Mapping Social Movements: User Network Analysis of Black Lives Matter and its Countermovements

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***Abstract*—This paper explores user networks of Black Lives Matter and its countermovements on Twitter. Building upon the previous studies that compare these countermovements, our analysis delves into the cohesion of distinct sub-groups within each movement. Findings reveal varying levels of sub-group interaction, inversely related to movement breadth i.e. more fragmented community structure for All Lives Matter and White Lives Matter in comparison to Police & Blue Lives Matter. In addition, temporal analysis indicates that the sub-group interactions within these sub-communities changes during the protests following the murder of George Floyd.**

***Index Terms*—Social Network Analysis, Black Lives Matter, Social Movements, All Lives Matter, Blue Lives Matter, White Lives Matter**

I. Introduction and Prior Work

The increasing use of social media has provided an opportunity for social movements to convey their messages, gather support, and raise awareness. An important case is the Black Lives Matter movement, which has been active on Twitter particularly active after tragic murder of George Floyd on May, 25 2020. This surge in support has also raised responses from various groups in the form of countermovements, such as All Lives Matter, Blue Lives Matter, and White Lives Matter. Scholars utilized both qualitative and quantitative techniques to analyze the general themes, framing of the problems, and communication strategies for BLM and its countermovements [1]–[6]. Among those, the ones using computational methods use social media for a variety of analyses, such as hashtag co-occurrence networks, user-retweet networks, time series analysis, etc. For example, Ince and colleagues [4], analyzed how user interactions change the framing of BLM movement using a combination of qualitative analysis as well as temporal changes and the co-occurrence network of hahstags. Klein and colleagues [5] take a different perspective and analyze how distinct subgroups in the retweet networks interact with each other and how quickly the sub-groups attention diminishes with respect to George Floyd protests. The authors also apply topic modeling, a natural language processing methodology used to obtain general themes that are present in text-based data, and analyze how the presence of different themes changes during the protests. One closely related study that utilizes a similar methodology, not to BLM but to its countermovements, is the comparison of countermovements with respect to the diversity of topics that they encompass and the continuity of the claims raised by its supporters [6]. Taraktaş and colleagues conclude that broader definitions, like "All Lives Matter," tend to attract a more diverse range of supporters (from religious groups to animal rights activists), although these supporters may not consistently advocate for the causes raised by the movement compared to movements with narrower definitions, like Blue or Police Lives Matter [6]

While prior research has examined how movements and countermovements relate in terms of problem framing and temporal patterns [1]–[3], there remains a gap in understanding their differences at the user network level. Additionally, countermovements that share the "Lives Matter" (LM) label offer a unique opportunity to investigate how a movement's definition affects its ability to mobilize support. Although [5] covers sub-group interactions within BLM and [6] analyzes different topics covered in each countermovement, no research has delved into a user-level analysis of how distinct communities interact within the countermovements.

In this paper, we aim to address these gaps by first comparing three countermovements: All Lives Matter (ALM), Police-Blue Lives Matter (P-BLM), and White Lives Matter (WLM). The analysis includes the Black Lives Matter (BLM) movement to explore whether there are significant differences in how users interact within the original movement compared to countermovements. Finally, the paper concludes with an analysis of temporal changes in these networks with respect to the protests following the tragic killing of George Floyd.

II. Approach

TABLE I
Number of filtered and total tweets for each movement.

	ALM	P-BLM	WLM	BLM
Initial	365,983	243,336	99,903	5,961,970
Filtered Tweets	33,975	27,164	22,959	464,301
After Filter	332,008	216,172	76,944	5,497,669

A. Data Collection

To analyze the user networks in social movements, a dataset containing tweets posted between January 1, 2020, and December 31, 2021 has been utilized for Black Lives Matter and countermovements (All LM, Blue LM, Police LM and White

LM) using the query terms as hashtags of movement names (e.g., #BlackLivesMatter or #BLM). As the spammers were identified in the preliminary analysis, a simple spam filter was employed, which excluded tweets displaying identical textual content from the same author. In addition, PLM and BlueLM datasets merged due to their thematic similarities. The resulting number of tweets is shown in Table I .

