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On Message Exchange Motifs Emerging during Human/Bot Interactions in Multilayer Networks: The Case of Two Riot Events

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***Abstract*—In this paper, we analyze the message exchange patterns that emerge when social bots and human users communicate via Twitter. In particular, we use a multilayer network to analyze the emergence of the corresponding representative and statistically significant sub-graphs (so called *motifs*). Our analysis is based on two recent riot events, namely the Philadelphia Superbowl 2018 riots and the 2017 G20 riots in Hamburg (Germany). We found that in these two events message exchanges between humans form characteristic and re-occurring communication patterns. In contrast, message exchanges including bots occur rather sporadically and do not follow a particular statistically significant pattern.**

***Index Terms*—motifs, multilayer network, social bots, Twitter**

I. Introduction

With about 330 million active users per month[1], Twitter is considered one of the most popular online social networks (OSNs) worldwide. With the increased use of OSNs in our daily life, these online platforms have become a vital part of our society with a potential to influence, inspire, and facilitate information seeking behavior, political actions, and societal movements [1].

In addition to human users, Twitter also enables automated accounts, so called *social bots* [2], to disseminate information via tweets[2]. For the year 2017, it has been estimated that 15% of all registered (i.e. active as well as temporarily inactive) Twitter accounts are bots [3] (resulting in roughly 49,5 million bot accounts). Recent studies have shown that bots exhibit behavioral patterns that are different from those shown by human accounts. In particular, they disseminate different emotions [4] and tend to retweet more, post more URLs, and form less reciprocal relationships [5], as compared to human accounts. In recent years, different scientific studies also found that bots actively participated in the OSN discussions related to important social events such as political elections (e.g., the 2017 German federal elections [6], or the 2016 US presidential elections [7]).

[1]https://about.twitter.com

[2]Originally, a *tweet* was a short message with a maximum length of 140 characters. In 2017, this limit has been lifted to a maximum of 280 characters per tweet.

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With respect to studying the role of bots in a Twitter discourse, existing studies have predominantly focused on the investigation of content-related features (such as the hashtag count, or the URL count), sentiment polarities and specific emotions conveyed in OSN messages, as well as the retweet rate of bot accounts, to name a few. However, the question remains, how does the messaging behavior of humans compare to the messaging behavior of bots on a structural level. A particular question is if distinct structural patterns emerge when humans and bots exchange messages.

In this paper, we study the *network motifs* that emerge when humans and bots directly exchange messages via Twitter. In 2002, Milo et al. [8] proposed network motifs as basic building blocks of complex networks. Since then, motifs have been applied to various biological networks (see, e.g., [9]). However, up to date, there is a lack of studies which apply network motifs to investigate communication patterns in OSNs, and in particular patterns that emerge when bots communicate with human users.

To study the characteristic subgraphs in bot-human communication networks, we analyze two real-world data-sets that have a potentially high involvement of bot accounts. In particular, we study message exchanges that happened during the 2017 G20 riots in Hamburg (Germany) and the 2018 riots in Philadelphia (Pennsylvania, US). We identified 2,970 bots from a pool of 26.5 thousand Twitter users that participated in the Twitter discussions on the two events. In our analysis, we found that human-to-human message exchange behavior can be characterized via significant and re-occurring structural patterns, while the same does not hold for bot accounts.

The remainder of this paper is organized as follows. In Section II we briefly repeat the basic network concepts used in our analysis, followed by a description of the events of study in Section III. Section IV describes our research method. We present the results of our analysis in Section V and further discuss the findings in Section VI. Section VII discusses related work. Section VIII concludes the paper and outlines directions for future work.

II. Preliminaries

The Twitter communication network forms a directed graph. We assume our graphs to contain multi-edges and self-loops, i.e. a user A can send multiple messages to another user B and a user can send a message to him/herself (by adding his/her own @screenname to a tweet). Given the set of OSN users N, a *communication graph* is then defined as a subgraph $G_C \subseteq G$ (i.e. $N_C \subseteq N \wedge E_C \subseteq E$). A *k-subgraph* is a subgraph containing exactly $k = |N_C|$ nodes (OSN users). Moreover, two graphs G_1 and G_2 are *isomorphic* if there exists an adjacency-preserving bijection between them [10].

