Pro-Russian Disinformation and Propaganda in the German Telegram Network around ‘Neues aus Russland’

Prepared by a volunteer data science team from CorrelAid
Maja Guseva, Marina Fridman, Andrii Grygoryshyn

Oct 2023

Telegram is a social media platform that originated in Russia and is a highly popular communication channel for individuals and groups. According to Telegram, Groups can be public or private and up to 200,000 members can participate in the chat. In contrast, channels allow top-down communication only, but the number of Followers is not limited. Channels, groups and users can reference each other by mentions, forwards, or sharing Telegram links.

Telegram’s channels and groups have become communities where discussion and information dissemination takes place. This rapid exchange facilitates the spread of misinformation across networks which becomes particularly problematic in critical political and societal contexts such as the Russian invasion of Ukraine in February of 2022. The dissemination of false information or propaganda can have real-world consequences.

We set out to find Russian disinformation and propaganda narratives around their invasion of Ukraine that are spreading into German-speaking channels on Telegram. For this we used a dataset scraped from Telegram by CORRECTIV. We analyzed data **from January 2022 to April 2023** using a two-fold approach. First we built a network graph to visualize and analyze the relationships between channels and groups via forwarded messages. Second, we used text similarity metrics to detect messages that had the same content in both Russian and German.

In the center of this analysis: the network around the channel ‘Neues aus Russland’. This channel is a major spreader of disinformation in German language, which is confirmed by the German Center for Monitoring, Analysis and Strategy CeMAS (PDF, page 10). Several media reports were able to show that the channel spreads pro-Russian disinformation. But who spreads these posts further – and where do they come from?

1. Key findings

- The channel ‘Neues aus Russland’ and the group ‘Fakten Krieg der Ukraine’ are hubs of translating and spreading Russian-language messages. Especially ‘Neues aus Russland’ experienced a dramatic rise in intra network importance.
  - The analysis identified other influential chats, e.g. Solovyev and CHVK Media on the Russian side and Fairdenken Wien or Q-anons on the German-speaking side.
  - Influential chats are those that are highly interconnected with other channels and commonly serve as a bridge between two channels.
- “Neues aus Russland” is a channel that posts and translates news and perspectives from Russian into German. These posts are collected from a wide array of sometimes obscure and small Russian-language chats. The German translations are a source for large German channels, which also forward these messages to a German-speaking audience.
- Searching for messages in the two languages with highly similar meaning also surfaces primarily message pairs from the channel ‘Neues aus Russland’, further highlighting this channel as a main hub of direct translations from German to Russian.
- Through this analysis CORRECTIV.Faktencheck was able to identify groups and channels on Telegram, who spread pro-Russian narratives in German language via ‘Neues aus Russland’ and how this network grew over time.
- The CorrelAid team e.g. traced several fact-checked claims further back to Russian-language Telegram channels. Furthermore the analysis helped CORRECTIV to identify some claims their fact-checking team missed.

2. Methodology & Results

The dataset covered the time period January 1, 2022 until April 26, 2023 and was scraped using the channel ‘Neues aus Russland’ as a seed. We converted the data into a network graph following the schema (Fig. 1) below.

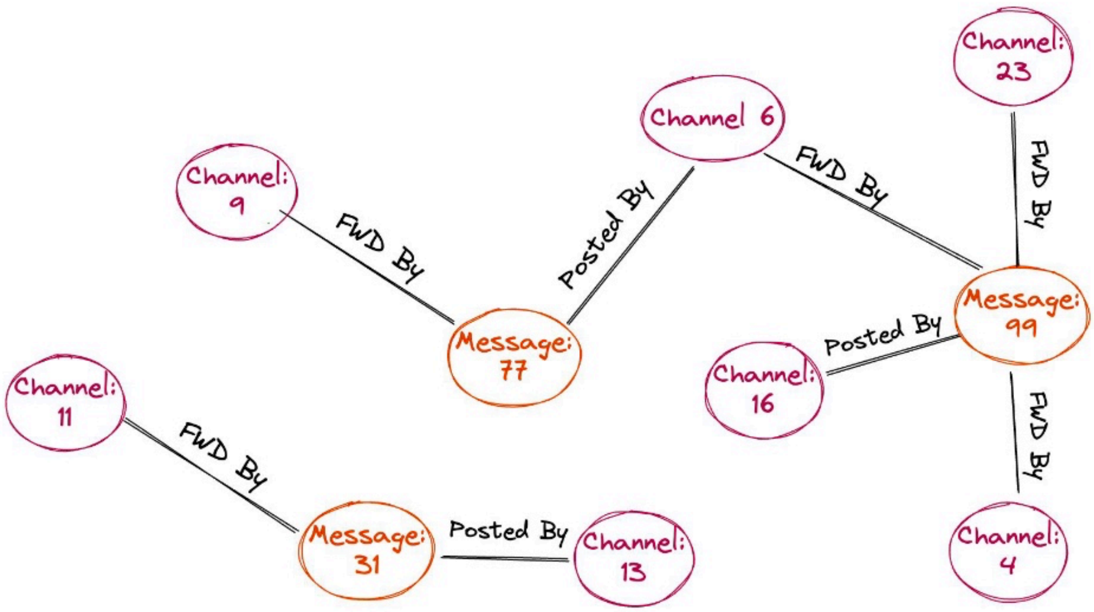


Fig 1: Schema of Telegram graph

We used the networkx library in Python to build the graph. Due to the presence of two different node types (messages and chats), we used a graph projection to create a network with only chats as nodes and connections (edges) that correspond to messages forwarded between the chats[1]. The resulting graph was then filtered to contain only Russian and German speaking chats. Chat language was determined by first computing the language of each text message posted by the chat. Then, the most frequently occurring language within each message was assigned as the chat language. PyCLD2 Python package was used for the language computation itself. For simplicity, we will refer to this network as the RUSSGER network. To allow for a comparison of centrality measures across time, the network was divided into months ranging from January 2022 to April 2023.

