Amplification of Anti-West and Western Allies Sentiment on Telegram in the Wake of 10/7

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1 Introduction

On October 7th, 2023 Hamas and other Palestinian militant groups staged a land invasion of Israel which sparked the currently ongoing Israel-Hamas war [1]. The conflict has stoked broader geopolitical tensions, as demonstrated by military exchanges between Israel and Iran and increased aggression from Houthi militants, including towards Western ships in the Red Sea [2]. In the week following 10/7, the United States and other Western aligned nations were quick to declare support of Israel and certain pundits predicted direct Western military involvement. The universal resonance of the Israel-Palestine conflict (from which the Israel-Hamas war was born) has triggered widespread praise and criticism of Western military aid to Israel. Such commentary has dominated social media and increased divisions in Western politics. In the United States, Palestinian sympathizers have decried political leaders for Israeli support and primary election boycott movements have gained traction [3]. At the same time, misinformation undermining American foreign intervention has circulated. In October, a US congresswoman promoted a conspiracy, endorsed by prominent Russian officials, that NATO weapons provided to Ukraine were used by Hamas to perpetrate 10/7 [4][5]. Congressmen used the story to bolster opposition to US foreign military aid, a move directly aligned with Russian interests [6]. Such narratives deepen Western political divisions and could weaken influence on the world stage. Thus, this report will analyze such dynamics via a two-part investigation: 1.**How did anti-West and Western allies sentiment shift in the week following 10/7?** 2.**Was this stance artificially amplified by motivated actors or mis/dis-information narratives?** The analysis is based on Telegram data collected in the week following 10/7. Telegram makes a good choice for such investigation not only as the Ukraine weapons conspiracy circulated on this platform [4], but more due to Telegram's weak content-moderation [7].

2 Literature Review

These papers helped solidify Telegram as the chosen platform for this research and provided tips for tracking amplification and misinformation (relevant for the research question's part 2), particularly the importance of analyzing forwarded content and identifying communities and opinion leadership.

Identification of Opinion Leaders in a Telegram Network of Forwarded Messages In this paper by Giulia Tucci of Federal University of Rio de Janeiro, Tucci argues that Telegram is particularly suited for the propagation of opinion leadership. Some of these reasons are inherent to Telegram's implementation. Unlike other messaging platforms such as WhatsApp, the original authors are displayed whenever a post is forwarded. The paper also provides practical approaches for filtering Telegram data to identify key voices, for example, siloing forwarded content. Furthermore, due to the structure's promotion of opinion leadership, Tucci remarks on the transferability of social analysis methods which previously succeeded with Twitter, such as the Open-Ord algorithm [8].

Misinformation and professional news on largely unmoderated platforms: the case of telegram In the second paper, first-authored by Aliaksandr Herasimenka of Oxford University, the authors detail the dynamics of misinformation flow on Telegram. The key findings were that, what the authors call reliable or "professional news", has far greater reach on Telegram than misinformation. By contrast, misinformation is spread within a smaller subset of communities, but within those communities, the content receives very high engagement. Furthermore, the authors found that forwarding messages was the most common mechanism for spreading misinformation [7].

3 Methodology & Data

3.1 Data

Overview & Collection This study covers a Telegram dataset collected by Ian Kloo of Carnegie Mellon University's Societal Systems department. According to Kloo the data "was collected using a list of 40 channels posting primarily pro-hamas content after the 10/7 attacks". The list was provided in a now inactive google doc sourced by the Reddit community. "[Mr. Kloo] did a 1-hop snowball sample from that list of 40 to capture any channels that the original 40 had forwarded content from. The resulting set includes the major news/media/blog channels that were active during this 1-week period after 10/7. All of the [resulting] data is from public channels."

Pruning Given the scale of the dataset, pruning of the message nodeset (the larget) was needed to reach a manageable size. This included the following: 1.Removed messages with blank text fields 2.Removed messages with no relationship data (no replies, forwards, or authorship data) 3.Removed messages with text shorter than 4 characters

3.2 Stance Detection

The next step was propagating stance for network nodes via the ORA visualization software Stance Detection report. The report applies an algorithm, developed by Sumeet Kumar, which leverages weak supervision to propagate stances from a set of seed nodes judiciously labeled in ORA [9]. For this research, first seed nodes were collected manually by searching the dataset for messages and hashtags which indicated at the text-level

