# Modeling Information Narrative Evolution on Telegram during the Russia-Ukraine War

**Anonymous submission**


## Abstract

Following the Russian Federation's invasion of Ukraine in February 2022, a multitude of information narratives emerged within both pro-Russian and pro-Ukrainian communities online. As the conflict progresses, so too do the information narratives, constantly adapting and influencing local and global community perceptions and attitudes. This dynamic nature on the evolving information environment (IE) underscores a critical need to fully discern how narratives evolve and affect online communities. Existing research, however, often fails to capture information narrative evolution, overlooking both the fluid nature of narratives and the internal mechanisms that drive their evolution. Recognizing this, we introduce a novel approach designed to both model narrative evolution and uncover the underlying mechanisms driving them. In this work we perform a comparative discourse analysis across communities on Telegram covering the initial three months following the invasion. First, we uncover substantial disparities in narratives and perceptions between pro-Russian and pro-Ukrainian communities. Then, we probe deeper into prevalent narratives of each group, identifying key themes and examining the underlying mechanisms fueling their evolution. Finally, we explore principal influences and factors that shape the development and spread of these narratives.


## Introduction

Operations in the Information Environment (OIE) are fundamentally linked to information narratives. Defined in JP3-04 as *a way of presenting or understanding a situation or series of events that reflects and promotes a particular point of view or set of values (ibid. p. I-7)*, these narratives play a critical role in shaping audience perceptions. Consequently, with the growing ease of global dissemination, particularly driven by technologies such as generative AI (Goldstein et al. 2023) and social media platforms, there is an increasingly urgent need for automated, sophisticated tracking and analysis of these narratives

The Russia-Ukraine conflict serves as a prime example of this dynamic. In the buildup and aftermath of Russia's invasion on February 24, 2022, numerous narratives surfaced, each playing a significant role in molding public understanding and perception. From Russia's "denazification" claims to its assertions of Ukrainian biological weapons labs, these narratives have deeply impacted the collective viewpoint surrounding the conflict.

Considering the significant role information narratives play in shaping perceptions of the war globally, understanding comprehending how these narratives disseminate and transform is vital to grasping the evolving viewpoints of diverse populations (Volkova et al. 2021). However, while there has been research focused on identifying information narratives, these methods typically analyze them in a static, broad manner (Saldanha et al. 2024) and either focuses on topic modeling or social network analysis approaches. These methods overlook a crucial aspect that influences public interpretation of events: the construction and *evolution* of narratives over time. At their core, narratives are fluid constructs, composed of ever-evolving elements that continuously adapt to incoming external information and emerging influential threads. Consequently, current research's tendency to focus on the static, superficial facets of themes or topics fails to acknowledge this inherently fluid nature and thus often overlooks the intricate and evolving internal dynamics that dictate how narratives evolve and influence how and why people engage with them.

To overcome these challenges, we introduce a novel approach to capture and analyze the fluid, evolving nature of information narratives. We deliver a two-tiered analysis of narrative evolution on Telegram (as an example platform), offering both a broad, macroscopic perspective of the narrative's overall structure and a detailed, microscopic exploration of its components, providing fresh insights into how narratives evolve and transform over time e.g., appear, disappear, merge and split.

First, we first show how an automated approach to revealing trending stories allows us to understand how a community responds to and understands external events. Then we utilize our approach to perform a comparative analysis of the discourse in Russian-oriented and Ukrainian-oriented communities during the first three months of the invasion. We uncover a striking divergence in the narratives that emerge and gain prominence, underscoring substantial differences in how each side engages with and perceives the conflict. Next, we investigate narratives within each community, identifying central themes and exploring the mechanisms that shape their development and transformation. Lastly, we explore the key influencers and dynamics that contribute to the evolution and dissemination of narratives.

## Methodology

The goal of this study is to understand how information narratives surrounding the Russia-Ukraine war form and evolve across communities online. Here, we define a narrative and how our approach utilizes this definition to model the evolution of such narratives.