B. User Networks

To analyze whether two users support the same idea or not, hashtags are chosen as the unit of analysis, as it is often that activists convey their messages through hashtags [7]. The hashtags containing the movement names are excluded since the data set is constructed using the same logic, which would result in a trivial case where every node is connected. Therefore, in the constructed network, users are represented as nodes, and there exists an edge between two users if they both supported at least one common hashtag. The edges are weighted according to the number of unique hashtags supported by both users.

Given the size of the data set, to alleviate the computational complexity, we randomly sample 10,000 authors from each movement and extract all tweets posted by these authors, subsequently constructing the networks using this subset of tweets. The sampling has been done randomly as each movement has a different composition, and other sampling methods, such as sampling among users that tweeted at least some threshold value might be biased with respect to the movement.

C. Community Detection and Graph Visualization

After constructing networks, five community detection algorithms are employed using igraph library for Python: Leiden [8], Louvain [9], Infomap [10], Walktrap [11], and Label Propagation [12]. As evident from Table II, Louvain resulted in the highest modularity value for each dataset which is utilized to detect communities. Then, the communities that are larger than 1% of the total size are visualized using Gephi.

TABLE II
MODULARITY SCORES FOR DIFFERENT COMMUNITY DETECTION ALGORITHMS.

	ALM	P-BLM	WLM	BLM
Leiden	0.159	0.134	0.145	0.119
Louvain	0.496	0.371	0.547	0.379
Infomap	0.482	0.348	0.510	0.323
Walktrap	0.461	0.303	0.504	0.322
Label Propagation	0.073	0.307	0.525	0.270

To assess the connectedness of each community with the rest off the users, an additional measure EI index is calculated for each community. Instead of the regular definition of Krackhardt E/I Ratio [13], EI index is calculated as:

$$EI \text{ Index} = \frac{I}{E+I} \tag{1}$$

where I is the sum of weighted edges within community and E is the sum of weighted edges with the other communities. Therefore, the index takes values between [0,1], zero meaning all interactions are with the users outside of the community, and one meaning all interactions are within the community.

III. RESULTS

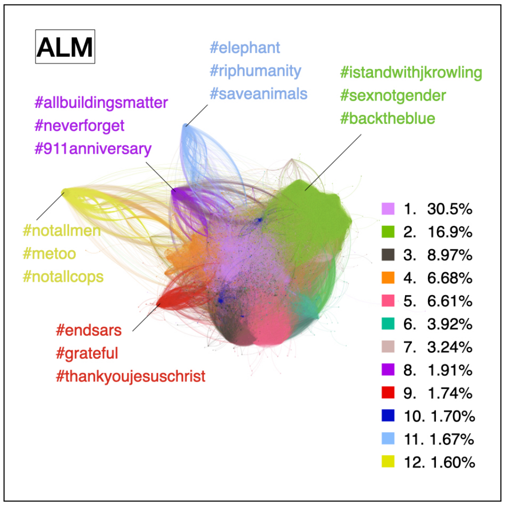
A. User Communities

Table III shows the communities that have a larger size than 1%, their fractional sizes, calculated EI Index values, and the most frequent hashtags that are utilized within each community. In addition, Fig. 1 presents the network visualizations obtained by the "Force Atlas 2" layout in Gephi, which incorporates a spring-based layout assuming a repulsive force between all nodes and a proportional attraction of connected nodes with respect to edge weights. Thus, the visualizations as well as the EI Index values aid in determining communities that are separated from one another.