A) General network properties

Fig. 2 shows the network with blue nodes representing the Russian speaking chats and red nodes representing the German speaking ones. This network contains 6,687 nodes and 77,098 edges.

[1] The graph object containing the entire dataset was a bipartite graph, as seen in Fig X. In this kind of graph there are two disjoint sets of nodes, chats and messages. Each node of one type is exclusively linked to a node of the other type (see e.g. here), complicating standard centrality calculations. To reduce this bimodal network to a unimodal graph, we applied networkx's projection algorithm (see here). As a result we obtained a collapsed graph with chats as nodes and edges as connections that emerged when a message was forwarded from one chat to another.

We calculated the degree for each chat within the whole RUSSGER network. This metric indicates the number of edges connected to a node (see here). In this way we could assess the global structure of our network. The degree distribution of the RUSSGER network, shown in Fig. 3, is typical for a complex system such as a social media network - there are a handful of very influential (high-degree) chats have many connections and many chats that have few connections and are therefore less influential (lower-degree) chats (Albert, Barabási2002).

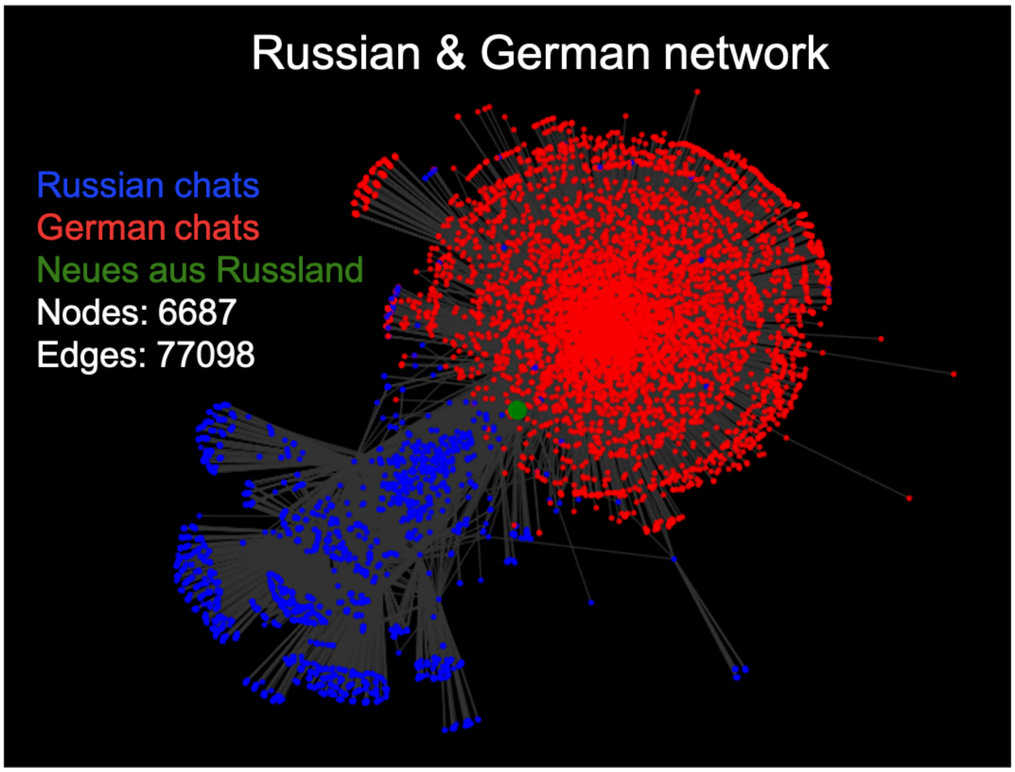


Fig. 2 Network of russian (blue) and german (red) speaking chats

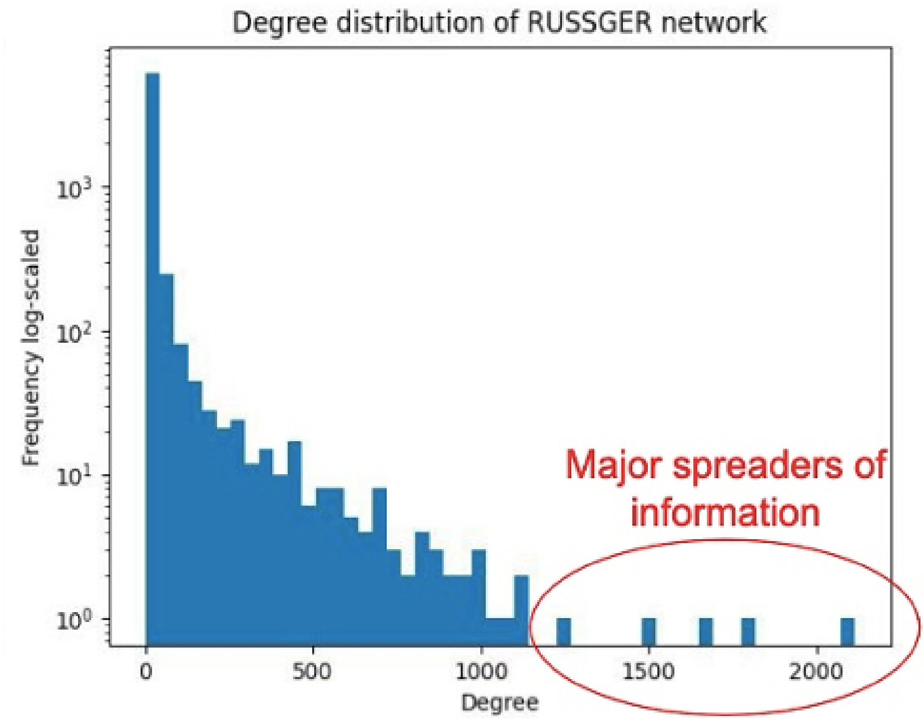


Fig. 3 Distribution of degrees in RUSSGER network

B) Network interconnectivity

To get a sense of the interconnectivity of the network, we used the common betweenness centrality (BC) metric that gauges the importance of a node in a network, or in other words the degree to which a node serves as a "bridge" in the information flow of the network. BC is calculated by determining the number of shortest paths within the graph that traverse a given node and divide it by the overall count of shortest paths connecting two different nodes (see here).