### Information Narratives

The concept of 'narrative' has been a longstanding subject of study within the discipline of narratology (Todorov and Weinstein 1969; Barthes and Duisit 1975; Smith 1980; Chatman 1990; Labov 2013); however, while the field generally agrees on the components of narratives, it still lacks a standard definition. Previous studies posit "narrative frameworks" as being comprised of stories which may align otherwise disparate domains of knowledge (Shahsavari et al. 2020). To build on this definition and follow the JP3-04, we adapt an information narrative framework detailed and used by similar recent works on narratives (Hanley, Kumar, and Durumeric 2023b), utilizing the Event Registry (Leban et al. 2014) idea where collections of documents seek to address the same event or issue (Miranda et al. 2018). As an example, a narrative found in our dataset may be "There are Biological Weapons Laboratories in Ukraine" This narrative would then be comprised of the stories that fall under this narrative, which are made up of individual posts contributing to each story. For instance, the text "We confirm the facts that were revealed of the emergency cleansing by the Kiev regime of traces of the military-biological program" would fall under the "Cover-up and Destruction of Biological Weapon Development" story which falls under the "There are Biological Weapons Laboratories in Ukraine" narrative.

### Data Used

We use posts collected from Russian-oriented and Ukrainian-oriented Telegram channels (Theisen et al. 2022) spanning from October 2015 to August 2023. These channels and their posts were collected using a combination of an expert-generated queue of telegram channels and snowballing via those channels.

Overall, there are 989 channels represented with over 9.67 million total posts, written mostly in Ukrainian and Russian. We sampled this data to focus our analysis on thee months starting Feb 2022 in which we track 568 channels and approximately 2 million posts.

**Telegram** Telegram is a messaging application that supports private and public groups for interactions between users as well as channels for one-way broadcasting to subscribers (Ghasiya and Sasahara 2023). Representing a more "free" Internet to many Russians, Telegram has become a source that (since 2020) operates without the same bans or restrictions platforms like Facebook, Instagram, and TikTok face (Oleinik 2024).

Moreover, beyond its uniquely unrestricted status in Russia, Telegram has increasingly become a dominant platform for military bloggers covering the Russo-Ukrainian war and has come to position itself as a critical source of information Ukrainians and Russians alike, with recent studies indicating that about 39% of Ukrainians and 19% of Russians regard Telegram channels as their primary information source (making Telegram the "second [...] and third most important source of information" in Ukraine and Russia, respectively) (Oleinik 2024). Thus, Telegram represents a key platform to study in order to understand Russian and Ukrainian discourse about the war as well as how narratives surrounding the war emerge and evolve.

### Modeling Approach

We employ a novel, multi-step pipeline to capture the evolution of narratives and their comprising components over time. Before applying the pipeline, we construct and partition the author network into separate Ukrainian-centric and Russian-centric networks. Next, we embed posts utilizing a multilingual embedding model; then, we employ a novel online agglomerative clustering algorithm to cluster the posts into evolving stories (which we we refer to as micro or story clusters later in this work). Using these story clusters, we construct evolving information narratives (which we will refer to as macro or narrative clusters later in this work) using a combination of algorithmic discovery with human-in-the-loop validation. Finally, we leverage Large Language Models (LLM) and Natural Language Inference (NLI) techniques to analyze the progression of narrative clusters and their constituent story clusters; this allows us to extract and assess the underlying themes that propel these narratives, examining both their overt content and their internal dynamics.

### Telegram Network Construction and Partitioning

Given that our data was collected to focus on the Russia-Ukraine war, it consists of mostly Ukrainian-centric and Russian-centric communities. To understand how each community discusses and understands the war in the beginning of the invasion, we first separate the data into these communities. To do this, we construct author networks amongst Telegram users and then use label-propagation algorithm to separate these networks (Garza and Schaeffer 2019).

**Network Construction** We aim to discover relatively homogeneous communities (Ukrainian-centric or Russian-centric) within our data so that we may understand and compare how each community discusses the conflict. To construct our networks, we lean on previous findings that retweets act as a relative indicator of endorsement-based connections (Metaxas et al. 2015). For Telegram data, we build a reference network of channels where a directed link with weight $w$ connects channel $A$ to channel $B$ if $A$ references or forwards a post of $B$ $w$ times within the period.

**Network Partitioning** For Telegram channels, we are able to view the biography and recent posts of each channel using telegrams native channel search service (t.me/channel_name). This allows us to inspect random "seed channels" that can guide the propagation of labels. Utilizing 3 classes "Ukrainian-centric", "Russian-centric", and "Other", we inspect and label 100 random "seed" channels (approximately 14% of channels) and run the label-propagation algorithm on the Telegram network.

**Telegram Data Sample Statistics and Validation** We inspect 75 random channels from each partition to ensure the validity of each partition. We show the partitions and their statistics in Table 1.

