

#Criming and #Alive: Network and Content Analysis of Two Sides of a Story on Twitter

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ABSTRACT

On December 3, 2014, after a grand jury decided not to indict the white police officer in the death of Eric Garner, the social networking platform Twitter was flooded with tweets sharing stances on racial profiling and police brutality. To examine how issues concerning race were communicated and exchanged during this time, this study compares differences between tweets using two trending hashtags #CrimingWhileWhite (#cww) and #AliveWhileBlack (#awb) from December 3 through December 11, 2014. To this end, network and content analysis are used on a large dataset of tweets containing the hashtags #awb and #cww. Findings indicate that there are clear differences, both structurally and in linguistic style, between how individuals express themselves based on which hashtag they used. Specifically, we found that #cww users disproportionately shared informational content, which may have led to the hashtag gaining more network volume and attention as a trending topic than #awb. In contrast, #awb tweets tended to be more subjective, expressing a sense of community and strong negative sentiment toward persistent structural racism.

Keywords

Twitter, race, network, topic model, sentiment analysis

INTRODUCTION

On December 3, 2014, a grand jury decided not to bring charges for the death of an unarmed black man named Eric Garner, who was put into a chokehold by an NYPD officer in Staten Island, New York City. Following the verdict, individuals became active on Twitter in organizing and providing information about protests, as well as sharing their stances on racial profiling and police brutality.

Two instances of the latter were conveyed using hashtags (indicated by the # symbol), which were employed to organize and label communications around specific topics (e.g., the jury decision, racial profiling). The first came following the verdict on December 3rd when Jason Ross, a writer for the *Tonight Show*, tweeted the following: "OTHER WHITE PEOPLE: Tweet your stories of under-

*punished f-ups! It's embarrassing but important! Let's get #CrimingWhileWhite trending!"*¹ Other white-identified individuals began to share their stories of privilege experienced when dealing with the police. Shortly after, #cww became the number one domestic trending topic (i.e., ranked by Twitter's algorithm as the most popular hashtag) in Twitter and also trended worldwide².

While the ostensible motivations for #cww were to highlight racialized disparities in police treatment, the hashtag was criticized by commentators for aggrandizing privilege while obfuscating the significant issues people of color face. Ebony.com senior editor Jamilah Lemieux responded on December 4th, "*Hey Black folk, how have police treated you for being #alivewhileblack.*"³ Within minutes, hundreds of black-identified individuals had responded to Jamilah with their stories and retweeted others. The hashtag #AliveWhileBlack (#awb) became a domestic trending topic, albeit not number one or trending worldwide, such as #cww⁴. Commentators began to juxtapose the two hashtags and urged individuals to consider both in tandem as reinforcing the idea that police treatment differs based on race. Tweet examples include:

- *At 13 I stole a car with my friend...Only one charged was black. #CrimingWhileWhite*
- *Drove to Kroger to get mom Nyquil. Pulled over unexplained...4 backup cop cars #AliveWhileBlack*

Based on the origins to these hashtags and media framings of them as direct counterparts, we set out to explore whether there were significant differences between tweets with the #cww versus #awb hashtags. To accomplish this, we collected a large number of tweets (N=176,741) containing the hashtags #awb and #cww and analyzed them based on their network structure (n/w) and textual content. This paper addresses one of the first attempts to combine structural and textual analysis of tweets to compare directly the use of two hashtags. First, network analysis was

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¹ twitter.com/jasonjross/status/540259742073909248

² cnn.com/2014/12/04/us/criming-while-white-hashtag/

³ twitter.com/JamilahLemieux/status/540515291516907520

⁴ tt-history.appspot.com/

completed by mapping #cww and #awb n/w's based on how content was shared (i.e., retweeting, replying, or mentioning), and comparing the two network graphs (Wasserman & Faust, 2004). Second, we employed Natural Language Processing (NLP) inspired methods, including topic modeling (Blei et al., 2003) to understand the abstract themes expressed in these tweets, and sentiment analysis to demonstrate the differences in sentiments and linguistic style (Pang et al., 2002; Brubaker et al., 2012). In making these comparisons, we sought to address the following research questions:

RQ1. In what ways do the structural qualities of the retweet, mention, and reply networks of #awb and #cww differ?

RQ2. In what ways do the topical content of the tweets for each hashtag differ?

RQ3. In what ways do the sentiment content as well as the linguistic style of the tweets for each hashtag differ?

RQ4. Can we relate findings from structural (n/w) and content analysis to one another?

Implications of our findings are methodological and also conceptual in nature, in describing how individuals express race within this networking medium.

This paper is organized as follows. In the next section we discuss related research. Subsequently, we overview our data collection strategy, followed by a detailed analysis of differences in how content is exchanged based on both hashtags' network structures. The following section presents finer-grained content analysis using NLP methods that expands our understanding of the abstract themes and linguistic characteristics described in these tweets. We then end with future work and conclusions.