Table 1. Data breakdown

Node Types	Channel (1,096), Hashtag (2,784), Message (879,938), User (115,325), Url (310)
Networks	Channel x Channel - Forwarded From Channel x Hashtag (contains in channel message) Channel x Url Message x Channel (contains) Message x Channel - Forwarded From Message x Channel - Replied by Message x Hashtag (contains) Message x Message - Replied By Message x Url Message x User - Forwarded From Message x User - Replied By User x Channel - Forwarded From User x Channel - Posted To User x Hashtag User x Message - Authors User x Url User x User - Forwarded By User x User - Replied By
Ties	Binary

"pro" or "anti" West and Western allies stances, and when found, assigned stances accordingly. The criteria used to label a message as having a "pro" West and Western allies stance was whether the text demonstrated alignment with Western military or political interests, or depicted Western or Western aligned individuals or entities as having attractive or admirable qualities. Such qualities can range into the very abstract. Some examples are demonstrations of strength, unity, loyalty, compassion, and morality. Messages were assigned an "anti" stance which displayed the opposite, for example, weakness, incompetence, or wickedness, or displayed aggression towards Western figures.

Table 2: Example Stance Detection Seed Nodes

Stance	Message
Pro	President Biden: -"Many more families are waiting to hear what happened to their family members, Holocaust survivors were kidnapped, every code of humanity has been broken here." -"Israel has the duty to respond to the brutal attacks." -"Our aircraft carrier, our fighter jets in the area and our weapons in the area are ready to be used at any moment" -"I warn those who plan to harm Israel - don't do it! Don't do this!" -"In Israel, over 1200 civilians, female soldiers, and children were murdered. The United States mourns together with Israel" President of the United States Joe Biden with an amazing speech. newskodkodgroup *[GoogleTranslate from Hebrew]*

Anti	#Update: Nato members countries will be face an cyber attack by us for support Israel and being silent about PalestineGaza. Turkey excluded. Asian Country - India will be attacked soon. If they support Zionism you better secure your site because we are coming. #MTB #AnonGhost #GhostClan #GHOSTSofPalestine #AlAqsaFlood #OpIsraelV2

When finding critical messages masses (>2 exclusively of one stance) associated with a hashtag, channel, or url these nodes earned the same stance label.[1] The result was the classifying of **82** seed nodes, **41** for each stance. After running the stance detection algorithm through ORA, these stances were propagated in **4,255** nodes, including **3,194** "pro" nodes (channels: **4**, hashtags: **1**, messages: **3,180**, users: **7**, urls: **2**) and **1,061** "anti" nodes (channels: **11**, hashtags: **111**, messages: **902**, users: **26**, urls: **11**).

3.3 Dynamic Network Analysis

The stanced datasets will be split temporally into two networks. Each will have a constant set of hashtags, users, urls, and channels. Time Period 1 will contain all messages **10/7 through 23:59 10/9**. Time Period 2 will contain all messages **10/10 through 23:59 10/13** These networks will be compared to detect shifts in stances over **10/7 - 10/13**.

3.4 BEND Analysis

To identify opinion leaders or potential mal-actors the research will leverage the BEND & Community Assessment report in ORA, on largely forwarded data, stated by literature to be a vehicle of opinion leadership. The BEND framework is used to taxonomize agent maneuvers which aim to negatively or positively impact individuals or groups online. The report identifies such maneuvers in one's dataset. To help answer part 2 of the research question, such classification can identify actors intentionally swaying Western sentiment via targeted language or the spread of misinformation.

4 Results

4.1 Stance-Detection and Dynamic Network Analysis

Stance-Detection and Dynamic Network Analysis helped answer the research question **How did anti-West and Western allies sentiment shift in the week following 10/7?**

Table 3. Time Period 1 (10/7 - 10/9) Metrics

119,791 nodes	# Nodes	% Total Nodes	% Stanced	Avg TDC	Avg BC.	# Messg. Views
Pro nodes	1,620	1.352355352	79.45	9.459876543	8.571296296	66,863,290
Anti nodes	419	0.349775859	20.54	57.79236277	321.2136373	1,413,121

[1] For logistical reasons, 0 Users were selected as seed nodes for this paper's stance detection