Table 1: Telegram data statistics.

| Leaning | Channels | Posts | Median Posts per Timestep |
|---|---|---|---|
| Ukrainian | 243 | 4.2M | 71K |
| Russian | 325 | 4.4M | 77K |
| Total | 568 | 8.6M | 148K |

## Data Preprocessing

For each post, we first remove all URLs, emojis, and hashtags. Next, we remove any duplicate posts. We define a duplicate post as having the same text and author so as to avoid duplicates that occur likely by mistake while preserving duplicates that arise out of the observed accounts copying each other's posts. Next, following the findings of previous work (Hanley and Durumeric 2023), we remove any posts that have fewer than four words. Finally, we break up the post into 2-sentence texts; this follows the logic and findings of prior works which posit that posts or articles often address multiple narratives but that smaller sentence-level components will typically discuss the same narrative (Piktus et al. 2022; Hanley and Durumeric 2023).

## Embedding Encoding

We utilize the multilingual MPNet embedding model (Song et al. 2020) to embed each text; specifically, we use the MPNet model fine-tuned for clustering and semantic search[1]. We chose it due to its ability to handle 50 languages (including the primary languages in our dataset: Russian, Ukrainian, and English) as well as its performance on similar tasks (Hanley and Durumeric 2023; Hanley, Kumar, and Durumeric 2023b).

## Semantic Similarity

We utilize cosine distance (rather than Euclidian or Manhattan distance, for example) to drive our clustering algorithm due to cosine similarity's (where cosine distance = 1 - cosine similarity) observed relationship with semantic similarity (Rahutomo, Kitasuka, and Aritsugi 2012). To guarantee high semantic similarity in our story clusters, we tested various cosine similarity thresholds, ranging from 0.60 to 0.85 in increments of 0.05, for grouping "similar" texts. Following prior research suggesting a 0.60-0.80 range for topical similarity (Hanley, Kumar, and Durumeric 2023a), we had a researcher label 200 randomly paired texts at each threshold as either "semantically similar" or "not semantically similar." We then compared these labels to each threshold's predictive accuracy of semantic similarity. Our findings indicate that a threshold of 0.85 yields the highest accuracy for semantic similarity, which is in line with similar work (Hanley, Kumar, and Durumeric 2023a).

[1]https://huggingface.co/sentence-transformers/paraphrase-multilingual-mpnet-base-v2

## Online Agglomerative Clustering

Text clustering methodologies are designed for static environments and, thus, fall short in their ability to effectively capture the dynamic and evolving essence of semantic clusters. While the overarching challenge of effectively modeling clusters over time has led to many works exploring evolutionary clustering techniques (Hruschka et al. 2009), the application SOTA approaches have been generally limited in the realm of information narrative modeling.

Drawing from dynamic community detection (Rossetti and Cazabet 2018) and previous work on extending agglomerative and k-means clustering (Chakrabarti, Kumar, and Tomkins 2006), we introduce a novel `OnlineAgglomerative` procedure. This procedure adapts these concepts for narrative analysis, grouping text by similarity while tracking cluster evolution over time. Through stepwise validation, we demonstrate its effectiveness in identifying and following evolving story clusters within larger narrative clusters, thus revealing the dynamic nature of narratives and their components.

## Hierarchical Agglomerative Clustering (HAC)

`OnlineAgglomerative` class is built upon Hierarchical Agglomerative Clustering. Hierarchical Agglomerative Clustering is a widely used method in data analysis for grouping objects into clusters based on their similarity (Müllner 2011). Unlike other clustering methods that require the number of clusters to be specified in advance, Hierarchical Agglomerative Clustering builds a hierarchy of clusters in a data-driven manner, making it particularly effective in data analysis where the underlying structure of the data is unknown. The process involves treating each data point as an initial cluster, computing a similarity measure (like cosine similarity), iteratively merging the most similar clusters, and stopping when merging would reduce similarity below a set threshold (e.g., cosine similarity of 0.85), ensuring cluster homogeneity (Lukasová 1979).

**Adapting HAC to Evolving Data** While traditional HAC provides a flexible method to derive clusters in an environment where the underlying structure is unknown, its fundamental design is inherently constrained to static environments. The `OnlineAgglomerative` class addresses this limitation by dynamically integrating new data at various timesteps. This allows the model to leverage HAC's strengths in identifying complex data structures, while also tracking the temporal evolution and formation of clusters.

**The `incremental_fit()` Procedure** The `OnlineAgglomerative` algorithm's `incremental_fit()` method adapts the Hierarchical Agglomerative Clustering algorithm for streaming data over timesteps. Initially, it runs hierarchical agglomerative clustering on the first batch of embeddings, creating clusters with tracked centroids and radii. Centroids represent the average of all points in a cluster, and radii are the cosine distances to the farthest points.