A network *motif* [8] is a k-subgraph pattern (manifested as frequently occurring isomorphic k-subgraphs) that emerges significantly more often in a real-world network as compared to a similar synthetically generated network, also called a *null model*[3].

In this paper, we search for motifs in a multilayer network. A *multilayer network* [12] is a quadruple $M = (\mathscr{A}, \mathscr{L}, N, E)$ where $\mathscr{A}$ stands for a set of actors (social network users), $\mathscr{L}$ for a set of layers, E for a set of edges in a graph, and $N \subseteq \mathscr{A} \times \mathscr{L}$. Typically, edges can be observed on a single layer (*intralayer edges*) and among different layers (*interlayer edges*).

III. Events of study

We analyzed data-sets related to two recent riot events.

A. The 2017 G20 riots in Hamburg

The 2017 G20 summit took place on July 7-8, 2017 in Hamburg, Germany. About a week before the summit, minor clashes occurred between the protesters and the local police. On July 6th, 8,000 protesters gathered in a so-called “Welcome to Hell” march which escalated in violent confrontations between the protesters and the local police, leaving 14 injured demonstrators and 76 injured police officers. The first day of the G20 summit (July 7th) was met with further acts of civil unrest, with the protesters setting cars on fire, looting shops, and clashing with the local police. In the aftermath, 160 police officers were reported injured[4].

B. The 2018 Philadelphia riots

In the 2018 Superbowl (February 4, 2018), the Philadelphia Eagles beat the New England Patriots. Following the win, on February 5, 2018, thousands of Eagles fans gathered on the streets of Philadelphia to celebrate the victory. However, the celebration evolved into several acts of vandalism and a riot, with people flipping over cars, attempting to tear down traffic lights and lamp posts, and setting objects on fire[5].

	Hamburg	**Philadelphia**
Period	July 6-17, 2017	Feb. 4-10, 2018
Tweets	653568	22073
Screennames	human: 176038, bot: 2841	human: 11812, bot: 129
Nodes	human: 25082, bot: 347	human: 1158, bot: 6
Edges	58768	1022

TABLE I
Basic information about each event (data extraction period, number of tweets, and number of screennames) and the derived communication networks (number of nodes and edges).

IV. Method

Data extraction. We used Twitter’s Search API to extract publicly available data related to the two riot events (for details see Table I). For our data extraction, we used the following list of hashtags and search terms. For the Hamburg riot: #G20HH2017, #G20Hamburg, #G20HAM17, #G20HAM, and combinations “#G20 #Hamburg”, “Hamburg riot”, “Hamburg Unruhe”. For the Philadelphia riot: #PhillyBurning, #Phillyriot, and combinations “#superbowl #Philadelphia”, “#Philadelphia #riot”, and “Philadelphia riot”.

Reconstruction of the communication network. From our data-set, we extracted the subset of tweets that are not retweets and contain an @screenname string, indicating that a particular tweet is a message directed at another Twitter user. We then derived an edge list which contained the following entries: source (author of a tweet), target (@screenname), and time-stamp when the tweet was published. Next, we ran each screenname in our list through Botometer[6] to obtain bot scores for all the nodes in our communication network. Finally, we classified the nodes as either a *bot* (score 60-100) or a *human* account (0-59) and added the corresponding labels (bot or human) to the nodes’ attribute list. In total, 353 nodes were identified as bots (i.e., 353 out of 2970 bots engaged in a direct message exchange with other Twitter users, see Table I).

Representing the communication network as a temporal multilayer network. We separated the interactions between human users in a layer that we labelled as *H-layer*, the interactions between bots in a layer labelled as *B-layer*, and interactions between bots and humans as an interlayer labelled *HB-interlayer* (see Figure 1). Details on the number of node types (human, bot) and the corresponding edges are shown in Table II. In order to consider the temporal dimension, we constructed a multilayer network for each day in our data-set.