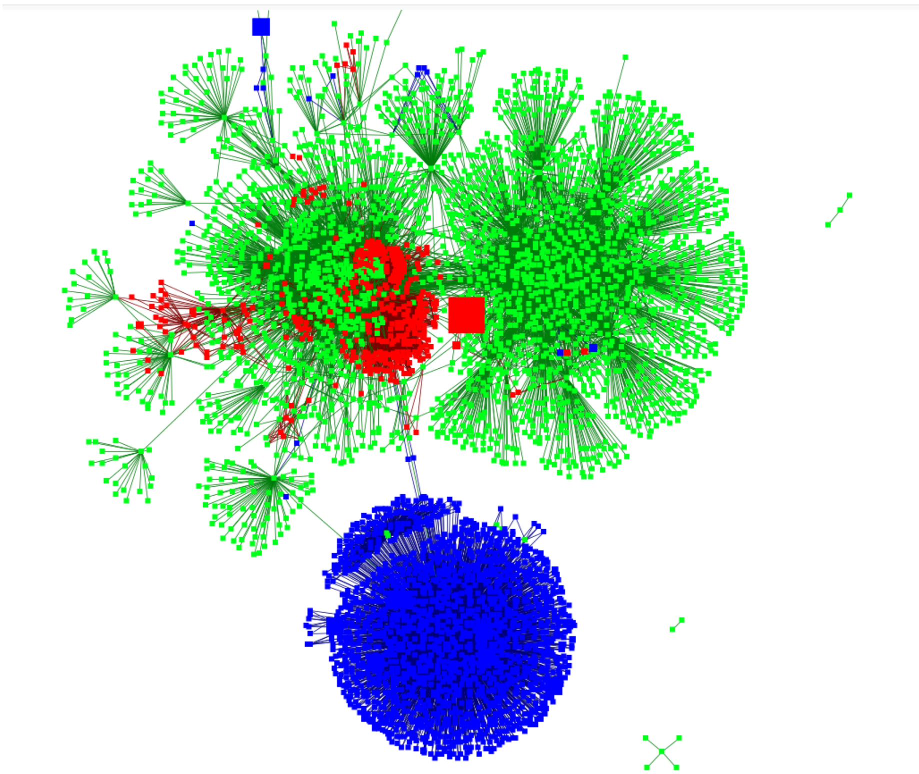


Figure 1. Time Period 1 (10/07 - 10/09) Network visualization generated via ORA. **(a)** Red = "Anti" West stance **(b)** Blue = "Pro" West stance **(c)** Green = Neutral stance **(d)** Nodes are sized by view count **(e)** For clear visualization (given the size of the full message nodeset), neutral messages (assigned no stance by Stance Detection) are removed from the visualizations. **(f)** For clear visualization (given issues with populating stance to user nodes), user nodes are removed from the visualizations. **(g)** Interactions by neutral nodes on stanced messages provide important engagement information. Even if the entity engaging is neutral, that node can later adopt a stance through this interaction or cause another node to be "infected". Thus neutral channel and url nodes were kept, also practical visually considering the relatively low number of such nodes

Analysis Based on the Time Period 1 metrics (see Table 3), though “pro” nodes outnumber “anti”, "anti" nodes' superior Total-Degree Centrality (TDC) and Betweenness Centrality (BC) metrics confirm what is visible in this period's network graph (see Fig. 1). The “pro” nodes cluster together in one large group (that seems to have 2 or 3 sub clusters). This group appears to be an echochamber as the vast majority of its nodes have the same stance and appear largely connected to each other (compared to other nodes with different stances in the network). Furthermore, after inspecting this group in ORA, it appears the vast majority of these nodes are for Hebrew-speaking audiences, justifying the insularity somewhat. In the main network graph, the vast majority of nodes are in Arabic and English. The “anti” nodes are spread across these two languages (as well as some Russian) and are more intertwined with neutral nodes while forming a few independent clusters. The relative diversity of the “anti” audience is echoed by "anti" nodes’ higher total-degree centrality and betweenness scores (compared to the “pro” nodes). By accessing more of the network the “anti” nodes have access to more connections (TDC) and can connect nodes of different groups (BC). Despite this contrast in stance dispersion throughout the network, it is worth noting there are a few dyads, triads, and quadrads of “pro” nodes interacting with neutral and “anti” nodes.

Table 4. Time Period 2 (10/10 - 10/13) Metrics

119,791 nodes	# Nodes	% Total Nodes	% Stanced	Avg TDC	Avg BC.	# Messg. Views
Pro nodes	1,588	1.32564216	66.47	9.638539043	8.681570109	65,833,048
Anti nodes	801	0.66866459	33.53	44.06242197	358.9929187	2,827,168

Analysis When comparing Time Period 2 (see Table 4 and Fig. 2) to the previous, two trends can be observed to answer research question part 1. <u>Trend #1</u>: “Pro” West nodes declined across multiple metrics (see Table 5). <u>Trend #2</u>: “Anti” West nodes increased across the same three metrics (see Table 6). From a network perspective, this growth could be due to the influence of "anti" nodes (indicated by relatively high TDC and BC).

Table 5. <u>Trend #1</u>: “Pro” west sentiment nodes declined across multiple metrics.