Then, incoming embeddings, the method determines if they fall within an existing cluster's radius. Embeddings outside any radius are classified as outliers and gathered until they reach a threshold, after which they are clustered anew. Embeddings within a radius are merged into the closest cluster, leading to updates in both the centroid and radius. After each batch, the algorithm evaluates if clusters can merge, based on silhouette scores or a pseudo-F index. It also maintains a history of each cluster's centroid and radius, tracking their evolution over time.

Ultimately, the `incremental_fit()` method modernizes HAC for dynamic data, blending continuous clustering with automated tracking. By integrating its continuous clustering capabilities with automated monitoring of evolution, the `incremental_fit()` allows for efficient dynamic analysis of narrative evolution.

## Story Cluster Discovery and Validation

**Discovery** During the incremental fitting process, the history of cluster characteristics is recorded at each timestep $t$. We record the number of data points it contains, its centroid (computed as the average of its points), and its radius (computed as the cosine distance from its centroid and its furthest point); this allows us to both understand how the cluster evolves in the lower-dimensional embedding space and track which pieces of text comprise the cluster at each timestep $t$.

**Validation** To ensure the validity of the evolving clusters, tracking that each cluster (1) is *cohesive* within a timestep and these results are (2) *consistent* across timesteps. To do this, we ran our incremental fitting process across 15 weeks, each week comprising an average of 120 thousand messages. We find that each point had an average cosine similarity of 0.935 with its respective cluster centroid on any given timestep – which is comfortably above our set similarity threshold (and indicating *cohesion*) – and an average cosine similarity of 0.245 with remaining clusters. Additionally, we manually inspect 10 random clusters to ensure the validity of our quantitative measures. Furthermore, we find that these similarity results are *consistent* across timesteps (i.e., it does not degrade as our algorithm considers more timesteps), suggesting that the algorithm effectively encompasses new data, correctly discerning when to fold data into existing clusters (and adjust the characteristics of these clusters) or create new clusters.

## Narrative Cluster Formation and Validation

After applying the `incremental_fit()` method to our data, we examine how story clusters form larger narrative clusters. For accurate narrative clustering, it is crucial that these encompass their constituent story clusters. As such, our approach starts by broadly linking related story clusters, followed by human-in-the-loop review and refinement to form "seed" story clusters. This approach ensures that 1) all potentially relevant stories are considered and 2) the resulting seed clusters are both *relevant* and *robust*. Figure 1 illustrates and further details this process.

**Evaluating Trends in Story Clusters** A pivotal aspect of our narrative analysis is the systematic evaluation of story cluster trends using the `analyze_micro_cluster_trends()` function. At each timestep, this function assesses the growth and contraction of story clusters by comparing the change in the number of data points relative to the previous timestep. We find that this logic of tracking growth and contraction tends to correlate best with trending stories and community reactions to external events (as opposed to just evaluating the clusters with the most points in that timestep, which often just correlated to common topics rather than trends).

**Discovery and Refinement of Narrative Seed Stories** To begin our formation of narrative clusters, we start with a story cluster uncovered in the previous step. This story cluster serves as the initial 'seed' from which we methodically unravel additional seeds, laying the groundwork for constructing a comprehensive narrative cluster.

**Human-in-the-Loop (HITL) Refinement** Our methodology emphasizes a balance between automated clustering and HITL refinement. First, we use a queue-based system to assess the seed over time. For each timestep, story clusters within a cosine similarity threshold of 0.7 to 0.8 (adjustable based on the narrative topic's scope) are added to a queue for testing and a separate list for human evaluation. This approach, akin to a breadth-first search (BFS), ensures thorough and *robust* identification of potential seed stories for further human refinement. After automated clustering, each potential seed cluster is evaluated by a human analyst. The analyst examines a representative sample of 20 randomly selected points at each timestep to verify the cluster's *relevance* and *alignment* with the narrative trajectory.

**Macro-Narrative Class and Narrative Centroid** Building on the SME's curated seed clusters, the `MacroCluster` class then utilizes these seed clusters to construct a 'Narrative Centroid' that moves through time with its seed clusters. This dynamic centroid is continually re-calibrated based on the movement and development of the seed story clusters, allowing the narrative cluster to evolve over time and mirror the fluid nature of the narrative through time. Then, by setting similarity thresholds for the inclusion of story clusters through time, the `MacroCluster` class allows for stories to dynamically fall under its purview throughout time, facilitating a nuanced and responsive understanding of the narrative evolution.