Subgraph enumeration and isomorphism classification. After deriving the multilayer network, we enumerated all subgraphs of size k=3 by applying the ESU algorithm [13]. Next, we classified the subgraphs by applying the VF2 algorithm [14] and assigned a label to each class of isomorphic subgraphs.

[3]In order to determine if a network motif has a semantic meaning and results from the communication patterns in a real-world network, we have to make sure that it does not appear by chance. To this end, one generates corresponding null models and checks if the motifs found in the real-world network are also found in the corresponding null models. If the motifs appear significantly more often in the real-world network, they most likely result from the corresponding real-world communication patterns rather than a random process [8], [11]

[4]https://www.theguardian.com/world/2017/jul/07/g20-protests-hamburg-altona-messehalle

[5]http://www.bbc.com/news/world-us-canada-42943824

[6]https://botometer.iuni.iu.edu/

Event	Human layer	Bot layer	Interlayer
Hamburg G20	$\|N_h\|$=24947, $\|E\|$=57542 (0.43%)	$\|N_b\|$=0, $\|E\|$=0 (0%)	$\|N_h\|$=919, $\|N_b\|$=5, $\|E\|$=1226 (0%)
Philadelphia	$\|N_h\|$=1154, $\|E\|$=1009 (0.99%)	$\|N_b\|$=0, $\|E\|$=0 (0%)	$\|N_b\|$=6, $\|N_h\|$=13, $\|E\|$=13 (0%)

TABLE II

NODE ($|N_h|$ HUMAN, $|N_b|$ BOT) AND EDGE ($|E|$) COUNT IN EACH (INTER-)LAYER OF THE MULTILAYER NETWORK. THE NUMBERS IN BRACKETS SHOW THE RELATIVE NUMBER OF SELF-LOOPS ON EACH (INTER-)LAYER.

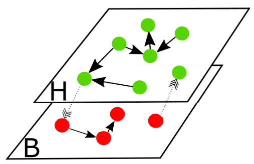


Fig. 1. Multilayer network consisting of a human layer (H), a bot layer (B), as well as the inter-layer dependencies reflecting the human/bot (HB) communication (dashed arrows).

	Naïve	Custom	Factor
$max(\delta_{HB})$	275.08, 0.69	1.6, 0.001	171.93, 690
$min(\delta_{HB})$	0.46, 0.09	0.33, 0.09	1.39, 1
$\mu(\delta_{HB})$	10.5, 0.34	9.95, 0.13	1.05, 2.6
$max(\delta_B)$	14.81, 0.71	0.08, 0.03	185.13, 23.7
$min(\delta_B)$	0.1, 0.03	0.1, 0.03	1, 1
$\mu(\delta_B)$	0.32, 0.15	0.05, 0.01	6.4, 15

TABLE III

THE RELATIVE DIFFERENCE BETWEEN THE INPUT AND THE AVERAGED NULL MODEL NETWORKS WITH RESPECT TO THE MAXIMUM, MINIMUM, AND AVERAGE (μ) DEGREE (δ) OF A HUMAN NODE CONNECTED TO A BOT NODE (HB). AS WELL AS MAXIMUM, MINIMUM, AND AVERAGE (μ) DEGREE (δ) OF A BOT NODE (B) IN THE AGGREGATED NETWORK. THE RESULTS IN EACH ROW ARE SHOWN FIRST FOR THE HAMBURG RIOT FOLLOWED BY THE RESULTS FOR THE PHILADELPHIA RIOT.

Constructing a null model. When studying motifs, it is important to find a suitable null model. Over the years, multiple null model generation algorithms have been proposed, such as a random $G(n, m)$ model [15], the switching algorithm [8], [16], or the stub-matching algorithm [17], [18]. As noted in [19], [20], using an inappropriate null model impacts the motif significance and may introduce bias in the subsequent analysis (e.g. some subgraphs may be wrongly regarded as motifs and vice versa). For our multilayer network, we applied a customized stub-matching algorithm (see Algorithm 1).