LITERATURE REVIEW

Three lines of research are directly relevant to our work: 1) studies on race and social media, 2) network analysis of Twitter users, and 3) analysis of language use in social media via topic modeling and sentiment analysis.

Research addressing the relationship between race and digital technologies spans academic disciplines. This research has argued that despite the relative anonymity afforded by specific contexts, racialized expressions of identity still permeate within digital platforms (see Nakamura & Chow-White, 2012). Examples include white flight from MySpace to Facebook (boyd, 2012) and the presence of Blacktags (i.e., racialized hashtags about black experiences) on Twitter (Sharma, 2012).

Researchers and commentators have noted that Blacktags have the opportunity to trend due to the specific networks enacted by their users (Manjoo, 2010), as well as the use of cultural signifiers such as repetition (Florini, 2014) and call and response (Thurston, 2010). These latter studies, which characterize race based on content exchanged, have been criticized as identitarian and do not consider how race might manifest itself based on the materiality of the

network (Sharma, 2012). This observation motivates our analysis of the n/w structures of #cww and #awb tweets.

From a network standpoint, social media researchers examine how individuals communicate information on Twitter to mobilize individuals to action. Mobilization efforts include politicians campaigning for votes (Larsson & Moe, 2012), activists coordinating protests (Lotan et al., 2011), and individuals disseminating information about natural disasters (Starbird et al., 2010). Findings from these studies suggest that activists, individuals, and bloggers use Twitter to annotate and curate content by replying, mentioning, and retweeting.

Researchers have analyzed language use in social media in many different settings. We will focus on the two types of analysis performed in this study, topic modeling and sentiment analysis. Topic models can leverage the capacity to collect and analyze large-scale data to discover the thematic structure of text and reveal the patterns of individual's behaviors. To this end, topic models have been successfully implemented to model perspectives in political debates (Lin et al. 2008, Hardisty et al., 2010), study the history of ideas (Hall et al., 2008), and analyze framing in ideological debates (Nguyen et al., 2013), to name a few. Sentiment analysis has been performed using linguistic pattern analysis, which provides information about the private states of individuals (i.e., subjectivity) by observing the use of linguistic features in the content (i.e., written text/social media communication) and constitutes a well-studied field in the Natural Language Processing (NLP) community (Pang et al., 2002; Liu, 2010). Researchers have also successfully applied quantitative analysis of linguistic patterns in social media research. For instance, Kivran-Swaine & Naaman (2011) detected expressions of joy and González-Ibáñez et al. (2011) identified sarcasm in Twitter. Another way to perform sentiment analysis is using the Linguistic Inquiry and Word count (LIWC) dictionary. For example, Brubaker et al. (2012) captured linguistic characteristics in messages posted in MySpace that describe emotional distress using LIWC variables. The authors argue that LIWC variables, such as greater use of singular pronouns, past tense verbs, negations, and higher word count, are strong markers for bereavement comments.

DATA COLLECTION

Data collection occurred between December 5 and December 11 for the periods of December 3 through December 11 using the Twitter Streaming API⁵. This API allows individuals to retrieve up to 1% of all Twitter data within the past seven days and was queried using the hashtags #alivewhileblack and #crimingwhilewhite. The corpus we collected constituted of N=196,552 unique tweets containing the hashtags #awb and #cww. From this corpus, 30.03% (n=59,026) tweets contained #awb only,

⁵ dev.twitter.com/streaming/overview

59.89% (n=117,715) contained #cww only, and 10.08% (n=19,811) contained both hashtags.

Given that we collected data over the period of seven days, we argue that the data collected provides an adequate representation of what was occurring between both hashtagged networks (Morstatter et al., 2013). For the current analyses, we did not include tweets with both hashtags due to the desire to differentiate between the hashtags. Therefore, we removed data containing both hashtags, resulting in a final corpus of N=176,741 tweets.

RESEARCH AND DISCUSSIONS

Findings will now be discussed, beginning with the structural analysis of the network, followed by topical and semantic analyses of the content exchanged.

Social Network Analysis

Social network analysis was performed to determine if there were significant differences between how individuals shared information when using the #cww versus the #awb hashtag. Studies on the materiality of digital media (see Sharma, 2012 and Gillespie, Bockowski, & Foot, 2014) argue that the elements comprising an online platform like Twitter (e.g., servers, code, 140 character limit, ability to retweet) influence how social processes and identities, such as race, are expressed on the platform. Therefore, these elements and their generative effects should be examined. Sharma (2012) identifies three elements that facilitate the emergence of Blacktags based on a materialist standpoint: 1) network structures, 2) trending algorithms⁶, and 3) tweet content, such as hashtags. Therefore, n/w analysis was performed to determine how network structure and content contributed to both hashtags becoming trending topics.