Initially, we computed the Betweenness Centrality (BC) metric for the entire RUSSGER network on a monthly basis. Here the algorithm assigns a single BC value to each node. When summarizing the betweenness dynamics for each month, we refrained from using the mean because the network exhibits scale-free dynamics (Albert, Barabási 2002), characterized by a few high-degree hubs and many low-degree hubs. Instead, we used the maximum BC value for a given month.

Fig. 4 shows the evolution of BC measures of the whole RUSSGER network over time (based on the maximum values). The trend is upwards, indicating that some nodes in this network become more important to maintain connectivity in the network.

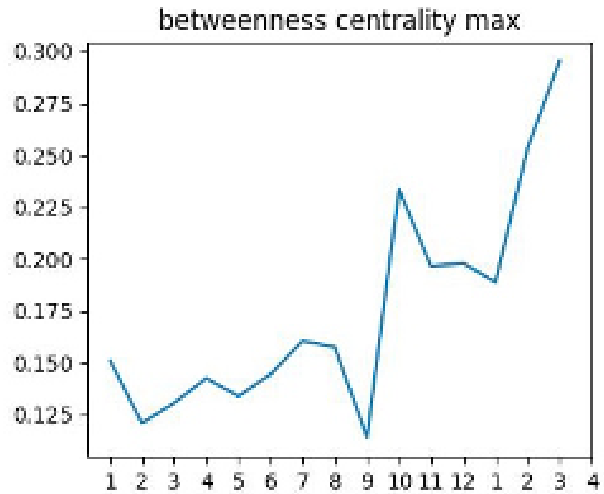


Fig 4. Betweenness centrality max values for the whole RUSSGER network over time. The numbers on the horizontal axis refer to the months of 2022 (1-12) and restarts with the first four months of 2023.

However, to interpret these results one needs to take into account that such a Telegram dataset can not be complete, but only a sample. The CORRECTIV dataset started off with channels and groups related to the topics Covid denial, Reichsbürger and right-wing disinfo – few were Russian-speaking. After Russia's invasion the CORRECTIV team searched for pro-Russian channels and groups via Telegram search, news reports, Forwards and mentions, also in other Social Networks. One of the first channels found was 'Neues aus Russland', who at times made a decisive contribution to extending the network.

C)Most influential chats

To identify which chats specifically drive this upwards trend and to create an overview of the most influential chats in the network, we used the two metrics, BC and degree. First, we calculated these two metrics for the RUSSGER graph for every month. We then identified those German and Russian language chats that have the maximum value in each month. In the next step, we extracted those top chats that appear most often in this list, see table 1.

Table 1. Top influential chats as identified by degree and betweenness centrality. Phonetic spelling of Russian-speaking chat names in order of appearance (top to bottom): Solovyev, CHVK Media, Neues aus Russland, Otryad Kovpaka, Yuzhnyy Region/Novorossiya, WAGNER Z GROUP/PMC WAGNER'Z.

Russian-speaking chats	German-speaking chats
СОЛОВЬЁВ	FAIRDENKEN WIEN 1 AT 🇦🇹

ЧВК Медиа	Q&ANONS 🕊🇩🇪🇦🇹🇨🇭
Neues aus Russland 🪆📢	Einmal hin, alles drin, wo Engel drauf steht, ist auch das Feuer 😇
Отряд Ковпака	Patriot Sandra Chat
Южный Регион/Новоро́ссия	Fakten Krieg der Ukraine
WAGNER Z GROUP/PMC WAGNER‘Z	Sue Fortruth - in truth we trust

To identify which chats specifically drove the upward trend observed in Fig. 4, we calculated for every Russian top chat the number of connections to a German chat and vice versa for each month (Fig 5). In the figure we can clearly observe that the chat ‘Fakten Krieg der Ukraine’ has experienced a dramatic rise in intra network importance as well as the chat ‘Neues aus Russland’.