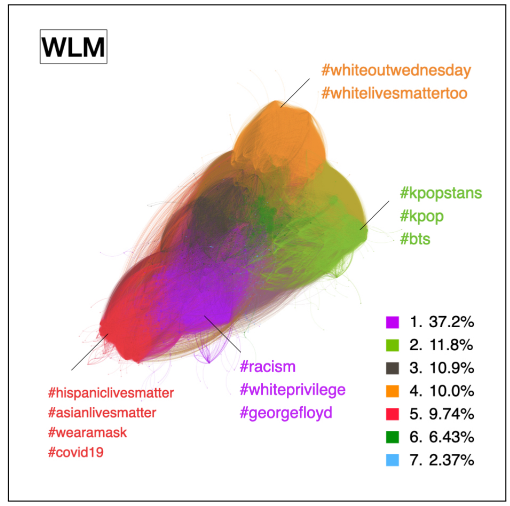
TABLE III
FRACTIONAL SIZES, EI INDICES AND THE MOST FREQUENT HASHTAGS USED IN EACH COMMUNITY

ALM	**Size**	**EI**	**Hashtags**
1	30.5%	0.67	#justsayin, #thruthmatters, #americafirst
2	16.9%	0.85	#istandwithjkrowling, #sexnotgender
3	9.0%	0.53	#justiceforgeorgefloyd, #policebrutality
4	6.7%	0.67	#asianlivesmatter, #muslimlivesmatter
5	6.6%	0.73	#georgefloyd, #icantbreathe
6	3.9%	0.62	#blackouttuesday, #blackoutday
7	3.2%	0.58	#prolife, #nolivesmatter, #allvotesmatter
8	1.9%	0.84	#allbuildingsmatter, #911anniversary
9	1.7%	0.78	#endsars, #grateful, #thankyoujesuschrist
10	1.7%	0.52	#justiceforgeorge, #qanon, #childtrafficking
11	1.7%	0.87	#elephant, #riphumanity, #saveanimals
12	1.6%	0.95	#notallmen, #metoo, #notallcops
P-BLM	**Size**	**EI**	**Hashtags**
1	53.0%	0.64	#backtheblue, #police, #thinblueline
2	16.4%	0.72	#maga, #trump2020, #maga2020
3	15.9%	0.80	#backtheblue, #livepd, #policewifelife
4	3.1%	0.62	#whiteoutwednesday, #kpopstans
WLM	**Size**	**EI**	**Hashtags**
1	37.2%	0.77	#racism, #whiteprivilege, #georgefloyd
2	11.8%	0.78	#kpopstans, #kpop, #bts
3	11.0%	0.69	#maga, #trump2020, #maga2020
4	10.0%	0.83	#whiteoutwednesday, #whitelivesmattertoo
5	9.7%	0.83	#hispaniclivesmatter, #asianlm, #covid19
6	6.4%	0.56	#whitelivesmattermore, #whitelivesmattertoo
7	2.4%	0.52	#trumpout2020, #junkterrorbillnow
BLM	**Size**	**EI**	**Hashtags**
1	54.6%	0.62	#racism, #defundthepolice, #georgefloyd
2	12.1%	0.76	#justiceforfloyd, #justiceforbreonnataylor
3	11.7%	0.67	#georgefloyd, #breonnataylor, #icantbreathe
4	7.2%	0.57	#raisethedegree, #vidasnegrasimportam
5	3.9%	0.52	#blackouttuesday, #blackoutday2020

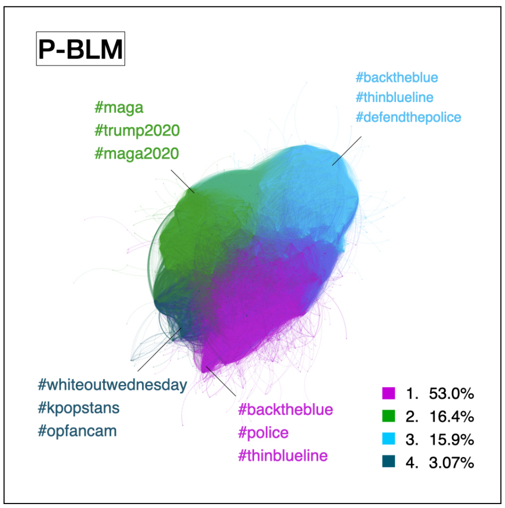
Firstly, considering Table III and Fig. 1, ALM and WLM present a fragmented view characterized by numerous communities of smaller sizes, whereas P-BLM and BLM have a small number of distinct sub-groups with comparatively larger sizes. Additionally, considering the EI Index values, ALM and WLM have a higher count of communities with high EI Index values, some reaching as high as 0.95, indicating the level of segregation of some communities from the rest of the user groups. In fact, a weighted average of EI Index values