Algorithm 1: Customized stub-matching null model.

```
Input: input_H_layer, input_HB_layer, [bot_unique_labels], [HB_edges];
Output: null_model = [null_layer_H, null_layer_B, null_interlayer];
Initialize: edge = [to, from], null_layer_HB = directed_graph();
in_degrees = input_H_layer.indegree();
out_degrees = input_H_layer.outdegree();
null_layer_H = stub_matching(in_degrees, out_degrees);
for i in [bot_unique_labels] do
    if i in [input_HB_layer.nodes()] then
        bot_labels = repeat(i, times = input_HB_layer.degree(i));
    end
end
foreach input_H_layer.nodes() in input_HB_layer.nodes() do
    d.append(input_H_layer.degree());
end
foreach d do
    index = which_index(H_layer_null.degree() == d);
    candidate_human = H_layer_null.node(index);
    human_chosen = random.select(candidate_human);
    bot_chosen = random.select(bot_labels);
    remove bot_chosen from bot_labels;
    HB_edge = assign random(edge) to ordered_pair(bot_chosen,
      human_chosen);
    null_layer_HB.add_edge(HB_edge);
end
aggregated_network.add_edges(null_layer_H.edges(), null_layer_HB.edges()) ;
```

To account for the inter-dependencies between the human and bot layers, it is not sufficient to independently construct two null model layers. Thus, we extended the stub-matching algorithm [17] and introduced additional heuristics to also consider such inter-layer dependencies. The procedure is shown in Algorithm 1. In particular, bot accounts in our real-world communication networks interact with human accounts without following a particular pattern with respect to the human account's degree. To preserve this interaction pattern in the null models, we randomly selected human candidates that exhibited a particular degree (as induced from the real-world network) on the H-layer of a null model and formed an edge with a bot node on the corresponding B-layer.

In total, we generated 1000 null models for each day included in our data-set, resulting in 19,000 synthetic random networks.

Testing the null model algorithm. We tested the suitability of our customized null model algorithm against a layer-independent naïve stub-matching null model. In this naïve variant, the stub-matching procedure is applied over each layer separately, disregarding the interlinks between bot and human nodes. Again, we generated 1000 null models for H-layer, B-layer, and the HB-interlayer independently.

Figure 2 shows the degree distribution over an aggregated network for the real-world network, the custom null model, and the naïve stub-matching model. Although the overall degree distribution of the resulting naïve stub-matching null models and the custom null models are comparable, the two models differ in the selection of the human node candidates that are interacting with a bot node. In Table III, we present the relative degree differences between the real-world network and the two null models, indicating that the custom null model is a considerably better representative of our real-world multilayer network.

Motif significance testing. To test for motif significance, we use the Z-score[7] and a p-value [11]. Moreover, to compare the motifs in the data-sets, we apply the *significance profile* concept which normalizes the Z-scores of a set of motifs [11].

V. RESULTS

We first examine the daily communication frequency among human accounts as well as among human and bot accounts. As

[7]It is generally accepted that a subgraph with a Z-score of 2.0 or larger is considered a motif [11].

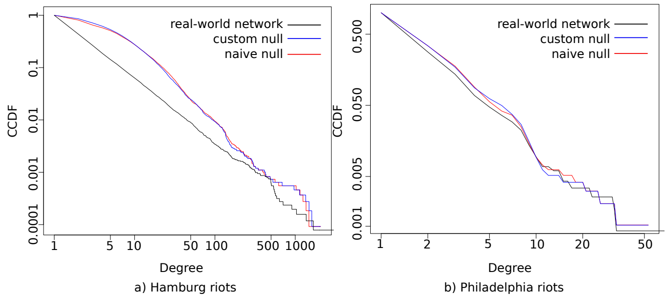


Fig. 2. Degree distribution of the nodes in the real-world network, custom null model, and the naïve null model.