As an example, in our study of the Ukrainian community's Bucha Massacre narrative, we witnessed the interplay of various story clusters pertaining to the liberation of Bucha within the narrative cluster. While these clusters were initially identified as during the automated discovery stage, their generalized focus on liberation precluded them from being considered as grounding seeds. However, during the appropriate time period (i.e., when they were discussing the liberation of Bucha), their interactions with the established narrative were still captured and analyzed through the narrative centroid's adaptive framework, demonstrating the ability to reflect both the stability and fluidity of narrative elements within a broader context.

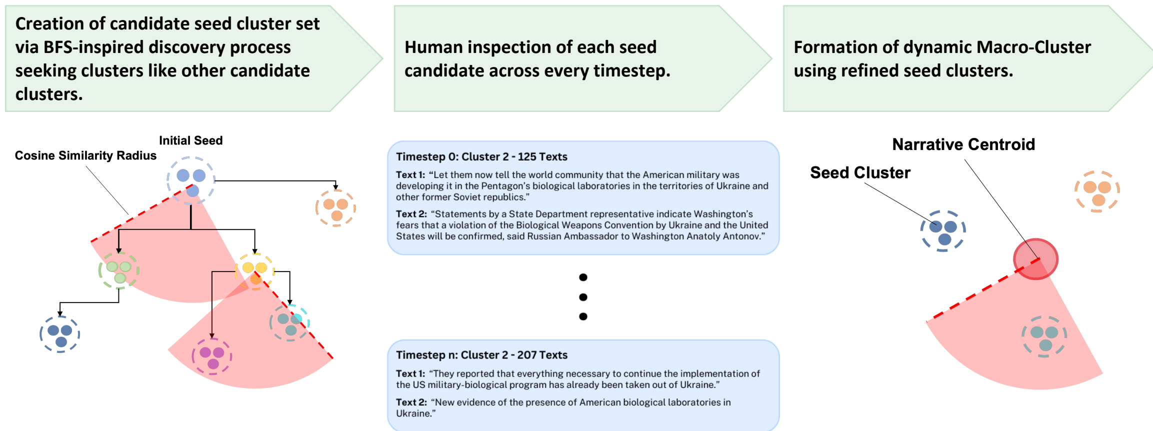


Figure 1: Overview of narrative cluster formation: the process starts with the initial creation of candidate seed clusters followed by human-in-the-loop evaluation, culminating in the formation of a dynamic macro-cluster around a narrative centroid.

## Narrative Summarization and Classification

Following our story and narrative clustering and monitoring of narrative macro-clusters, we sought to understand what themes emerge and how themes evolve within narratives. To do this, we employed a combination of the Llama2 Large Language Model (LLM) (Touvron et al. 2023) and a multilingual deberta model (He, Gao, and Chen 2023) fine-tuned for multilingual zero-shot. classification[2]

**Narrative Summary Generation** To ensure interpretability of our approach, we utilize the Llama2 LLM to extract themes from each narrative. To do this, we prompt the large language model with representative points from each story cluster across each timestep, asking it to list out themes it finds. Then, we utilize these themes in conjunction with zero-shot classification model to understand how themes emerge and interact within both stories and narratives.

**Narrative Summary Classification** To assess theme representation across messages in a narrative, we employ an off-the-shelf zero-shot classification model. This model, which has not seen the specific categories during training, classifies texts from narrative clusters based on context and semantics (Wang et al. 2019). We use a multi-label setting (in which a data point can belong to multiple classes rather than just one) because we found that some texts can indeed represent more than one theme effectively and that by choosing this setting, the model analyzes each theme/label independently of the others. Then the model then returns a list of corresponding model scores and confidences for each label.

**Narrative Summarization Validation** We seek to extract a set of narrative themes that provide and maximize both *coverage* and *nuance*. To do this, we first extract 15 dictionaries of *candidate themes*. To do this, we process each timestep by examining story clusters within the narrative centroid's similarity threshold. An empty map is initialized to track the emergence timestep of each theme. The Llama2 model is then provided with the 10 points closest to each story cluster's centroid. If the Llama2 model has previously generated themes, these are also fed back into the model. The Llama2 model identifies new themes or generalizes existing ones. Each identified theme, along with its corresponding timestep, is recorded in the map. The final output is a map of all generated themes, along with their emergence timesteps.

