16,319 opponents posted 17,239 tweets. Table 3 describes the result of sentiment scores with respect to chosen aspects.

	Neutral	Negative	Positive
murder (Topic 1)	0.38	0.19	**0.42**
black (Topic 2)	**0.46**	0.26	0.27
peac (Topic 3)	0.22	**0.52**	0.27
loot (Topic 4)	0.30	**0.45**	0.24
justic (Topic 5)	0.17	**0.50**	0.33
violenc (Topic 6)	0.12	**0.64**	0.24
happen (Topic 7)	**0.45**	0.33	0.22
white (Topic 8)	**0.43**	0.32	0.25
antifa (Topic 9)	0.24	**0.42**	0.34

Table 3: The average score of sentiment for aspects from supporters' tweets. The score is rounded off to second decimal digit.

Overall, tweets of supporters show negative more on the aspects, such as *peac*, loot, *justic*, *violenc*, and *antifa*. The results in Table 3 indicate that supporters of the protest also show negative sentiment to looting and violent situation. This may imply that the supporters of the protest also show sympathy toward those who are attacked by violence during the protest. Similarly, for the possible involvement of antifa, (Cummings and Phillips, 2020) the supporters expressed negative sentiment when antifa was involved. Contrariwise, only *murder* has the higher positive score, meaning the tweets relevant to murder contains more positive sentiment toward the protest. This may have to do with the death of George Floyd and supporters may have related the death of George Floyd with a possible chance of the change of system. For the race-related aspects; *black* and *white*, the supporters expressed neutral sentiment to the race. Also, as *happen* is more closer to delivering information in the twitter network, this aspect was more discussed in neutral sentiment from supporters of the protest.

Table 4 summarizes the average score of sentiment for aspects from opponents' tweets. The

	Neutral	Negative	Positive
murder (Topic 1)	**0.40**	0.22	0.38
black (Topic 2)	**0.51**	0.33	0.16
peac (Topic 3)	0.22	**0.54**	0.24
loot (Topic 4)	0.30	**0.44**	0.26
justic (Topic 5)	0.19	**0.52**	0.29
violenc (Topic 6)	0.13	**0.62**	0.24
happen (Topic 7)	**0.45**	0.32	0.23
white (Topic 8)	**0.43**	0.39	0.18
antifa (Topic 9)	0.25	**0.42**	0.34

Table 4: The average score of sentiment for aspects from opponents' tweets. The score is rounded off to second decimal degit.

opponents of the protest show similar sentiment to the aspects. For *black*, *white*, *happen*, the major sentiment was neutral, suggesting that there was no significant difference in sentiment across supporters and opponents. Both supporters and opponents mostly shared neutral sentiment toward black community and white community. However, a slight difference was observed that opponents have a higher average negative sentiment score than supporters with the margin of 0.04 for *white* and 0.07 for *black*. For *peac*, *loot*, *justic*, *violenc*, and *antifa*, the major sentiment expressed by opponents was negative. Plus, there was no significant differences across sentiment from supporters and opponents when they talk about the aspects above. Both supporters and opponents expressed negative sentiment toward *peac*, *loot*, *justic*, *violenc*, and *antifa*. This may indicate possible caveats in analyzing the stance with sentiment analysis. Although both sides are showing the similar magnitude of sentiment, supporters and opponents are not agreeing on the controversial issue. On the other hand, *murder* was the only aspect where the majority of supporters and opponents show different sentiments. There were more supporters positive to the aspect *murder* while more opponents were neutral to the aspect *murder*.

8 Conclusions and Discussions

Adopting ABSA to the social movement and leveraging tweets posted over the course of the protest at scale, this study attempted to answer the fluctuation of the stance and explore how many of the users change the stance. Corroborating the argument of the anti-racism movement experienced the change of the stance, (Dincelli et al., 2016), this study supported that the protest is far from plain and monolithic. In this study, supporters of the protest and opponents of the protest do not show significant differences in sentiment toward the aspects. This may suggest that there is a caveat in heuristic approach that classifies the stance of the users. Gao et al. (2018) classified the stance of the users by emoticon they use to express their opinion to news articles. Also, Dincelli et al. (2016) used sentiment polarity to distinguish whether the user is in favor to the protest or against to the protest. However, the findings of this study suggest that the sentiment toward the protest may not mark the stance differently: the sentiment and the stance may not be congruent. Therefore, we need to give a caution to relate sentiment and stance of the text.

9 Limitations

The first limitation of this study arise from data annotation process. Ground truth data consisted 200 samples of the whole dataset, which is insufficient to use as a training dataset. Also, stance labeling has been done solely by the author of this study, not taking possible interpretations of the stance into account. Thus, as introduced in the Validation section, the classifier returned false positives and false negatives, which makes the critical caveat of this study. False positives and false negatives makes the findings of this study dubious if the predicted stance of the tweet is incorrect. However, due to the volume of the data, it was hard to manually validate all the tweets. Also, as this study relies on a simple calculation of similarity score, this study does not show the margin between sentiment across supporters and opponents is meaningful or not. For instance, *black* has a higher negative score from opponents than supporters by the margin of 0.07. Lack of statistical validation led lack of statistical inference of the study.

References

Christos Baziotis, Nikos Pelekis, and Christos Doulkeridis. 2017. Datastories at semeval-2017 task 4: Deep lstm with attention for message-level and topic-based sentiment analysis. In *Proceedings of the 11th international workshop on semantic evaluation (SemEval-2017)*, pages 747–754.