For this analysis, we used n₁=154,041 tweets, comprised of retweets, replies, and mentions. The other 42,511 tweets were original tweets and were therefore removed. Data was cleaned using Open Refine⁷. After cleaning, we then created a *user X user* graph in which each node, or actor in the network, was 1) a user who was retweeting, replying, or mentioning another user, and 2) a user who was being retweeted, replied to, or mentioned. The edges between the nodes were directed, which indicates the direction in which information was being disseminated within the tweets. For example, if *user a* retweets *user b*'s tweet, there was a directed edge between nodes *a* and *b* with the direction indicated from *a* to *b*. An edge pointing from *user a* to *user b* indicates an in-degree measure for *user b* (e.g., being retweeted) and an out-degree measure for *user a* (e.g., retweeting). Also, edges were weighted by the sum of edges between two nodes, signifying that if *user a* retweets *user b* ten times, the edge weight would be ten.

Table 1 denotes some basic centrality and clustering measures describing the #awb and #cww social networks,

respectively. These measures were calculated using the tnet package for weighted networks in R⁸. Minimum, maximum, and standard deviation are depicted in parentheses when appropriate.

	#awb	#cww
<i>Nodes</i>	17037	36209
<i>Edges</i>	32476	59279
<i>Avg. Wtd. Degree</i>	2.03	1.46
<i>Wtd. In-Degree</i>	(0, 867, 3421.50)	(0, 38, 5632.94)
<i>Wtd. Out-Degree</i>	(0, 273, 3421.41)	(0, 1910, 5633.03)
<i>Avg. Path Length</i>	4.77	1.45
<i>Network Diameter</i>	24	15
<i>Network Density (%)</i>	9.52%	3.59%

Table 1. Network characteristics of #awb and #cww

When comparing the two networks, it appears that each #awb user shares content or has their content shared 2.03 times on average by users in the network, while for #cww, content is shared per user about 1.46 times, as indicated by the weighted degree measure. However, this observation must be made with caution, given that the distributions divided by degree all experience high levels of variability, as indicated by their standard deviations and the skewed distributions of their kernel density plots (see Figure 1).

The kernel density plots of weighted in-degree distributions indicate that a small group of the same individuals using #cww had their content shared frequently, while a larger group of different individuals using #awb had their content shared less frequently. The opposite appears to be true when comparing weighted out-degree distributions. That is, a small group of the same individuals shared #awb content frequently, while a larger group of different individuals shared #cww content less frequently.

These observations suggest that in both networks, the influence of various actors varies greatly and, therefore, advantages related to influential positions within the network are unevenly distributed. Observations about the #awb network key into findings and arguments that Blacktags have the opportunity to trend based on specific network characteristics, specifically here, the utilization of repetitive tweeting by a smaller group of users to quickly accumulate tweet volume (Sharma, 2012). In contrast, the #cww network appears to have content shared by a larger number of different users. This sharing pattern may also contribute to the #cww hashtag trending, given that the content is shared by novel users over time.

⁶ See blog.twitter.com/2010/trend-or-not-trend

⁷ github.com/OpenRefine

⁸ cran.r-project.org/web/packages/tnet/index.html

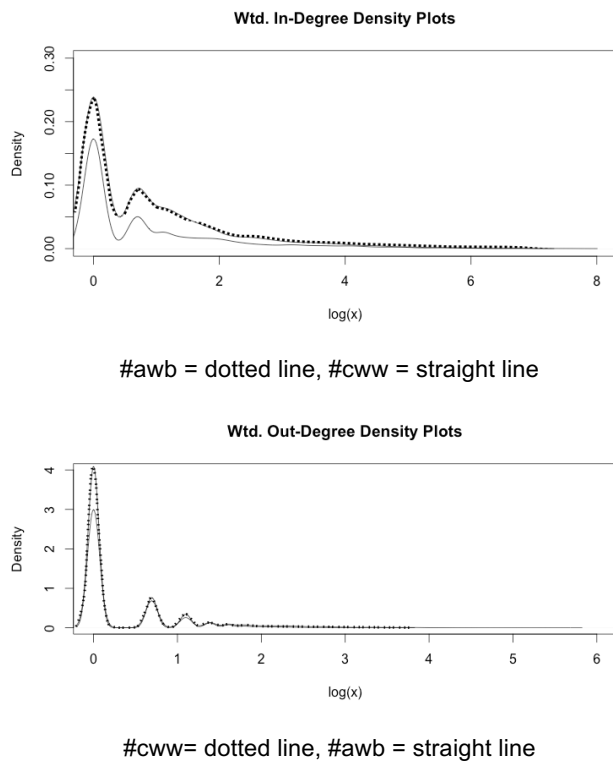


Figure 1. Kernel density plots

The average path length and network diameter contribute to these findings. Average path length is a measure that indicates the shortest path between two nodes. Although this path may not be taken in reality, this measure indicates how quickly it is possible to transfer information within the network, accounting for weight. On the other hand, network diameter represents the largest number of nodes that would need to be traversed to travel from one node to another. Both centrality statistics appear to suggest that the #awb network is more decentralized. In other words, it is more difficult for information to diffuse within the #awb network than in the #cww network. Although one must make the comparison between two networks of different sizes with caution, if anything, given the difference in network size one would expect larger average path length and network diameter values for #cww.