Then, we use SOTA auto-regressive classification model to test each dictionary and find its *Theme Coverage Score*. Theme Coverage Score (TCS) which utilizes the model to quantify how much a set of themes is represented in the messages. TCS sums across all timesteps the percentage of texts above the set threshold for at least one theme; thus, a higher score signifies greater theme recognition and thus a more comprehensive and representative collection of themes. Calculating TCS for every theme dictionary, we then choose the theme dictionary that achieves the highest score for further analysis. We note these scores generally do not vary much, with the main differences in theme dictionaries being slightly disparate number of themes and slightly different wording of themes.

**Narrative Summary Classification Validation** To validate theme classification, we establish a “confidence threshold” for each narrative. Text must exceed this threshold (0-1) to be assigned a specific theme. We determine this threshold by initially running our theme extraction model, then manually examining how the classification model labels 200 texts at varying thresholds. Prioritizing specificity to minimize noise, we choose a threshold that optimizes accuracy. We note that theme trends stay consistent across various thresholds, reinforcing our confidence in our method's reliability.

## Analysis and Key Findings

We evaluate the proposed approach for narrative modeling across communities for the first 3 months (15 weeks) of the war, from February 20, 2022, through May 28, 2022. We examined the communities leaning towards Russia vs. Ukraine

[2]https://huggingface.co/MoritzLaurer/mDeBERTa-v3-base-xnli-multilingual-nli-2mil7

separately, utilizing weekly timesteps, with each timestep containing on average 120 thousand messages.

## Micro-Narrative Cluster Analysis

To understand how both communities discuss the events during the war, we extract and analyze story clusters at each timestep. Our pipeline first outputs translations of 10 messages near each cluster's centroid and 5 random messages, followed by a Llama2-generated summary. We condense these clusters into monthly summaries (see Table 7). These stories reveal three main findings: the speed and uniformity of community responses, differing focuses on specific events, and distinct perspectives on identical situations.

First, both communities react very quickly and consistently to events: in each timeframe examined, the majority of the leading story clusters were closely linked to external events. Second, the events and stories capturing each community's attention differ greatly, reflecting their unique focuses and concerns. Ukraine's trending clusters primarily highlight critical developments like airstrikes and humanitarian efforts, whereas Russia's narratives, often disconnected from ground realities, emphasize topics like international reactions (frequently framing Russia as a victim) and economic impacts. To get a sense of this disparity, we have a human annotator label the top 10 trending stories from either community for each week as "Military/War," "Politics - Internal," or "Politics - International;" the results are shown in Table 2.

Table 2: Micro-narrative story clusters on Telegram.

| Community | Military/War | Politics | |
|---|---|---|---|
| | | Internal | International |
| Ukrainian | **46.5%** | 9.3% | 44.2% |
| Russian | 16.7% | 31% | **52.4%** |

As shown in Table 2, the primary focus of each community was markedly distinct. Furthermore, it should be noted that even within their most common topic – international politics – the focus varied greatly; Ukraine's stories often centered on foreign aid and EU accession/NATO assistance, whereas Russian stories often concentrated on things like economic ties (like the mandate for "unfriendly countries" to purchase gas in rubles) and international reactions, typically portraying Russia as a victim of unfair international criticism.

An illustrative example of this divergence occurred during the week of March 6, 2022. Following a suspected Russian airstrike seen as a move to involve Belarus in the conflict, the Ukrainian community concentrated on both the airstrike itself and its potential repercussions[3]. In contrast, the Russian community paid little attention to this incident, instead prioritizing political issues like Russia's Foreign Ministry's allegations of US-backed biological weapons in Ukraine and the withdrawal of some Western companies from the Russian market. This difference in narratives underscores the profound disparity in the concerns and narratives of the two communities.

Finally, when both communities addressed a common narrative, their perspectives were strikingly different, highlighting their divergent interpretations. A clear example came in the wake of the widespread coverage of the Bucha Massacre by Western media in late March and early April. Whereas the Ukrainian community concentrated on detailing Russian atrocities and countering claims that the massacre was fabricated, the Russian community portrayed this coverage as propagandistic and a provocation by Ukraine, labeling it as "another staged act by the Kiev regime." These polarized views on the Bucha incident are a continuous theme in the conflict, as illustrated in Figure 2.