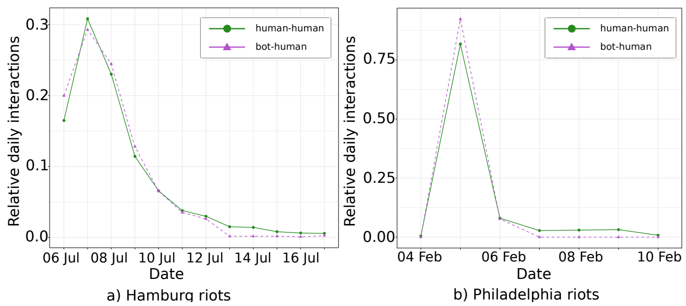


Fig. 3. Relative number of daily interactions between human and bot accounts. Human-to-human interactions are depicted as a solid green line, while human/bot interactions are depicted as a dashed purple line.

shown in Figure 3, human-to-human and human/bot message exchange behaviors are comparatively common throughout the data extraction period. Figure 3 also shows that message exchanges predominantly happened on the day of the event (Philadelphia riot: Feb. 5, 2018, Hamburg riot: July 7, 2017) with a sharp decline during the following days).

By using the observable @-mentioning traces on Twitter, we next detect the communication patterns that emerged during the two riot events. To this end, we search for significant subgraphs (motifs) that emerged when Twitter users communicated with each other via direct messaging (@-mentioning). In total, we enumerated 2,151,275 subgraphs and assigned each to a particular isomorphism class. For our Philadelphia data-set, we identified μ=6.43 (sd=9.2)[8] distinct isomorphism classes averaged over the time-period of the data extraction, while for the Hamburg data-set μ=190.42 (sd=236.58) classes emerged.

As shown in Table IV, by means of the Z-score and p-value measures, we identified 20 out of 196 motif candidates that were significant for our real-world networks. These 20 motifs differ in terms of their shape and message exchange frequency (repeated message exchanges are represented as multi-edges). In particular, we identified eight out-star motifs, i.e. a single user sends multiple messages to two other users (motif IDs: 1, 5, 6, 9, 15, 17, 19, 20), nine in-star motifs, i.e. a single user receives messages from two sources (motif IDs: 2, 7, 8,

[8]Note that we report on the mean (μ) standard deviation (sd) of the isomorphism classes with respect to the date when a particular isomorphism class of subgraphs emerged.

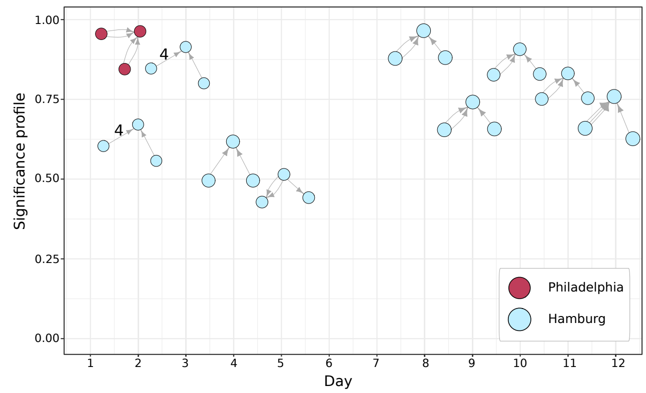


Fig. 4. Significance profile of the top one most significant motifs per day.

10, 11, 12, 13, 14, 16), one chain motif, i.e. a user receives a message from and sends a message to another user (ID 3), one transitive triad with a reciprocal edge, i.e. a pair of users exchange messages (ID 18), and two motifs with self-loops, i.e. a single user mentions him/herself (ID 12, 19).

Figure 4 shows the flow of the most significant motifs per day, where day 1 stands for the first day of the data-extraction period respectively (for the Philadelphia riot *day 1*: Feb. 4, 2018; for the Hamburg riot *day 1*: July 7, 2017). While observing the significance profile of the daily motifs, two in-star motifs repeat throughout the analyzed time-period (the in-star motifs with ID 4 and ID 16, see Table IV).