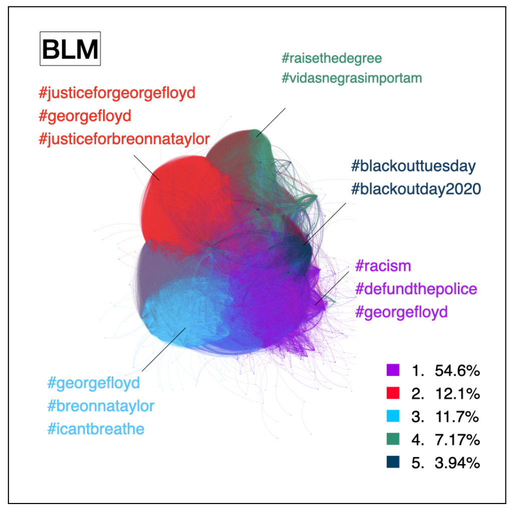
(a) ALM Communities larger than 1%



(b) WLM Communities larger than 1%



(c) P-BLM Communities larger than 1%



(d) BLM Communities larger than 1%

Fig. 1. Resulting communities larger than 1% using the Louvain Community Detection Algorithm (a) All Lives Matter, (b) White Lives Matter, (c) Police & Blue Lives Matter, and (d) Black Lives Matter. For ALM and WLM, the most frequent used hashtags are shown for communities that have larger than 0.75 EI Index value. For P-BLM and BLM, the most frequent hashtags used by all communities are shown.

using fractional sizes of the communities as weights reveals a descending order of EI Index values as follows: WLM (0.753), ALM (0.702), P-BLM (0.683), and BLM (0.637).

In the context of ALM, separated subgroups span topics like gender, animal rights, religion aligning with the previous findings utilizing topic modeling to obtain the different themes on Twitter for ALM supporters [6]. However, the user groups supporting these diverse causes seem to be isolated from the rest of the network as illustrated in Figure 1.a. The level of isolation is also evident in III since all of these communities exhibit EI Index larger than 0.75. Notably, 8th community stands out by using the hashtag #allbuildingsmatter which is used by users on the anniversary of the 9/11 attacks to point out the insensitivity and inappropriateness of countering BLM with the phrase ”All Lives Matter”. Therefore, distinct communities are not necessarily reflect supporters but also may contain opposing groups which are naturally separated from the rest of the users. A few communities exhibiting stronger relationship with other user groups i.e. communities having smaller EI Index values, cover more central topics such as abortion, politics, Asian and Muslim minorities, right-wing conspiracy theories, and Floyd protests.

Parallel to the ALM, White Lives Matter contains several sub-groups with a larger EI index than 0.75, spanning various themes such as racism, other minorities, K-Pop (Korean Pop), and George Floyd. Among these, the first two communities seem to correspond to opposing user groups that use the WLM hashtag to raise opposition to the hashtag itself. The first community highlights George Floyd and uses specific framing such as ”privilege” and ”racism,” indicating an opposition to White Lives Matter. On the other hand, the second one represents the K-Pop community that collectively posted various memes and