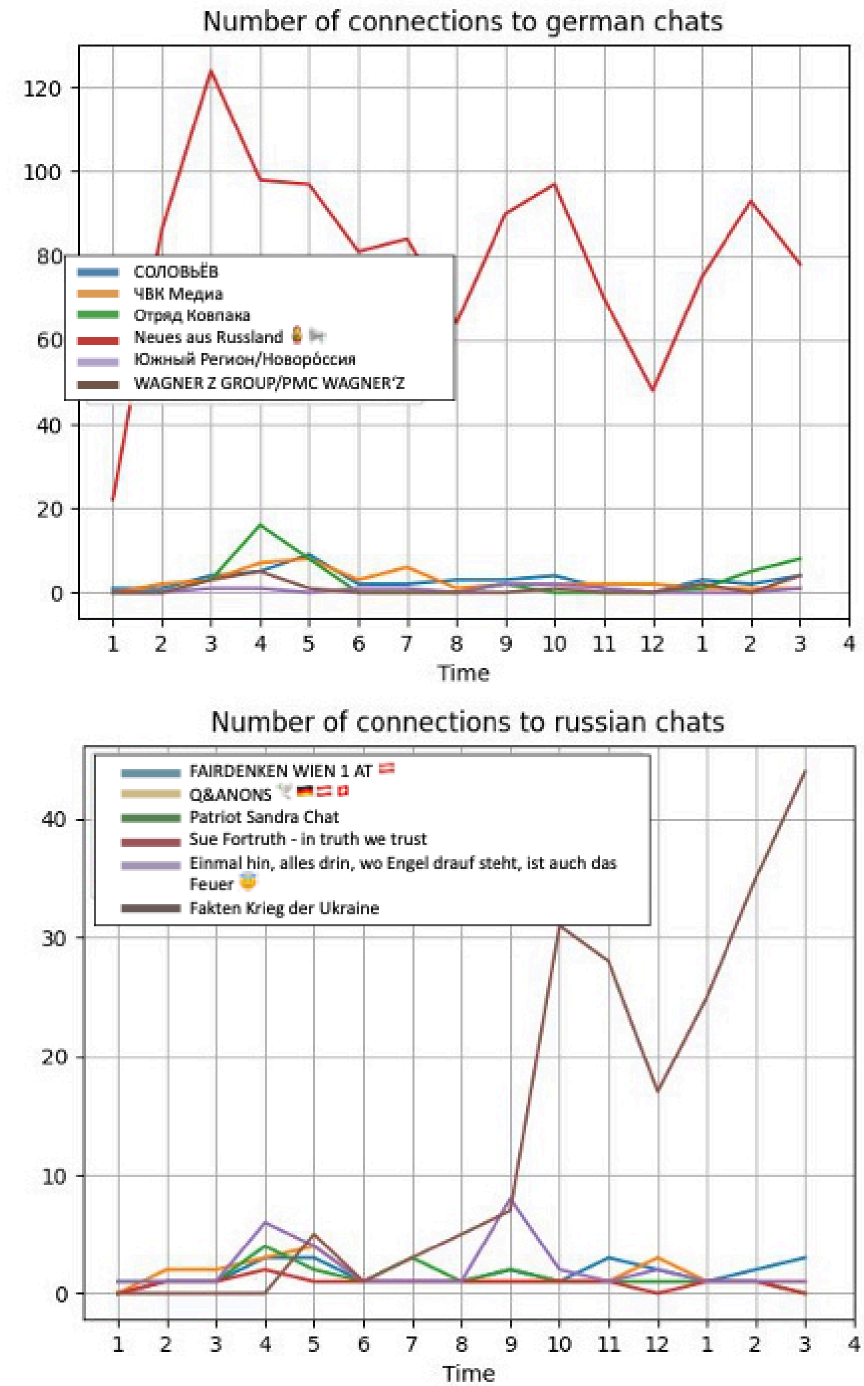


Fig. 5: Evolution of number of connections to a chat with the opposite language over time. The numbers on the horizontal axis refer to the months of 2022 (1-12) and restarts with the first four months of 2023.

D) Understanding the information flow in the network

Our network analysis identified a number of influential chats that drive both the Russian and German-speaking networks. In order to get a better understanding of the information propagation from one network to the other, we decided to look at the message level. For example, the channel ‘Neues aus Russland’ takes messages from the Russian side of the network and translates them into German before posting them as a separate message. As the two channels ‘Neues aus Russland’ and ‘Fakten Krieg der Ukraine’ are key nodes in the RUSSGER network, we centered our analysis on how these channels facilitate the flow of information from Russian to German circles.

In particular, we have plotted an Ego-Graph. This is a graph that visualizes a part of the network that is connected to a selected chat (called the ego). In the plot below, ‘Neues aus Russland’ is the ‘ego’ chat, and all the other circles are chats connected to ‘Neues aus Russland’.

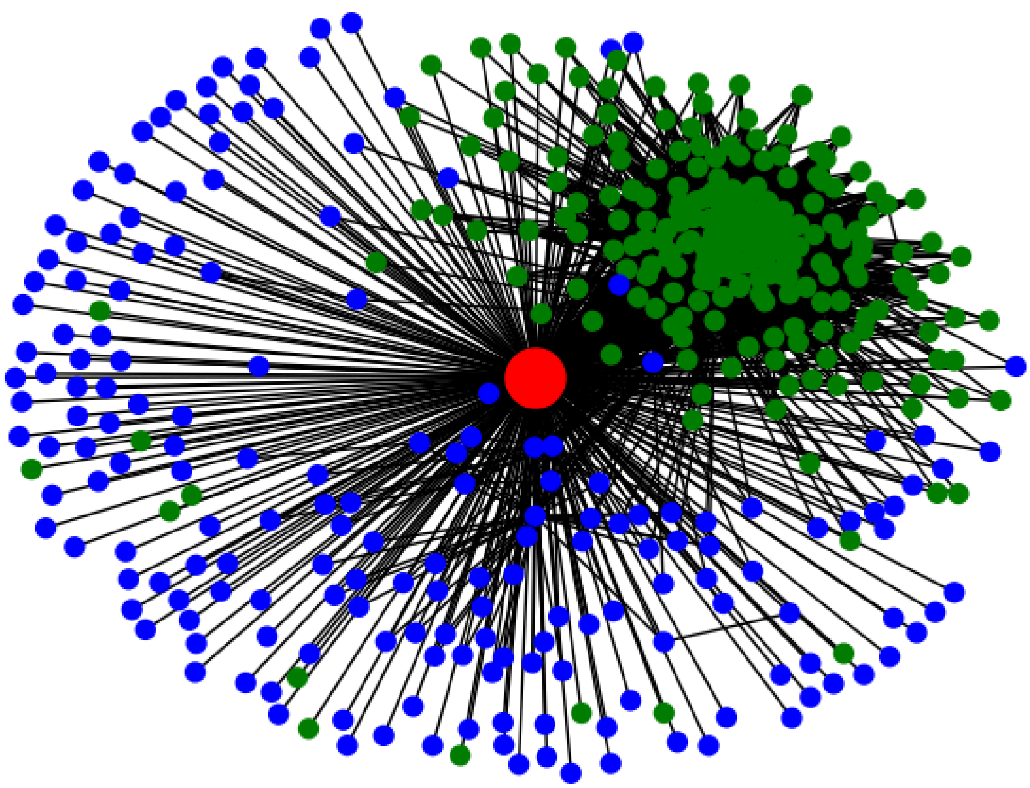


Fig. 6 Network of ‘Neues aus Russland’ (red) Russian (blue) and German (green) speaking chats. Connections from Russian chats to ‘Neues aus Russland’ indicate a forward of the Russian message by ‘Neues aus Russland’. Connections from ‘Neues aus Russland’ to the German chats indicate the forwarding of the translated German message by the German chat.