Given the fact that message exchange behavior follows a specific set of patterns (represented as motifs), the question remains which types of accounts (humans and/or bots) form these motifs. Our analysis showed that the distinct 3-subgraph patterns especially emerge when *humans* exchange messages with other humans. In particular, we found no such behavior when analyzing human/bot message exchange traces. Though a number of different types of 3-subgraphs are formed when humans exchange messages with bots (in the Hamburg data-set there were 1425 such subgraphs and 28 in the Philadelphia data-set), they tend to occur sporadically, i.e. they do not follow a particular over-represented pattern and are not significant with respect to the subgraphs that emerge in the synthetically generated HB-interlayer (Z-score < 2.0).

VI. Discussion

Since Twitter provides a convenient way of tracing user messaging behavior via @screenname, we were able to reconstruct the two communication networks that formed during the two riot events (see Section III). While previous studies have predominantly focused on the nature of messages sent over Twitter (e.g., information seeking, rumors, misinformation spread) and characterized their diffusion processes, the question remained which underlying structural patterns emerge when users communicate over Twitter.

In our analysis, we found that a number of common structural patterns emerged during the two riots. As shown in Figure 4, the most significant daily motifs are predominantly

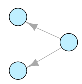
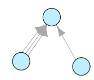
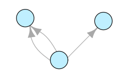
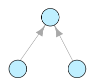
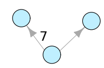
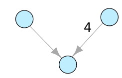
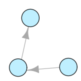
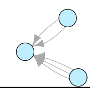
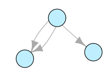
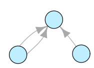
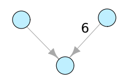
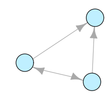
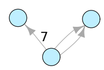
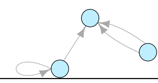
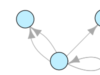
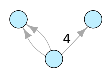
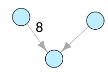
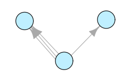
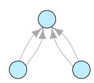
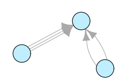
ID	Motif	Z-score	Day	ID	Motif	Z-score	Day	ID	Motif	Z-score	Day
1		9.22_p 30.67 4.9 2.68 3.77	2_p 8 9 11 12	8		6.87_p 33.87 65.97 4.71 19.44	2_p 8 9 11 12	15		2.86	4
2		14.04 9.62 3.93 5.79 6.38	2 3 4 8 9	9		33.87	8	16		20.49 26.16 2.49	2 3 4
3		3.25	8	10		5.87	2	17		2.18	5
4		3.41_p 185.05 85.44 6.91 9.21 5.31	2_p 8 9 10 11 12	11		15.34	2	18		6.75	12
5		9.9	8	12		2.61	9	19		2.26	12
6		2.45	8	13		15.34	2	20		5.92_p 13.08	2_p 12
7		104.98_p 5.37 41.07	2_p 8 9	14		3.43	3				

TABLE IV

MOTIFS IDENTIFIED DURING THE PHILADELPHIA AND HAMBURG RIOTS. Z-SCORES AND THE CORRESPONDING DAYS WHEN A MOTIF WAS IDENTIFIED FOR THE PHILADELPHIA RIOTS ARE INDEXED WITH p. THE EDGE WEIGHTS REPRESENT THE NUMBER OF MESSAGES SENT BETWEEN TWO TWITTER USERS. ALL MOTIFS IDENTIFIED FOR $p < 0.001$.

multi-edged in-star motifs. We also found that often a single user sends multiple messages to another user who does not respond (thus, no reciprocal edges in the identified motifs). Such unreplied messages are predominantly messages that express care. To anonymize the users, we replaced their names with the string @*NAME*, unless the person mentioned is an official account of a news channel or the local officials, such as the local police or the fire brigade: "*I hope that my friends in Hamburg @NAME1 @NAME2 stay safe over the next days #G20HAM!*" and "*@PolizeiHamburg, @FeuerwehrHH and everyone else at #G20HAM17. My thoughts are with you!*".