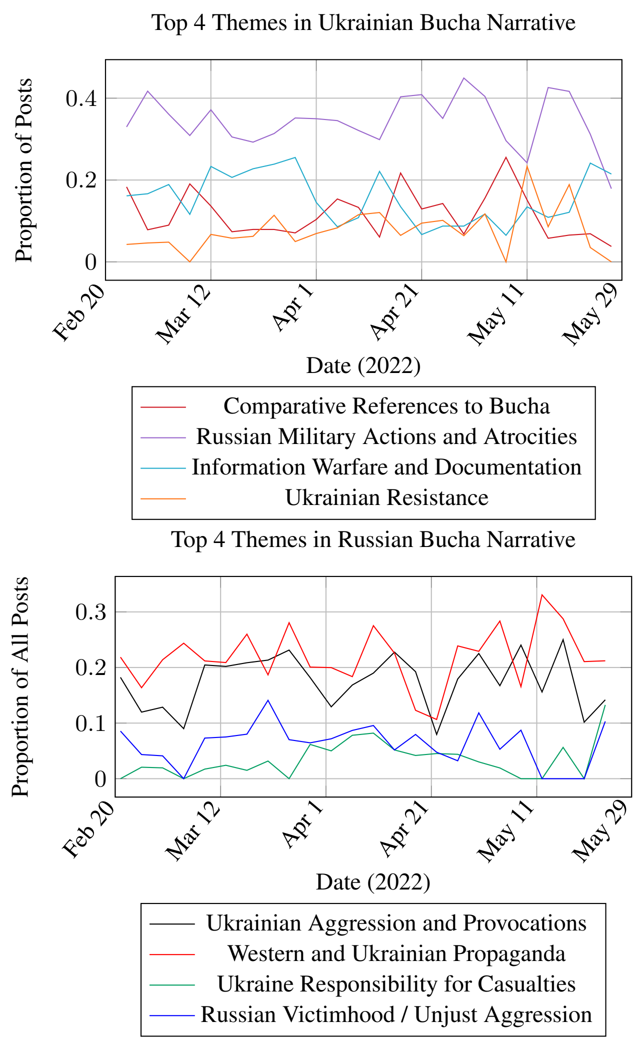


Figure 2: Contrasting information narratives surrounding the Bucha Massacre across Russian and Ukranian communities.

[3] https://www.reuters.com/world/ukraine-says-russian-aircraft-fired-belarus-ukrainian-air-space-2022-03-11/

## Information Narrative Analysis

We conduct an in-depth analysis of four major narratives from each community (shown in tables 5 and 6), examining their persistence, the micro-narratives they encompass, their summaries, and the key authors involved.

**Narrative Structure** We evaluate the narratives at both the story level and the summary (theme) level. First, we find that the number of story clusters comprising a narrative depends on the narrative. For example, the Russian narrative about denazifying Ukraine contained many more story (micro-narrative) clusters (7-10 depending on the timestep) than the Ukrainian narrative about Ukraine belonging in the European Union (4-7 depending on the timestep). Additionally, we find that the number of comprising stories can shift across timesteps and in response to external events. For example, following Russian accusations of biological weapons at the United Nations[4], the Russian narrative about bioweapon labs swelled with new stories of new-found "documents" proving the existence of "biolaboratories" created and financed by the United States in Ukraine, where experiments were conducted with samples of bat coronavirus."

Moreover, we find that the stories within narratives are typically characterized by 1-3 closely related themes, reinforcing the concept of these clusters as the foundational elements of narratives. The prevalence of multiple themes seems to stem from the interconnectedness of these themes. For instance, within the denazification narrative, messages containing the theme "Ukrainian leaders depicted as Nazi sympathizers" were significantly more likely to have the theme "Ukrainian nationalism linked with neo-Nazism" (with a Spearman correlation coefficient of 0.83 with a p-value $< 0.01$). These types of correlations between similar themes were found in multiple narratives and, when coupled with the lack of correlations found among more disparate themes, appear to support the notion that narratives may act as frameworks which may align otherwise disparate domains of knowledge (Shahsavari et al. 2020).

We then explore correlations between key contributors' posting patterns and narrative shifts in online communities. To analyze this, we first apply Granger causality analysis – a method to determine if one time series can predict another – to identify statistically significant (p-value $< 0.01$), predictive lag between an author's posts and later engagement with the narrative. Note that we exclude the author's posts from later post distributions so as to not bias analysis. We then measured strength and direction of these correlations using Spearman's rank correlation coefficient, a choice driven by its suitability for non-linear relationships.

We present the results in Tables 3 and 4. Here, we describe correlations with a minimum Spearman correlation of 0.3, significant at a p-value of less than 0.01. Notably, the most pronounced correlations for overall narrative shifts typically occur with a mere one-day lag, underscoring the rapid impact of specific events. However, correlations with changes in theme engagement display more variability, with some authors showing peak correlations several days later. Intriguingly, those who exhibited high theme correlations were not always the most prolific contributors, suggesting a nuanced dynamic in how individual posts can shape community discourse.