From the figure we can see that the Russian chats are quite spread out and there are few connections between them. Conversely, the German chats are quite close together and more highly interconnected. A possible interpretation here is that ‘Neues aus Russland’ looks for Russian messages in a wide range of smaller, lesser connected Russian chats. The German translations are forwarded by German chats that are well connected and popular. In other words, ‘Neues aus Russland’ plays a large role in spreading (dis)information. Not only does it pick up messages from relatively small/unconnected Russian chats, but also, the resulting translations are shared by large German chats where they are likely to get a big audience and be spread further.

‘Neues aus Russland’ being in the middle of the Russian and German networks may be explained by the fact that they post bilingual content. Additionally, as mentioned previously, ‘Neues aus Russland’ tends to forward messages from the Russian side of the network, but also translates them to German and posts them as a separate message. We wanted to identify such message pairs to collect a list of examples.

Approach 1: Detect translated messages based on time-of-posting and language.

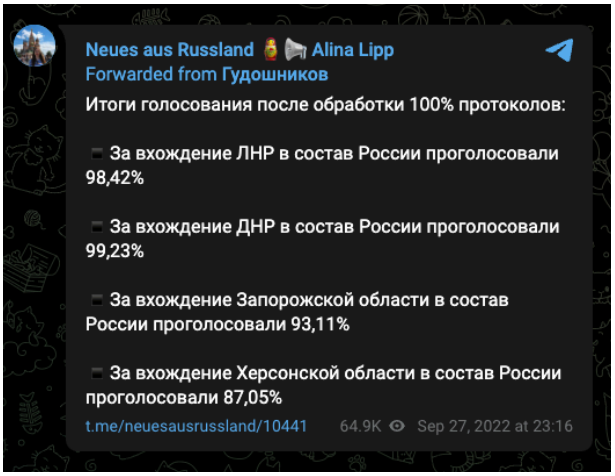
When analysing the RUSSGER network we found that ‘Neues aus Russland’ played a specific role. This chat forwarded messages from the Russian side of the network, but also translated them to German and posted them as a separate message. We wanted to investigate this further. To do this we first identified all such message pairs using the following heuristic:

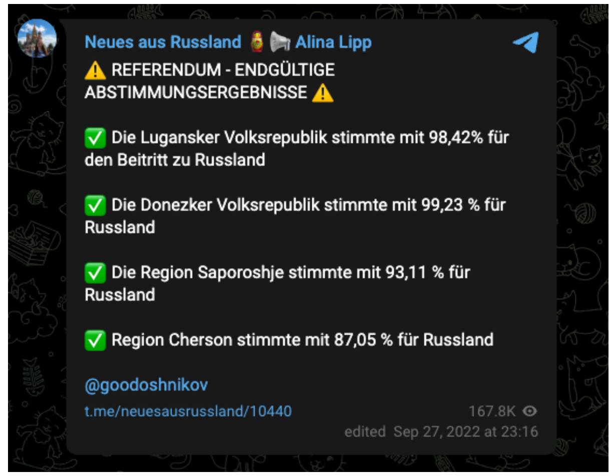
1. Find all messages that were posted within a minute of each other
2. If the one message was German and the other Russian, then add this to our collection of pairs.

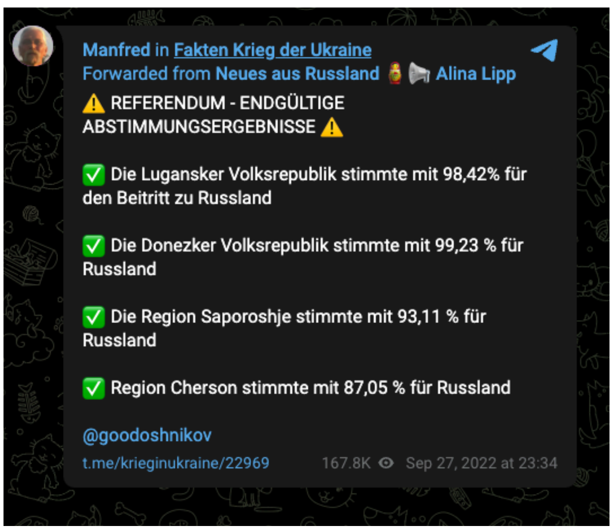
Using this method we found 480 message pairs.

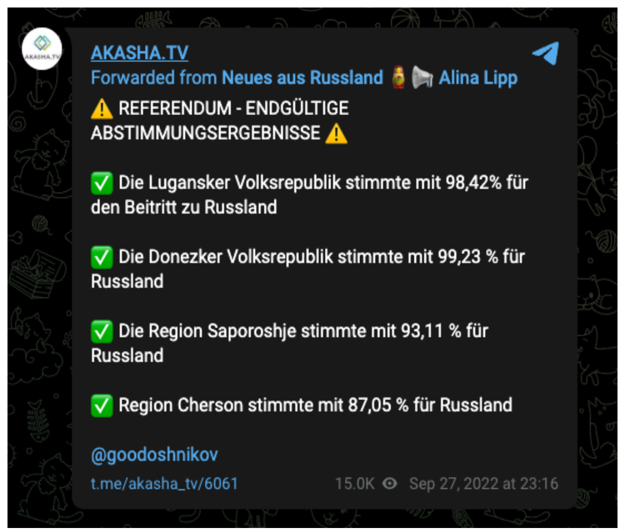
Examples

Below are two example identified message pairs. The first is a message about the LPR and DPR regions election results. These were carried out illegally and rejected by the EU. The translated message was later forwarded by a number of German chats, gathering more than 167,000 views in total.