In addition to caring messages, multiple edges also emerged due to the public expression of one's opinion, such as "*@NAME1 @NAME2 Its so bizarre; Win a game, burn your city down. Lose a game, go home. #Philadelphia #Riot*".

As noted in previous studies on the use of Twitter during crisis events, people often turn to Twitter to make sense of the situation or seek information by messaging other users (see, e.g., [21]) or officials such as the local police (see, e.g., [22]). Official accounts typically exhibit a higher in-degree compared to other Twitter users. Below we show some examples from our data-sets with the in-degree[9] of the respective official account in brackets:

- "*@PolizeiHamburg (δ_{in}=4,871) why is the main train station full of armed police officers? I don't feel safe with such a strong armament. #G20HAM17*",
- "*So when can we expect the Mr. @POTUS (δ_{in}=5) @realDonaldTrump (δ_{in}=22) to make a statement about the riots in Philadelphia??*".

In our analysis, we found that typical human-to-human message exchange behavior can be characterized via statistically significant and representative subgraphs (motifs). However, no statistically significant patterns for human/bot message exchange behavior emerged in our data-sets. This observation might be explained through a comparatively low number of bots which engaged in a direct human/bot communication in our data-sets. In particular, 353 out of 2,970 bots (as identified by Botometer) participated in direct message exchanges with human accounts (see Table I). Thus, in order to gain a deeper understanding of the message exchange patterns that emerge due to the involvement of bot accounts, we plan to extend our analysis to other data-sets which might provide us with additional insights.

[9]Note that the degrees shown in the example tweets are the degrees resulting from the event-specific communication networks derived from our data-sets. For example, @realDonaldTrump was mentioned in 22 messages included in our Philadelphia data-set.

VII. RELATED WORK

A number of existing studies investigated how people use Twitter during riot events. The focus of such papers was on the information seeking behavior and in particular the role of the officials (e.g. during the 2011 riots in London [21], or the 2017 G20 riots in Hamburg [22]). However, given the complexity and the volume of OSN data as well as the restrictions imposed by limited computational resources, the number of papers that applied motif detection to OSN communication networks is rather small so far. The existing studies on motif detection in OSNs include [23], in which the authors detected motifs in undirected monoplex friendship networks reconstructed from Google Plus, Facebook, and Twitter. In [24], Rotabi et al. applied motif detection on a Twitter data-set to study the strength of strong ties by considering the network of followers as well as the respective communication network (@-network). Barash et al. [25] further utilized motifs to study temporal propagation patterns of rumors on Twitter. In addition [26], [27], studied communication patterns that emerged on Facebook, with [26] utilizing the concept of temporal motifs to study the temporal flow of messages.

VIII. Conclusion and future work

In this paper, we analyzed the message exchange behavior among human and bot accounts during two riot events. For bot detection, we used the Botometer API and identified in total 2,970 bot accounts that participated in the Twitter discourse about the two events. After re-constructing the corresponding communication networks, we detected all 3-subgraph patterns that emerged when users (either bot or human) communicated with each other.

To distinguish between human-to-human, bot-to-bot, and human/bot messaging behavior, we modeled a multilayer network, generated 1000 null models for each day of the data extraction period (19,000 null models in total), and performed a motif detection procedure. In the two communication networks analyzed for this paper, we identified 196 (re-occurring) subgraph patterns and found that 20 of which are representative and statistically significant subgraphs (motifs). We also found that these 20 motifs exclusively emerged during human-to-human message exchanges, indicating that humans tend to form characteristic and re-occurring communication patterns. With respect to our data-sets, message exchanges including bots, however, do not follow specific over-represented structural patterns. Thus, in our future work we plan to apply the method proposed in this paper to further study the communication patterns that emerge during human/bot and bot-to-bot interactions.

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