Network density, which measures the actual dyadic (i.e., between two nodes) connections in a network as compared to the potential connections, suggests a higher level of connections (~10%) fulfilled within the #awb network than the #cww (~3.59%). When compared to average path length and network diameter measures, this statistic suggests that

while the #awb network is denser, the actual connections made in the #cww network appear to be more productive in linking different users to one another indirectly. This observation suggests that certain #cww users have influential positions within the network that more easily connect them to many other users as compared to #awb.

The graphs of the networks, which were generated using Gephi (Bastian et al., 2009), also reveal differences in how the type of content exchanged varies based on one's prestige within the network. Figures 2 and 3 depict graphs of the #awb and #cww networks. For each figure, the weighted degree size has been filtered to include interactions of ten or more, and, therefore, the network graphs depict those who created or shared content using each hashtag the most. Nodes were sized based on weighted in-degree size. The graph structures reflect the centrality statistics discussed above. In particular, the #cww network has two dominant clusters, which are bridged by a series of users, while the #awb network is more disconnected.

Discussion of Network Analysis

Based on these findings, we can make some observations of why #cww was a more persistent trending topic than #awb over time. First, based on degree measures, we can see that while both hashtags experienced high levels of sharing volume, #cww tweets were shared by a larger number of novel users. In addition, when examining network centrality measures, findings indicate that it is easier to connect any two users across the #cww network than the #awb network. These observations key into what has been documented about the functioning of the trending algorithm in that it privileges not only tweet volume, but also the velocity in which tweets are shared by novel users (see footnote 6).

The type of content exchanged based on one's position within the network also may play a role in rendering trending topics. From observing the tweet corpus, we found that influential individuals with higher weighted degree measures in the #cww network tend to exchange URLs more often than in the #awb network. Comparing the proportion of content with URLs across #cww and #awb using a z-test indicates a statistically significant difference ($p < 0.01$) between 58% of individuals sharing URLs when using the #cww hashtag versus 27% using #awb.

Consider an example of a #cww tweet with a high in-degree measure:

- *#Crimingwhilewhite: White people are confessing on Twitter to crimes they got away with with <http://t.co/X1497fILIN> via @washingtonpost*

Using Naaman et al.'s (2010) typology, this tweet represents an instance in which the individual is providing information, rather than engaging in self-broadcasting, by sharing a news article. Given that Twitter functions as a network in which individuals rapidly disseminate and exchange news (Wu et al., 2011), #cww content may have experienced more sharing across the network based on its inclusion of information, as opposed to opinion⁹.

We report a similar outcome in a finer-grained analysis of the exchanged content. For instance, the word “confession” indicates that the individual tweeting is providing a report of a past act and eliciting others to provide similar reports. This individual is therefore also providing information as well as eliciting responses and sharing content within the actual message of the tweet. Given that Asur et al. (2011) argue that the content of what is being retweeted holds more importance than user attributes (e.g., number of followers), this finding motivates our research in the next section. Specifically, we will turn to empirical content analysis methods to further explicate the content of tweets based on the hashtags, with findings indicating that #awb tweets tend to be more subjective than their #cww counterparts.

TOPIC AND SENTIMENT ANALYSIS

Based on the network analysis of the users, we have shown a reliable method of distinguishing between individuals who posted, mentioned, and retweeted the #cww and #awb tweets. Our next objective is to analyze the tweets' content to discover whether there are specific linguistic patterns that may assist in further differentiating them. To this end, we propose various empirical approaches to discover thematic and linguistic characteristics of tweets for each hashtag.

Here, we first attempt to identify latent topics in the tweets to uncover the thematic similarities and dissimilarities between the two hashtags. Second, we identify linguistic expressions of individuals' private states by analyzing features such as sentiment expressions. Specifically, we utilize the MPQA subjectivity lexicon (Wilson et al., 2005), which provides a rich source of sentiment and subjective vocabularies. We also utilize the language analysis dictionary (LIWC; Pennebaker et al., 1997) that recently has been successfully utilized in exploring the linguistic style of social media content (Brubaker et al., 2012).

Identifying Latent Topics in Tweets

We utilize topic models, a popular statistical approach for modeling different characteristics of a collection of data, such as a Twitter corpus. A specific approach is a

⁹ We recognize that the use of words such as “information” and “opinion” can infer different value-based assessments of information. Our observations of objective or information-based versus subjective, or opinion-based content are made based on content analysis coding schemas, and are not intended to invoke any value judgments about the nature of the content itself.