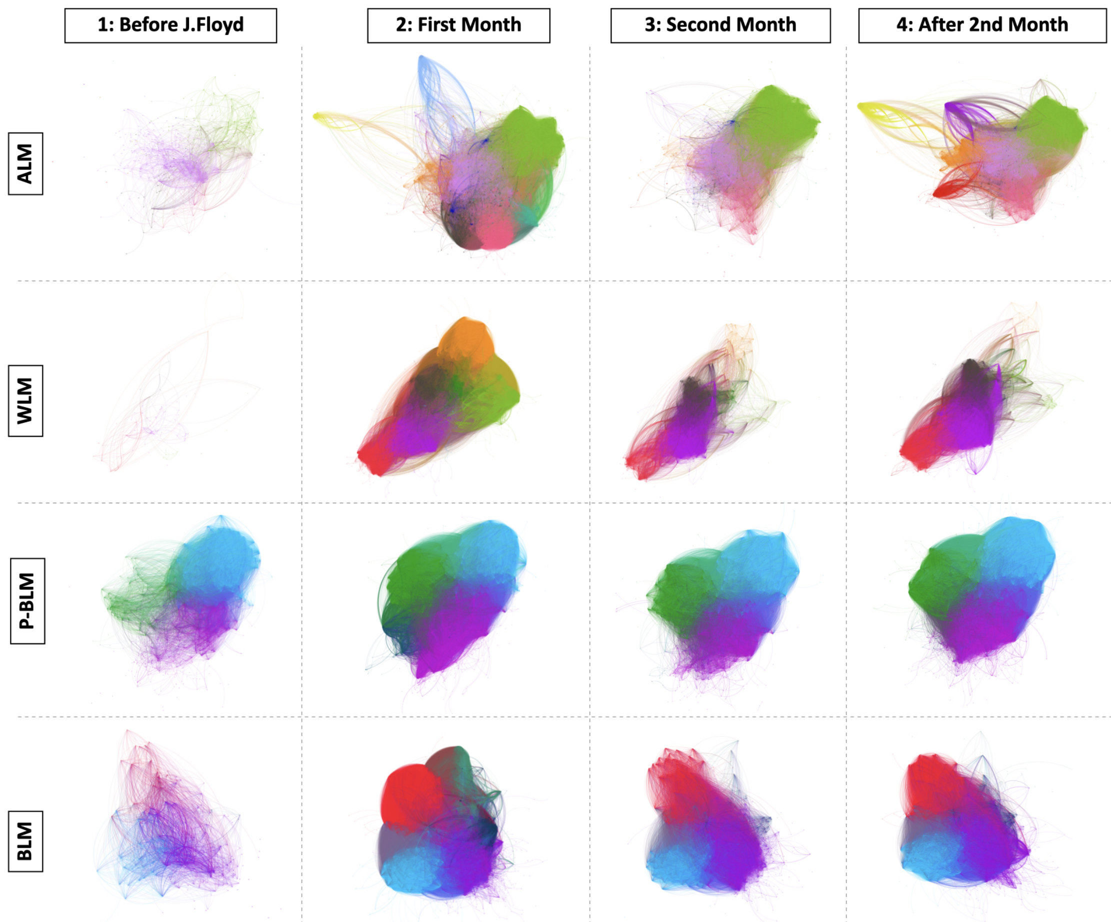


Fig. 2. Resulting communities for each movement in four different time periods: Before George Floyd protests, the first month of the protests, the second month of the protests, and after the second month of the protests.

audiovisuals of famous Korean Pop artists to spam the WLM hashtag during the peak time of the hashtag. A similar activity of such users, with considerably smaller size, is also evident in the 4th cluster in Police-Blue Lives Matter (Table III). Therefore, having the largest two user groups from possibly opposing sides, WLM seems to fail to construct a strong supporter base as opposed to the other two countermovements. The non-isolated community structures with lower EI indices are only evident for a few topics, such as 2020 elections, MAGA (Make America Great Again), and hashtags supporting white supremacy.

For Police and Blue Lives Matter, only the third community has a higher EI index than 0.75. However, upon considering the corresponding hashtags, they are still covering issues related to support for the police and the daily experiences of law enforcement officers. Hence, despite the distinct hashtags within the community, the topics covered in each sub-group do not extend beyond the existing theme; rather, they present a different view of the same issue.

Finally, Black Lives Matter presents the most mixed community structure as it has the least EI value on average. Only community with a high EI index, the second one, solely focuses on black victims George Floyd and Breonna Taylor. Considering that the other communities also have similar hashtags supporting the similar issues, we can say that BLM presents the most united community in terms of supporting one another.