"Pro" Node Metric	Calculation	% Difference
As a % of overall nodes	1.32564216/1.352355352	-2%
As a % percentage of stanced nodes	66.47/ 79.4	-16.28%
Message view counts	65,833,048/66,863,290	-1.54%

<u>Trend #2</u> is corroborated by metrics across both time periods, but more dramatically by Time Period 2's network visualization (see Fig. 2). The “pro” meta network looks fairly similar to that of Time Period 1 (see Fig. 1) however “anti” has a markedly stronger presence and appears more connected beyond its core cluster, confirmed by an uptick in Average Betweenness Centrality (BC) for "anti" nodes (**358.9929187** vs **321.2136373**).

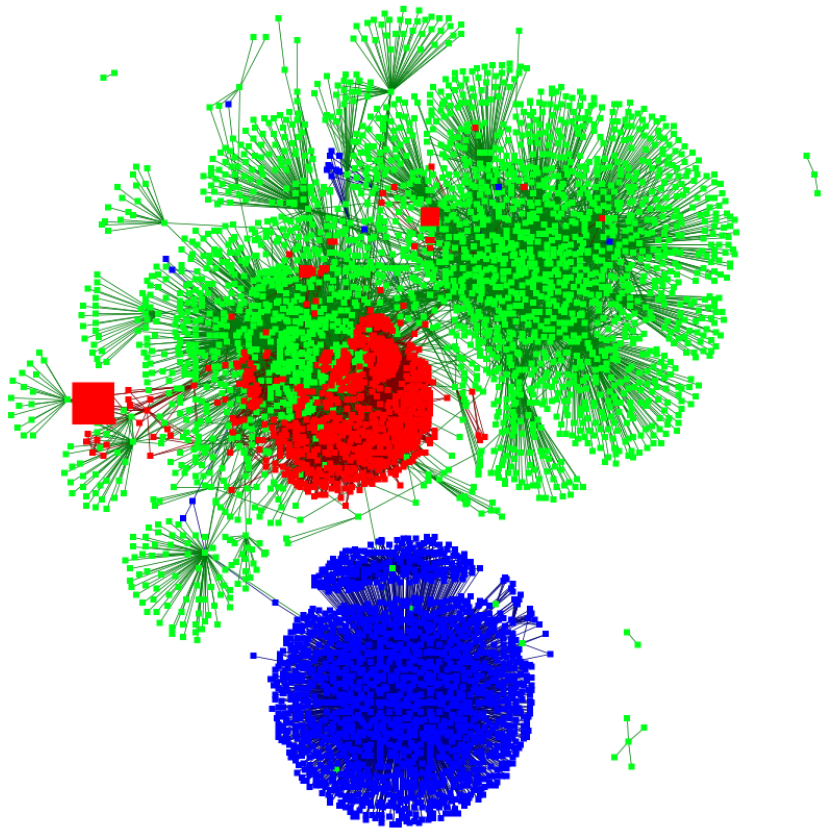


Figure 2. Time Period 2 (10/10 - 10/13) Network visualization generated via ORA. See Fig. 1 for interpretation notes.

Table 6. Trend #2 “Anti” west nodes increased across the same three metrics

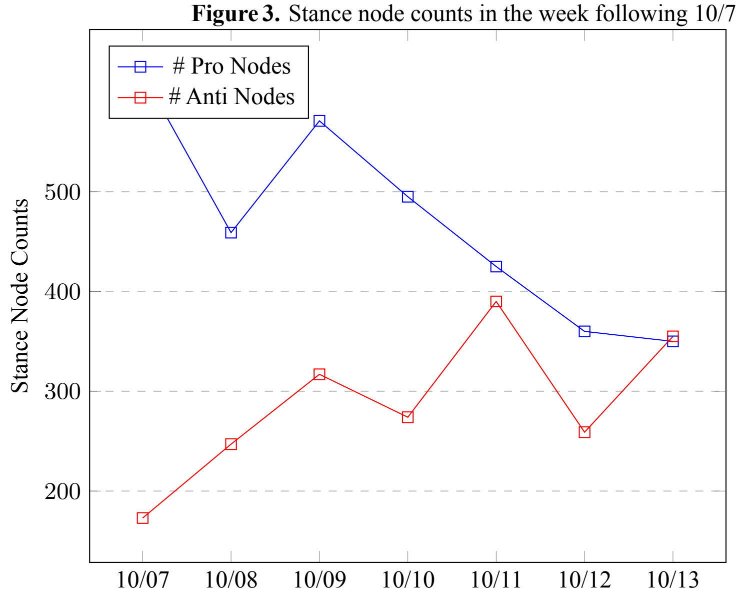
"Anti" Node Metric	Calculation	% Difference
As a % of overall nodes	0.66866459/0.349775859	+191.21%
As a % percentage of stanced nodes	33.53/20.54	+163.2%
Message view counts	2,827,168/1,413,121	+200%

Both trends are supported by daily stance node and message view counts (see Table 7, Fig. 3). The “anti” stance node count ultimately overtakes “pro” on 10/13.