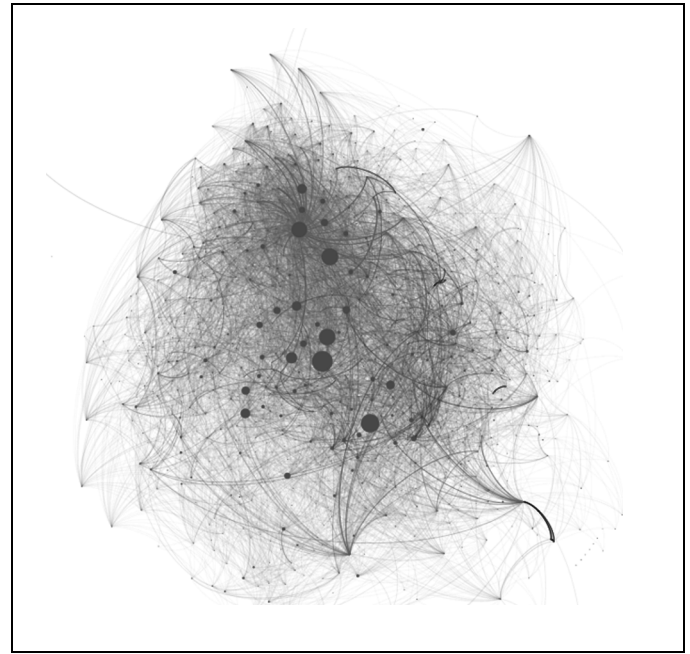


Fig. 2 #awb network, deg. ≥ 10 , Force Atlas Algorithm

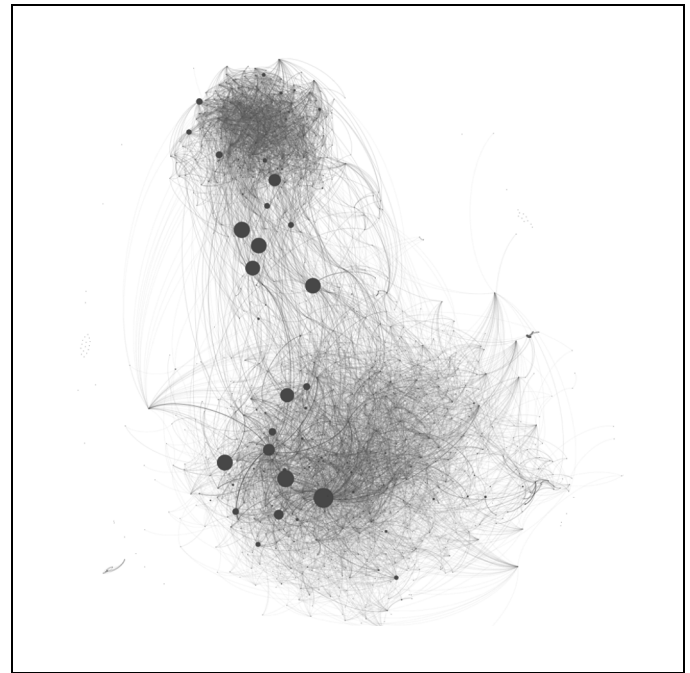


Fig. 3 #cww network, deg. ≥ 10 , Force Atlas Algorithm

generative model - Latent Dirichlet Allocation (LDA; Blei et al., 2011) – that effectively uncovers the “abstract” topics from a document collection. Here, each tweet is considered as a document in the LDA model. This model identifies topics in both sets of tweets and indicates whether they can be differentiated based on these discovered topics. Topic models function under the assumption that words are distributed according to a mixture of topics. A document, such as a tweet, is generated by selecting a topic with some mixture weights, drawing a word from the topic's word distribution, and then repeating the process. For details

about the generative process, topic estimation, and parameter selection, see Blei et al. (2011).

As stated earlier, we have collected 117,715 and 59,026 tweets that contain the hashtags #cww and #awb, respectively. After removal of the retweets, mentions, and replies, as well as tweets that are very short (e.g., tweets consisting of two words), we had 14,351 and 11,464 unique tweets for #cww and #awb, respectively. To these tweets, we applied standard tokenization using CMU’s Twitter Tokenizer¹⁰. To discover the thematic structure of the #cww and #awb tweets we employed LDA to build two separate topic models using a pre-specified number of topics. Given the relatively small size of these corpora, we empirically fixed the number to ten topics per corpus.

Tables 2 and 3 present examples of topics and associated words in each topic for #cww and #awb tweets. These words are chosen based on their high probability scores, as they are more likely to be associated with these topics. For the sake of brevity, only three exemplar topics per hashtag are shown. Despite their short length, #awb and #cww tweets had specific attributes identified by LDA, which corroborate that #awb users share more personal content while #cww users share more informational content.

An example of this difference is demonstrated in Topic 1, Table 2, which contains words related to societal privilege. The inclusion of these words indicates that individuals who posted tweets using #cww are aware of their privilege and further, that these tweets “confess” or remark on systemic racial bias. Topic 3, Table 2 also shows words related to the murders of Eric Garner and Mike Brown, as well as the Ferguson unrest. These topics are similar to those identified from #awb (Topic 3, Table 3) but with a noticeable difference. Whereas the #cww topic describes actions concerning crime (“crime,” “arrested,” “prison”), the #awb topic is more concerned with “discrimination” as well as the “ugly” nature of “justice.” Moreover, the majority of the #cww tweets are about only one kind of “crime,” related to speeding (Topic 2, Table 2). On the contrary, the #awb topic (Topic 2, Table 3) includes words related to speeding, as well as regarding discrimination and accusation. Thus, Topic 2 demonstrates that although users of #cww and #awb describe similar types of crimes, there is a stark difference between the words that describe the crime and its related acts. We also observe that #awb content describes other topics, such as discrimination-based practices. For instance, Topic 1, Table 3 depicts the experience of users who faced discrimination at work and school, and details how they discuss such discrimination with family and friends. This latter observation indicates another difference between the tweets, in that #awb tweets often use words related to family (“mom”, “dad”, and “neighborhood” are common words) whereas #cww tweets do not.