Noel Cass and Gordon Walker. 2009. Emotion and rationality: The characterisation and evaluation of opposition to renewable energy projects. *Emotion, Space and Society*, 2(1):62–69.

Yong Chen, Hui Zhang, Rui Liu, Zhiwen Ye, and Jianying Lin. 2019. Experimental explorations on short text topic mining between lda and nmf based schemes. *Knowledge-Based Systems*, 163:1–13.

Andreas van Cranenburgh. 2018. Active DOP: an active learning constituency treebank annotation tool. In *Proceedings of the 27th International Conference on Computational Linguistics: System Demonstrations*, pages 38–42, Santa Fe, New Mexico. Association for Computational Linguistics.

William Cummings and Kristine Phillips. 2020. Trump says he'll designate antifa a terror organization, blames group for violence at george floyd protests.

Ersin Dincelli, Yuan Hong, and Nic DePaula. 2016. Information diffusion and opinion change during the gezi park protests: Homophily or social influence? In *Proceedings of the 79th ASISamp;T Annual Meeting: Creating Knowledge, Enhancing Lives through Information amp; Technology*, ASIST '16, USA. American Society for Information Science.

Heather E Fields and Trishia E Shaw. 2020. Looting during a time of civil unrest affects pharmacies on the south side of chicago. *Journal of the American Pharmacists Association*, 60(6):e39–e40.

Mingkun Gao, Hyo Jin Do, and Wai-Tat Fu. 2018. Burst your bubble! an intelligent system for improving awareness of diverse social opinions. In *23rd International Conference on Intelligent User Interfaces*, pages 371–383.

Jeff Goodwin and Steven Pfaff. 2001. Emotion work in high-risk social movements: Managing fear in the us and east german civil rights movements. *Passionate politics: Emotions and social movements*, pages 282–302.

James M Jasper. 1998. The emotions of protest: Affective and reactive emotions in and around social movements. In *Sociological forum*, volume 13, pages 397–424. Springer.

Yohan Jo and Alice H Oh. 2011. Aspect and sentiment unification model for online review analysis. In *Proceedings of the fourth ACM international conference on Web search and data mining*, pages 815–824.

Daniel Lee and H Sebastian Seung. 2000. Algorithms for non-negative matrix factorization. *Advances in neural information processing systems*, 13:556–562.

Xin Li, Lidong Bing, Wenxuan Zhang, and Wai Lam. 2019. Exploiting bert for end-to-end aspect-based sentiment analysis. *arXiv preprint arXiv:1910.00883*.

Gilad Lotan, Erhardt Graeff, Mike Ananny, Devin Gaffney, Ian Pearce, et al. 2011. The arab spring—the revolutions were tweeted: Information flows during the 2011 tunisian and egyptian revolutions. *International journal of communication*, 5:31.

T Soni Madhulatha. 2012. An overview on clustering methods. *IOSR Journal of Engineering*.

Hee Min and Seongyi Yun. 2019. Role of social media and emotion in south korea's presidential impeachment protests. *Issues & Studies*, 55(01):1950002.

Saif Mohammad, Svetlana Kiritchenko, Parinaz Sobhani, Xiaodan Zhu, and Colin Cherry. 2016. Semeval-2016 task 6: Detecting stance in tweets. In *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*, pages 31–41.

Maria Pontiki, Dimitris Galanis, Haris Papageorgiou, Ion Androutsopoulos, Suresh Manandhar, Mohammad AL-Smadi, Mahmoud Al-Ayyoub, Yanyan Zhao, Bing Qin, Orphée De Clercq, Véronique Hoste, Marianna Apidianaki, Xavier Tannier, Natalia Loukachevitch, Evgeniy Kotelnikov, Nuria Bel, Salud María Jiménez-Zafra, and Gülşen Eryiğit. 2016. SemEval-2016 task 5: Aspect based sentiment analysis. In *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*, pages 19–30, San Diego, California. Association for Computational Linguistics.

Maria Pontiki, Dimitris Galanis, John Pavlopoulos, Harris Papageorgiou, Ion Androutsopoulos, and Suresh Manandhar. 2014. SemEval-2014 task 4: Aspect based sentiment analysis. In *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014)*, pages 27–35, Dublin, Ireland. Association for Computational Linguistics.

Alexander Rietzler, Sebastian Stabinger, Paul Opitz, and Stefan Engl. 2019. Adapt or get left behind: Domain adaptation through bert language model finetuning for aspect-target sentiment classification. *arXiv preprint arXiv:1908.11860*.

Chi Sun, Luyao Huang, and Xipeng Qiu. 2019. Utilizing bert for aspect-based sentiment analysis via constructing auxiliary sentence. *arXiv preprint arXiv:1903.09588*.

Derrick Bryson Taylor. George floyd protests: A timeline. *The new York Times*.

Jacquelien Van Stekelenburg, Bert Klandermans, and Wilco W Van Dijk. 2011. Combining motivations and emotion: The motivational dynamics of protest participation. *Revista de Psicolog´ıa Social*, 26(1):91–104.

Karin Wahl-Jorgensen. 2018. News media and the emotional public sphere— toward a typology of mediated anger: Routine coverage of protest and political emotion. *International Journal of Communication*, 12:17.