Table 7. Stance node counts in the week following 10/7

	# Pro Nodes	Pro Message View Count	# Anti Nodes	Anti Message View Count
10/07/2023	618	23,463,839	173	61,727
10/08/2023	459	20,183,898	247	618,528
10/09/2023	571	23,215,553	317	732,866
10/10/2023	495	21,640,921	274	671,410
10/11/2023	425	16,156,242	390	1,550,665
10/12/2023	360	13,910,265	259	371,505
10/13/2023	350	14,125,620	355	233,588

Figure 3. Stance node counts in the week following 10/7



Key Findings "Anti" West stances and viewership increased significantly and "pro" West stances and viewership decreased over the week of **10/7 - 10/13**.

4.2 BEND analysis to identify stance manipulation

BEND analysis is intended to answer the research question's part 2: **Were anti-Western stances artificially amplified by motivated actors or mis/dis-information narra-**

tives?. Thus far the ORA Bend report has been non-conclusive. As stated previously, the current stance detection run includes no user seed nodes. Manually categorizing “pro” or “anti” West users with the current dataset has proved difficult as not all users nodes have ties to messages in the dataset, and many post users messages with conflicting sentiments. Manual cross-checking of these profiles on Telegram itself has also yet to bear significant fruit (given time elapsed some users have changed their aliases, deleted their profiles or politically charged posts). **Next steps** for this project will prioritize finding a robust set of user seed nodes (possibly by expanding the research dataset to include active users linked to identified stance nodes). Partially due to the missing user seed nodes and other execution flaws, the stance detection algorithm has not populated many users, hindering BEND analysis. For this research question, the BEND report requires communities from the “pro” and “anti” West stances, but with a scant number of users labeled as such the results are not meaningful. Without stance-based communities BEND analysis is too noisy, concerning nodes irrelevant to the narrative. Thus no agents highlighted by the BEND analysis thus far have contributed to this research.

5 Limitations

The research currently has many limitations to be addressed as work is continued.

5.1 Data

As stated previously the dataset originated from a list of pro-Hamas channels. Thus the **Key Findings** are somewhat biased considering the voices in this dataset are more likely to oppose the West and its allies (considered Hamas’ enemy). A counterargument is that more nodes in the dataset are flagged as “pro” vs “anti” by stance detection, however the network analysis made clear that the "anti" nodes hold more influence (as demonstrated via TDC and BC metrics), and the visualization exhibited that many "pro" voices are disconnected from the network's main discourse. Going forward all analysis should be conducted on an expanded dataset which supplements the current data with more neutral and Western-leaning channels, to offset any systemic political bias.

5.2 Stance Detection

There are multiple flaws in the current stance detection utilization. Firstly, the stance detection algorithm is not optimized to use full messages as concepts, yet is being applied as such. One should instead use hashtags or convert messages into semantic networks [9]. Unfortunately given the size of the dataset (over 100k messages post-pruning), it has proved difficult to convert these messages en mass. For this paper’s analysis, the inferior method of messages as concepts was settled for. As a counterargument to this limitation, spot-checking revealed the propagated stances to be largely accurate, the main limitation was how broadly the stances populated via connections (for example as stated in section 4.2, failing to propagate stances to user nodes). Next steps will prioritize finding a solution to increase the effectiveness and accuracy of the stance detection utilization. Secondly, the labeling of seed nodes via untrained human assessment is not foolproof. To ensure unbiased classification either AI tools or a specialized third-party should be brought into the loop. Such precautions will strengthen confidence in the key findings. Though spot-checks provided confidence in the accuracy of each stance detection run before conducting analysis, without specialized expertise, such validation is as untrustworthy as the amateur seed node classification.

6 Conclusion

This paper's findings show a marked uptick in anti-Western sentiment in this large Telegram dataset, in addition to a less dramatic, but consistent decrease in pro-Western sentiment. The trend corresponds with public discourse worldwide. Furthermore the sequestered nature of "pro" and "anti" voices mirrors increased political division and polarity. However, it is not enough to sound-board real-world events with social media discourse. Recent history has demonstrated that social networks can be the instigators of real-world sentiment and not the echoers. Thus next steps in this research will focus on improving methods to identify the source of the identified sentiment shift in Telegram.

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