In summary, topic models uncover significant differences in #cww and #awb tweets. Further, even when the topics are similar (i.e., Topic 2 in Tables 2 and 3), they are described by different sets of words. In the next section, we capture fine-grained linguistic characteristics (i.e., sentiment expressions) by computing variables that capture the private states of Twitter users.

Topic1	Topic2	Topic3
white	cop	black
privilege	pulled	ericgarner
whiteprivilege	car	ferguson
livingwhilewhite	caught	crime
confessions	speeding	arrested
racial	drunk	charges
jury	police	death
bias	didn	kills
always	driving	prison
bragging	warning	mikebrown

Table 2. Examples of topics and the associated words with #cww (ordered by probability scores)

Topic1	Topic2	Topic3
black	cop	blacklivesmatter
school	pulled	icantbreathe
college	stopped	ericgarner
grade	asked	racism
nigger	searched	ferguson
work	neighborhood	discrimination
class	house	ugly
lady	reason	against
mom	discrimination	justice
friends	accused	mikebrown

Table 3. Examples of topics and the associated words with #awb (ordered by probability scores)

Sentiment Analysis of #cww and #awb Tweets

To study the sentiment content of the tweets, we utilized the MPQA subjectivity lexicon (Wilson et al., 2005), a rich source of sentiment and subjective vocabularies. MPQA contains English words that express sentiments (positive/negative/neutral/negation) as well as their degree of subjectivity (strong/weak). For instance, the word “racist” in MPQA is denoted as a word that expresses negative sentiment and strong subjectivity. Since many of the #cww and #awb tweets contain expressions of crime, discrimination, racism, and other negative situations, we are motivated by the question of whether the degree of negative sentiment differs between the hashtags.

To calculate the difference in negative sentiments within these two corpora, we first selected a random sample of 9,000 unique tweets for each hashtag. Then, using the MPQA corpus, we extracted words that express negative sentiment and computed their Relative Saliency (R.S.) (Mohammad, 2012) using the following equation:

¹⁰ ark.cs.cmu.edu/TweetNLP/

Relative Salience ($w \mid \#AWB, \#CWW$) = $f1/N1 - f2/N2 \dots$

$f1$ and $f2$ are the frequencies of w in the two corpora, whereas $N1$ and $N2$ represent total word count. Table 4 indicates the words that have highest R.S. in $\#awb$ as compared to $\#cww$ (left column) and in $\#cww$ as compared to $\#awb$ (right column).

#awb words	#cww words
black	drunk
discrimination	warning
ugly	weed
racism	crime
heartbreaking	stole
suspicious	confessions
prejudice	wrong
against	death
trying	confess
stolen	prison

Table 4. #awb and #cww words with highest R.S.

Words in $\#awb$ tweets express strong subjectivity (e.g., “heartbreaking”, “ugly”), presumably geared toward structural racism (as indicated by words such as “racism” and “prejudice”). Such sentiment is not present in $\#cww$ tweets, indicating that expression of sentiment is a strong indicator that distinguishes $\#awb$ tweets from $\#cww$.

In addition to sentiment, the linguistic style (e.g., pronouns, words expressing psychological processes) of the tweets also act as strong differential indicators. To analyze the linguistic style of the tweets, we utilize another lexical resource, Pennebaker et al.’s (2007) LIWC dictionary, which provides a dictionary for linguistic process (i.e., parts of speech and pronouns), psychological processes (e.g., social processes such as family; emotions such as anger), current concerns (e.g., work, religion, death), and spoken categories. For each category, LIWC provides a list of words that belong to that specific category. In the next section, we provide a detailed description of the analysis of $\#awb$ and $\#cww$ tweets with the LIWC resource.

Linguistic and Psychological Process Analysis

In the previous sections, we have shown that $\#awb$ and $\#cww$ tweets differ in their underlying themes as well as in expression of negative sentiments. Now, we will examine the underlying linguistic and psychological variables from the LIWC lexicon to determine whether there are distinguishable indicators for $\#awb$ and $\#cww$ tweets.

For LIWC analysis, we have used the same sample of 9,000 tweets for each hashtag as in the R.S. analysis. We represent each tweet as a feature vector where each feature encapsulates the frequency of occurrence of a LIWC category. LIWC (2007) contains 64 categories across the linguistic, psychological, and current process, and thus each tweet is represented with 64 feature values.