Below is another example for identified message pairs. The first is a message about the alleged grandfather of Klaus Schwab. According to reports there is no evidence for these claims – the family was monitored by the Gestapo. Similar narratives were spread about other politicians. The translated message was later forwarded by a number of German chats, gathering more than 297,000 views in total.


Шейх Тамир
Такая вот попалась информация
На фото слева – основатель «Всемирного экономического форума» Клаус Шваб. Справа – его отец, приближённый к Гитлеру промышленник и фашист Ойген Шваб.
Клаус родился в 1938 году в гитлеровской Германии. Его отец тогда руководил стратегическим предприятием нацистской Германии «Escher-Wyss» и имел собственный концлагерь, использовавший бесплатный труд узников.
t.me/sheyhtamir1974/19097
297.1K
Тамир Шейх, edited May 23, 2022 at 18:07


Neues aus Russland Alina Lipp
Diese Art von Informationen wurde gefunden
Auf dem Bild links ist der Gründer des Weltwirtschaftsforums, Klaus Schwab, zu sehen. Rechts steht sein Vater, Hitlers enger Vertrauter, der Industrielle und Faschist Eugen Schwab.
Klaus wurde 1938 in Hitlerdeutschland geboren. Sein Vater war damals Leiter von Escher-Wyss, einem strategischen Unternehmen des nationalsozialistischen Deutschlands, und verfügte über ein eigenes Konzentrationslager, in dem Häftlinge kostenlos arbeiten mussten.
@sheyhtamir1974
t.me/neuesausrussland/5722
286.5K
edited May 23, 2022 at 21:29


Alles Ausser Mainstream
Forwarded from Neues aus Russland Alina Lipp
Diese Art von Informationen wurde gefunden
Auf dem Bild links ist der Gründer des Weltwirtschaftsforums, Klaus Schwab, zu sehen. Rechts steht sein Vater, Hitlers enger Vertrauter, der Industrielle und Faschist Eugen Schwab.
Klaus wurde 1938 in Hitlerdeutschland geboren. Sein Vater war damals Leiter von Escher-Wyss, einem strategischen Unternehmen des nationalsozialistischen Deutschlands, und verfügte über ein eigenes Konzentrationslager, in dem Häftlinge kostenlos arbeiten mussten.
@sheyhtamir1974
t.me/AllesAusserMainstream/24729
38.5K
Boschimo (Bodo Schiffmann), May 24, 2022 at 15:41


LK News für ein Leben in Freiheit
Forwarded from Neues aus Russland Alina Lipp
Diese Art von Informationen wurde gefunden
Auf dem Bild links ist der Gründer des Weltwirtschaftsforums, Klaus Schwab, zu sehen. Rechts steht sein Vater, Hitlers enger Vertrauter, der Industrielle und Faschist Eugen Schwab.
Klaus wurde 1938 in Hitlerdeutschland geboren. Sein Vater war damals Leiter von Escher-Wyss, einem strategischen Unternehmen des nationalsozialistischen Deutschlands, und verfügte über ein eigenes Konzentrationslager, in dem Häftlinge kostenlos arbeiten mussten.
@sheyhtamir1974
t.me/LKNews2/21355
12.0K
May 24, 2022 at 13:06

Approach 2: Detect translated messages based on content similarity

Semantic similarity

While some Russian messages were forwarded directly to German speaking chats, we expected that for the most part, content would be translated from Russian to German before moving to the German Telegram community. In addition to the approach above which was limited to one chat and based on message language and posting time, we can also look for message pairs that were highly similar in their semantic content.
We quantified semantic similarity using the following two-step process.

1. We created a numeric representation of the message content or caption by embedding the text using a multilingual sentence transformer model[2].
2. We could then calculate the distance between message pairs using cosine similarity.

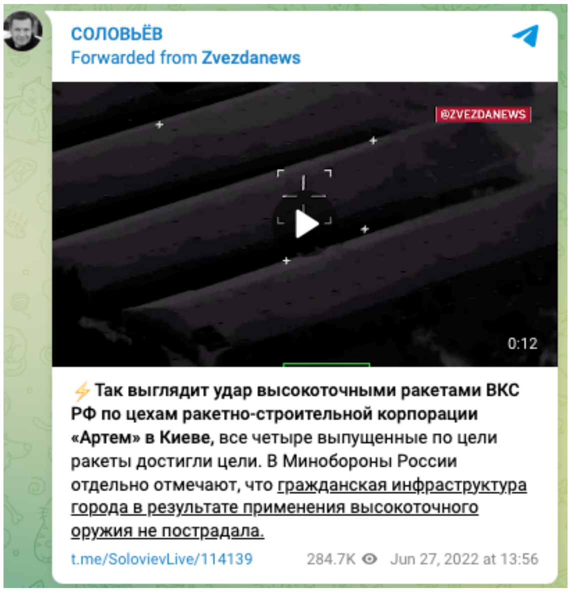
This generated a similarity score between -1 and 1. A score of 1 meant that the messages were identical, 0 meant that they were not related and -1 meant that they had opposite meanings. We used a cutoff of 0.7 to say that two messages were similar.