B. Temporal Changes with respect to George Floyd Protests

To analyze the user interactions over time, we divided the time horizon into four non-equal time periods spanning the days preceding George Floyd's incident on May 25, 2020, the first month of the protests (05/25/2020–06/25/2020), the second month of the protests (06/25/2020–07/25/2020), and after the protests (until Jan 01, 2022). Such an unequal time binning is determined by analyzing the daily posted tweets by each movement, which exhibits a significant increase after the incident. As a result, any change in the user interaction networks is likely to be observed during these times.

Fig. 2 depicts the user networks of ALM, WLM, P-BLM, and BLM over four different time periods. Networks for each period are obtained by inducing the nodes in the graphs obtained in the previous analysis into the authors who posted at least one tweet during the corresponding period.

WLM and ALM show little to no activity before the protests, as opposed to P-BLM and BLM showing moderate activity. Moreover, there are some distinct sub-groups in movements appearing in one period and disappearing in others.

It is natural to expect that communities that are solely concerned with George Floyd protests will appear in only the first month. For example, communities 4 and 5 in BLM (#raisethedegree, #blackouttuesday - a memorial event performed on tuesdays by turning out the light and music in the supporting businesses to commemorate the losses of the black community) and 3, 5, and 6 in ALM (#floyd, #blackouttuesday) seem to be prominent only in the first month. Moreover, the communities that are reacting to #blackouttuesday by using #whiteotwednesday, such as community 4 in P-BLM and WLM, also follow a similar temporal presence. Finally, the activity of "K-Pop" supporters in community 4 for P-BLM and 2 for WLM only appears in the first month of the protests since the activity of P-BLM and WLM supporters was at its peak during that period, which attracted an opposing action.

On the other hand, there are several other communities that have this transient characteristic but are not directly related to the protests, such as communities 11 (#saveanimals), 12 (#notallmen) in ALM, and 6 (#whitelivesmattertoo, #whitelivesmattermore) in WLM. Moreover, communities 8 (#allbuildingsmatter) and 9 (#endsars, #thankyoujesuschrist) in ALM appear in the post-protest period. Therefore, the distinct sub-groups corresponding to different topics in ALM also lack temporal consistency. Conversely, communities in P-BLM and BLM show consistent activity throughout the entire period.

IV. Conclusion and Future Work

In conclusion, we analyzed user contribution networks to hashtags for Black Lives Matter and its countermovements. The analysis indicates that countermovements show various patterns in terms of the user contribution to commonly used hashtags. Firstly, it is confirmed that the diversity of themes is highest in the ALM, followed by the WLM and P-BLM, in accordance with [6]. In our analysis, it was revealed that the number of distinct subgroups also has the same order: ALM has the highest number of small communities, followed by WLM and P-BLM. In addition, higher EI index values of subgroups in ALM and WLM indicate that these subgroups do not present a united picture when it comes to supporting the hashtags of one another. When we consider the temporal activities of these groups, they also lack temporal consistency, meaning that their activity peaks in different time periods. Conversely, P-BLM shows a more united picture, having a small number of large communities, and these communities show more consistent support throughout each time period. This complements the analysis in [6] suggesting that the broader the definition of the countermovement, i) the more diverse set of claims it includes, ii) the less consistent that these claims are being raised, and iii) the less coherent structure is present among the users supporting each diverse claim.

Among the countermovements, WLM seems to be the least effective since it shows almost no activity before the protests, and its largest two user communities are composed of users opposing the hashtag itself, as evidenced by the frequent hashtags they use and their diminishing after the first month of the protests. Lastly, considering the comparison of BLM with the countermovements, BLM has the lowest EI index value on average, indicating a more homogenous mixing between user groups, and user interactions stay the same during and after the protests, except in the few communities that are solely focused on the George Floyd protests, such as the community supporting #blackouttuesday hashtag.

All in all, the current analysis highlights important differences among countermovements and indicates the possible relationship of these community structures with respect to the scope of the countermovements. As a future work, one methodological extension might be utilizing "reply to" and "mention" networks instead of the commonly used hashtag networks. Another possible extension is the analysis of the important nodes, which can reveal whether the mobilization within each group is driven by political elites or a few influential accounts or whether it originates from the collectively distributed action of less central users.

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