A test was run that compared the means of raw counts for each factor of the LIWC between the hashtags within the

sample. Given the non-parametric distribution of the variables, the Mann-Whitney U test was chosen as the appropriate statistical test. Since the distributions for each variable differed in distributional shape among hashtags, both mean and median ranks were compared based on the distribution for the specific feature vector.

For tests in which the variables had the same distribution across $\#awb$ and $\#cww$, “certainty”, “biological process”, “leisure”, “money”, and “assent” have no significant differences ($p < 0.01$) between their medians. For tests in which the variables did not have the same distributions across $\#awb$ and $\#cww$, almost all of the remaining variables experienced significant differences in their mean ranks. When comparing the differences in mean rank values of the variables, those with largest differences in mean ranks are “social process”, pronouns such as “2nd person”, “common (C.) verbs”, and use of the “past tense.” Categories like “quantifiers” and “exclusive” did not experience a significant difference in mean ranks. Tables 5 and 6 denote the five highest differences between mean ranks (M.R.) for $\#awb$ and $\#cww$. Column “id” indicates the LIWC category.

Id	Tag	M.R.	Diff. M.R.
<i>Ingestion</i>	$\#cww$	7074.91	148.82
	$\#awb$	6926.09	
<i>Death</i>	$\#cww$	7067.56	134.22
	$\#awb$	6933.44	
<i>Imp. Person</i>	$\#cww$	7051.27	101.54
	$\#awb$	6949.73	
<i>Negations</i>	$\#cww$	7037.65	74.3
	$\#awb$	6963.35	
<i>Sexual</i>	$\#cww$	7036.08	71.17
	$\#awb$	6964.92	

Table 5. Top 5 mean rank differences for #awb

id	Tag	M.R.	Diff. M.R.
<i>Soc. Proc.</i>	$\#cww$	6220.2	-1560.6
	$\#awb$	7780.8	
<i>C. verbs</i>	$\#cww$	6394.5	-1212
	$\#awb$	7606.5	
<i>Work</i>	$\#cww$	6656.06	-688.88
	$\#awb$	7344.94	
<i>2nd Person.</i>	$\#cww$	6771.59	-457.81
	$\#awb$	7229.41	
<i>Family</i>	$\#cww$	6782.08	-436.83
	$\#awb$	7218.92	

Table 6. Top 5 mean rank differences for #awb

To capture the higher order interaction among the LIWC features we constructed three binary logistic regression models using the outcome variable (y) as 1 for #awb and 0 for #cww tweets. Model 1 analyzes linguistic processes; Model 2 assesses psychological processes; and Model 3 measures current concerns. Table 7 displays significance levels, odds ratios, β values and standardized errors for the variables in the logistic regression. For the sake of brevity, we have shown only those variables for which the p-values are most significant.

Feature	B	S.E.	Sig.	O.R.
<i>Interpt.</i>	-0.84	0.03	0	0.43
<i>2nd per.</i>	0.25	0.09	0.005	1.28
<i>C. verbs</i>	0.32	0.05	0	1.38
<i>Past tense</i>	-0.33	0.04	0	0.72
<i>Adverb.</i>	0.12	0.03	0	1.13
<i>Neg.</i>	-0.23	0.05	0	0.79
<i>Swear</i>	-0.22	0.08	0.003	0.8

Model 1

<i>Interpt.</i>	0.81	0.03	0	0.45
<i>Family</i>	0.26	0.02	0	1.67
<i>Anxiety</i>	0.61	0.13	0	1.83
<i>Sadness</i>	0.31	0.12	0.003	1.36
<i>Cogntv.</i>	-0.16	0.03	0	0.85
<i>Ingestion</i>	-0.96	0.19	0	0.38

Model 2

<i>Interpt.</i>	-0.21	0.02	0	0.8
<i>Money</i>	-0.35	0.04	0.34	0.97
<i>Home</i>	0.51	0.1	0	1.67

Model 3

Table 7: Details for Binary Logistic Regression Models

Model 1 denotes that categories such as using the 2nd person pronouns, common verbs, and adverbs have more of a tendency to be associated with #awb tweets. On the contrary, using the past tense, making negations and swearing are more likely to be found within #cww tweets. This finding is expected as the majority of the #cww tweets involve individuals confessing privileged experiences. Model 2 demonstrates that words mentioning family as well as negative emotions like anxiety and sadness experience higher levels of use in #awb tweets, whereas words that represent cognitive processes, sexual behaviors, and ingestion (i.e., words expressing drinking alcohol and smoking) are related to #cww tweets. Finally, Model 3 shows that words regarding “family” are more associated with #awb tweets.

Discussion on Linguistic Characteristics

In the previous sections, we demonstrated that there are

significant differences in both the topical content and linguistic style of #awb and #cww tweets. Specifically, #cww users tend to provide content informing others about an instance of experienced privilege, whereas #awb users tend to express more subjective, personal content related to emotions and a sense of experienced community.