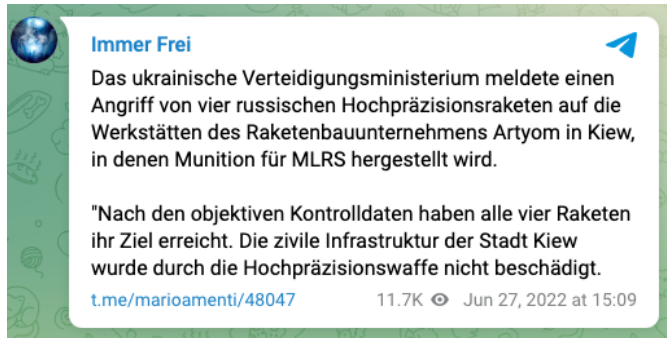
Due to computational restrictions, we could not calculate semantic similarity for all of the messages in the dataset. Therefore we did this analysis mostly as a proof of concept rather than an analysis on the whole dataset. We calculated similarity scores for messages in the top 10 most influential chats (5 in Russian and 5 in German) on 26th June 2022. We found 21 pairs of highly similar chats that day in Russian-German message pairs. 28 of the 42 messages were from the chat 'Neues aus Russland', again reinforcing its importance as a key player in this network.

Examples

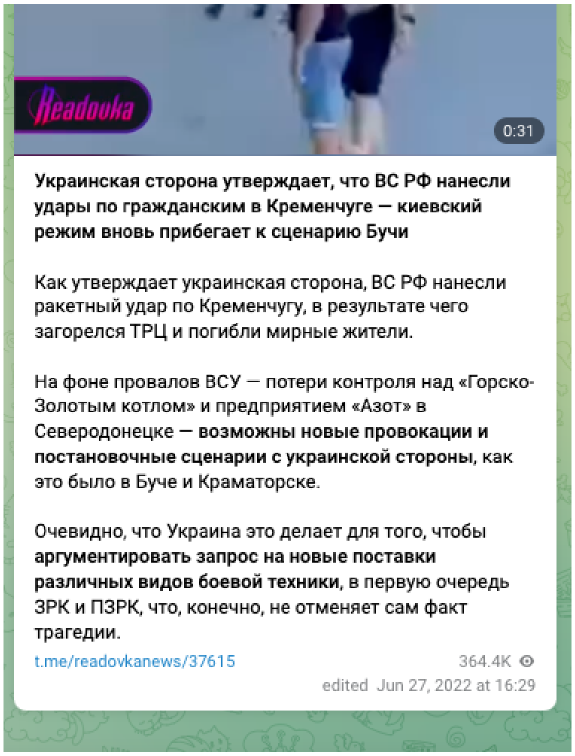
Below are two example message pairs identified through content similarity. In the first, a Russian message from SolovievLive is a caption of a video describing what a rocket attack on the Artem factory in Kyiv looks like. The caption includes a quote from the Russian Ministry of Defense. In the second, a German message from the marioamenti channel, there is a description of the attack and the same quote. The similarity score of these two messages is 0.71. The content is indeed very similar, although not identical, and is likely copied from the original statement from the Russian Ministry of Defense.

[2] https://huggingface.co/sentence-transformers/distiluse-base-multilingual-cased-v1





In the second pair of messages, there is a video present in both. The content casts doubt on Ukrainian reports of atrocities against civilians, suggesting that the Ukrainians attacked their own people, and that the Ukrainian allegations are a ploy to procure more Western military aid. The Russian message is from Readovkanews and the German message comes from 'Neues aus Russland'. The similarity score is 0.82. In this pair, the formatting and text look almost identical, suggesting that the German version is directly copied from the Russian post. We noticed that such direct copies were typical of 'Neues aus Russland'.



Украинская сторона утверждает, что ВС РФ нанесли удары по гражданским в Кременчуге — киевский режим вновь прибегает к сценарию Бучи

Как утверждает украинская сторона, ВС РФ нанесли ракетный удар по Кременчугу, в результате чего загорелся ТРЦ и погибли мирные жители.

На фоне провалов ВСУ — потери контроля над «Горско-Золотым котлом» и предприятием «Азот» в Северодонецке — **возможны новые провокации и постановочные сценарии с украинской стороны**, как это было в Буче и Краматорске.

Очевидно, что Украина это делает для того, чтобы **аргументировать запрос на новые поставки различных видов боевой техники**, в первую очередь ЗРК и ПЗРК, что, конечно, не отменяет сам факт трагедии.

t.me/readovkanews/37615 364.4K edited Jun 27, 2022 at 16:29

Ukrainische Seite behauptet, russische Streitkräfte hätten Zivilisten in Krementschuk getroffen - Kiewer Regime greift erneut auf Butscha-Szenario zurück

Die ukrainische Seite behauptet, die russischen Streitkräfte hätten einen Raketenangriff auf Krementschuk durchgeführt, wodurch das Einkaufszentrum in Brand geraten sei und Zivilisten getötet worden seien.

Vor dem Hintergrund der Misserfolge der AFU - Verlust der Kontrolle über den Kessel von Gorskoje und das Unternehmen Azot in Sewerodonezk - sind neue Provokationen und inszenierte Szenarien von ukrainischer Seite möglich, wie dies in Butscha und Kramatorsk der Fall war. Es ist sehr wahrscheinlich, dass die Ukrainer mit Tochka U erneut gegen ihr eigenes Volk vorgingen - ihre Beteiligung wurde bisher bewiesen, nachdem die Seriennummer der Rakete öffentlich gemacht wurde.

Offensichtlich will die Ukraine damit einen Antrag auf neue Lieferungen verschiedener Arten von militärischer Ausrüstung, vor allem SAMs und tragbare Luftabwehrsysteme, begründen.

t.me/neuesausrussland/7334 64.1K Jun 27, 2022 at 21:29

3. Discussion & Limitations

A) Dataset

One of the findings from both the graph analysis and the search for messages with semantic similarity was that the ‘Neues aus Russland’ channel features prominently in spreading Russian news to a German audience, frequently posting a Russian message quickly followed by a German translation. However, one caveat with this finding is that this channel was already flagged as a possible source of Russian disinformation entering the German Telegram space by journalists, and in fact was used as a seed to build the dataset. There is the potential for this finding to be a self-fulfilling prophecy - we cannot know whether it is a truly exemplary case of Russian disinformation spreading to German Telegram or whether that is just the case in our dataset because the data was collected around that channel.