The higher use of pronouns (2nd person), R.S., and LIWC categories demonstrates these differences. In regard to the former, we observe that many #awb tweets use 2nd person pronouns (“you”, “you’d”) to report their experience of racial profiling (e.g., *cop asked “what are you doing in this neighborhood?”*). Moreover, #awb tweets describe an orientation toward community via the use of words such as “neighbor,” “girlfriend,” and “friend” (e.g., *“Pulled over while jogging in my own neighborhood”*) and thus LIWC categories like “family,” “social process,” and “home” are more associated with #awb.

Words with the highest R.S. in #cww tweets detail actions surrounding crimes and police action (or rather, inaction) toward these crimes, rather than any specific experience of experiencing discrimination. On the other hand, words that have the highest R.S. in #awb clearly express strong subjectivity (e.g., high use of words such as “ugly”) toward social institutions (e.g., high use of words such as “racism,” “discrimination,” and “prejudice”). Finally, LIWC categories expressing negative subjective emotions, such as “anxiety” and “sadness”, are more present in #awb tweets, while words that express “negations” and “ingestion” are more likely to be associated with #cww tweets. In addition, the “causation” category is more likely to be associated with #cww tweets since these tweets often explain the actions taken by the police (e.g., *“i got out of a DUI because i was wearing a military dogtag...”*). Language styles that utilize more “adverbs” and “conjunctions” are also more associated with #awb tweets, an observation similar to one made by Brubaker et al. (2012).

Social identity theory (Tajfel, 1978) provides a means to account for the strong presence of community-oriented words and negative sentiment among the #awb tweets. According to this theory: “a social identity is a person’s awareness of belonging to a social category or group, together with the value and emotional significance of belonging.” (Tajfel, 1978). It can be measured based on self-identification as a member of a particular group and experience of an affective commitment (i.e., feelings of strong ties and affinity) for this group. Within that group, individuals also exercise a certain level of group self-esteem (i.e., attitudes toward the group). Self-identification and commitment, coupled with group self-esteem are not necessarily positively related, particularly among minority groups, who might feel strong ties to their communities, but exhibit low self-esteem due to discrimination (e.g., internalized racism) (Stets & Burke, 2000). However, previous research has shown that among black individuals, specifically African Americans, this relationship is often

positively related (Hughes et al., 2015). Our analyses indicate similar findings that self-identification and commitment among #awb users seem to relate positively to group self-esteem. Specifically, #awb users expressed affinity toward their racial group (indicated by words such as “family” and “home”), and also appeared to feel positively about being part of this group, as indicated by the presence of words implying the wrongness of police treatment toward them (e.g., “ugly,” “heartbreaking,” “racism”). In other words, #awb users were not exhibiting internalized racism in their tweets, but rather expressed recognition of the pervasive, institutionalized racism undergirding their treatment by the police.

CONCLUSION AND FUTURE WORK

Based on the findings from the n/w and content analysis, it is clear that there are differences between both how content is shared within both hashtag networks, as well as between the textual content within both hashtags. Using perspectives of materiality and social identity theory, we have attempted to explain these differences as due to both how tweets circulate within a Twitter network (i.e., via the popular practice of sharing informational content), as well as based on #awb users’ positive conceptions of their racial group self-identification, affinity, and group self-esteem.

This study was not without limitations. Through the use of the streaming API, sampling of tweets is not guaranteed to be random. However, given the large sample size and findings from past research (Morstatter et al., 2013), we believe that our dataset constitutes a representative sample of the communications at this period. Also, we did not consider external factors, such as mass media coverage and user profile information, in our discussion of why certain tweets might have been shared more within the networks. Future research should address these factors by performing predictive modeling of content sharing using metadata provided by the Twitter API (e.g., number of followers) and media coverage as predictors.

Additional areas for future work include examining the co-location of hashtags. When performing exploratory network analysis, we observed that when we highlighted areas of the network including the combined use of #awb and #cww, they appeared to provide a significant bridging role between the two largest #cww sharing networks (see Figure 2). This observation suggests that there is some importance to combining both hashtags within the #cww network, and we would like to explore this importance using content analysis in the future, particularly given the role the hashtags perform in calling attention to their juxtaposition, as indicated by the following example:

- #CrimingWhileWhite & #AliveWhileBlack illustrate two different Americas that exist but shouldn't. Take the time to read some of the tweets

We also found that individuals used #awb and #cww in concordance with other hashtags, such as #EricGarner and #ICantBreathe. Based on the transitory and

transformational nature of hashtags, we wonder whether the use of certain hashtags spread over time based on their introduction within a Twitter network, and which hashtags tend to co-occur.

Although a large number of studies on Twitter have emerged in the past few years, only recent research has begun to examine specific elements of the site, whether it is a particular group of users or type of content shared. Our research contributes to these studies by examining specific hashtags from two different, racialized expressions, #cww, and #awb. Our findings indicate that the ways in which race is generated on Twitter differs based on how these expressions interact with its structural and semantic mechanisms. Rather than viewing race on social media as fixed, our use of network and content analysis indicates that race expressed on social media is complex and subject to change based on system and network affordances.

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