This limitation stretches in some form to all the findings. Since the data used here is a sample of the full network, there is a chance that other findings, such as the higher interconnectedness of the German channels, could arise simply because the Russian channels or messages that make the link in the forwarding chain between channels are missing. As the data was not collected as a random sample of the German and Russian Telegram channels, the findings here cannot be generalized to make statements about the German and Russian Telegram networks as a whole.

One recommendation for future analyses would be to repeat these exercises using a dataset constructed by starting with a seed, and following the forwarding path a set number of "forwards", or "jumps".

B) Incomplete forwarding path information

A related issue is that the structure of the dataset does not show us the whole forwarding path of a message. In other words, the data lacks detailed information on the chain of events that led to the propagation of the message from one chat to another.

Say, message 1 was posted by channel 1 (Fig. 7). Channel 2 has found this message and forwarded it. Someone from channel 3 browsed through channel 2 and decided to forward it to channel 3 . The chain of events is hence: channel 1 -> channel 2 -> channel 3 (path 1 & 2 in Fig.7). Unfortunately, the way our dataset is structured does not tell us via which path channel 3 has acquired the message. We can only see where the message was originally posted and where it was forwarded. This would be a very interesting piece of information to assess information propagation dynamics within the network.

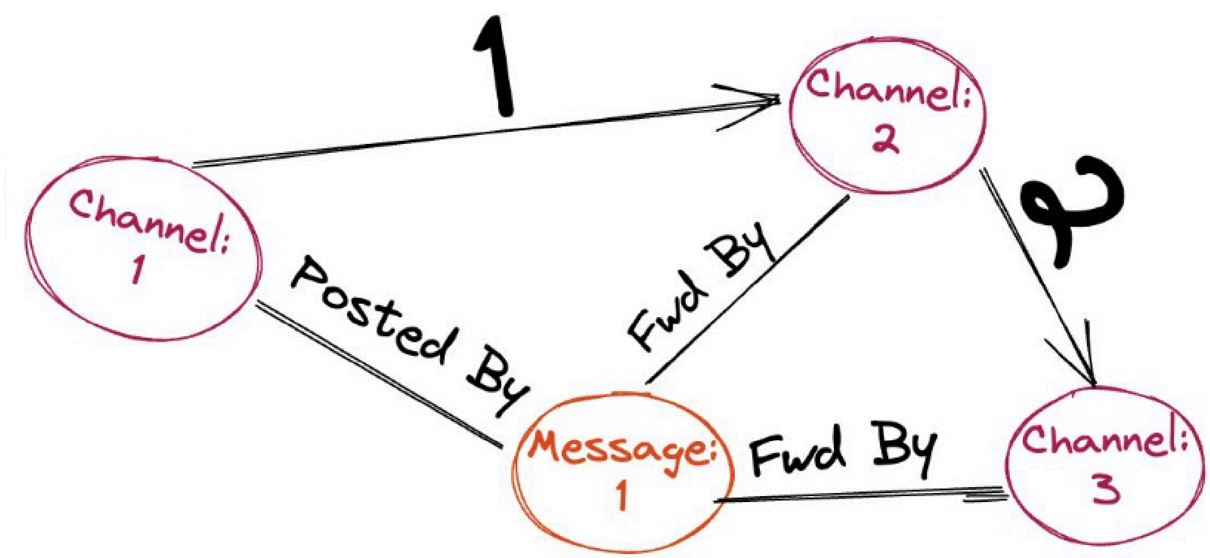


*Fig. 7. The given dataset only provides information about where the message was posted and who forwarded it. But we cannot see potential paths 1 and 2, i.e. we don't see that message 1 was propagated from channel 1 to channel 3 **via** channel 2.*

C)Semantic similarity

One limitation of the semantic similarity approach is that despite the similarity in video and content of the second pair of messages, we cannot say for certain that ‘Neues aus Russland’ was the source of the first German translation, nor which Russian post they translated from. They could have used a forwarded version of the Russian chat that is not in our dataset, or a completely different message that is not the forward chain of the Russian message. Therefore it is difficult to determine where exactly the “jump” happened. This semantic similarity approach is also limited because it captures many pairs like the first example pair, where both the Russian and German message are reporting news that likely comes from a third source.

4. Conclusions

A notable part of the investigated German and Russian channels was collected through ‘Neues aus Russland’. A Telegram channel, CORRECTIV.Faktencheck discovered a few days after the Russian invasion in Ukraine. Many of its posts also spread on Facebook, Twitter or on other Websites.

As this analysis shows, the channel plays a big role in translating content from Russian to German and serves as a source for at least 169 German Telegram chats. It mostly referenced messages from relatively small chats in Russian language and its translations were often shared by large German chats.

Through this analysis CORRECTIV.Faktencheck was able to identify other relevant groups and channels on Telegram, who spread pro-Russian Narratives. It gives insights into how their network grew over time (see chapter 2C) and shed light on the distribution of viral misleading claims as the supposed Nazi-father of Klaus Schwab.

References

Aric A. Hagberg, Daniel A. Schult and Pieter J. Swart, “Exploring network structure, dynamics, and function using NetworkX”, in Proceedings of the 7th Python in Science Conference (SciPy2008), Gäel Varoquaux, Travis Vaught, and Jarrod Millman (Eds), (Pasadena, CA USA), pp. 11–15, Aug 2008

Albert, R., & Barabási, A. L. (2002). Statistical mechanics of complex networks. *Reviews of modern physics*, *74*(1), 47.