Table 3: Narrative story associations across pro-Russian and pro-Ukrainian communities (p-value is $< 0.01$).

| Narrative | Channel | Lag | Spearman |
|---|---|---|---|
| **Russian** | | | |
| Denazification | boris_rozhin | 1 | 0.461 |
| Biological Weapons | regnum_na | 1 | 0.395 |
| Biological Weapons | regnum_na | 3 | 0.318 |
| Bucha - Russia | SolovievLive | 2 | 0.416 |
| **Ukrainian** | | | |
| Human Corridors | liganet | 1 | 0.423 |
| EU Accession | u_now | 7 | 0.350 |

**Narrative Patterns** We find that information narratives respond to external events in terms of both the volume of posts and the evolution of their themes and stories. This indicates a reaction not just in the sheer number of posts, but also in the shifting components of the narratives themselves.

The significance of narrative volume and its implications for each side are exemplified in their respective responses to the Bucha Massacre. As the atrocities in Bucha unfolded, the Ukrainian community actively reported on them, with vivid accounts of "shooting at civilians," "merciless shelling," and their defensive military efforts. In contrast, the Russian community was notably "quieter" during this period, with occasional mentions of sabotage and "propaganda" on Ukrainian Telegram channels amidst Russia's "liberation of Bucha." However, when substantial evidence and Western media coverage escalated in late March, both narratives rapidly evolved in volume. The Russian narrative predominantly focused on casting doubt, stating, "all photographs and video materials published by the Kiev regime, allegedly indicating some kind of 'crimes' of Russian military personnel in the city of Bucha, Kiev region, are another provocation." Meanwhile, the Ukrainian narrative intensively covered the specific atrocities, such as "Residents of Bucha talk about the Russian occupation: shootings, systematic murders, torture," evidence of these crimes, "the public has published yet another proof that the Russian military shot civilians in Bucha," and countering Russian misinformation, "They say about the killings in Bucha that it is not them, but supposedly us, although it is obvious to everyone that people were killed when the Russian army controlled this city."

The shifting themes within narratives reflect both the resonating narratives for each community and their attitudes towards external events. An example of this dynamics can be seen in Russia's denazification narrative, illustrated in Figure 3.In the invasion's early stages, the discourse primarily focused on the "Nazification of the peoples of Ukraine" and the suppression of Russians in Ukraine, emphasizing "the ban on the use of their native Russian language and

[4]https://www.washingtonpost.com/world/2022/03/11/un-council-ukraine-russia-chemical-weapons-zelensky/

Table 4: Narrative theme associations across pro-Russian and pro-Ukrainian communities (p-value is $< 0.01$).

| Narrative | Theme | Channel | Lag | Spearman |
|---|---|---|---|---|
| **Russian** | | | | |
| BioWeapons | Military-Bio Activities | SolovievLive | 1 | 0.439 |
| BioWeapons | Human Right Violations | SolovievLive | 3 | 0.453 |
| BioWeapons | Involvement of US | SolovievLive | 4 | 0.351 |
| Denazification | Neo-Nazi Policies Effects | boris_rozhin | 1 | 0.436 |
| Bucha - Russia | Bucha Conspiracy | SolovievLive | 4 | 0.320 |
| **Ukrainian** | | | | |
| Human Corridors | Humanitarian Aid | znua_live | 4 | 0.513 |
| Human Corridors | International Cooperation | znua_live | 4 | 0.506 |
| Bucha - Ukrainian | Humanitarian Crisis | u_now | 2 | 0.303 |

Table 5: Pro-Ukrainian information narrative and theme analysis.

| Narrative | Narrative Themes Discovered | Top Contributing Authors (Contribution / Std Devs Above Median) |
|---|---|---|
| Russian troops committed a massacre in Bucha. | Russian Atrocities, Ukrainian Resistance, International Diplomacy, Humanitarian Crisis, Information Warfare, War Crimes Accountability, Economic Impact, Refugees, Bucha Comparisons. | kyiv_n (4.4% / 5.8)<br>u_now (3.0% / 3.8) |
| Ukraine has a unique European identity and belongs in the European Union. | Ukraine's EU Aspiration, Accession Challenges, International Support, EU Bilateral Relations, EU Integration Progress. | verkhovnaradaukrainy (7.8% / 8.52)<br>u_now (3.7% / 3.9) |
| Russia is engaging in chemical warfare. | Chemical Weapon Concerns, Reports of Usage, Preparation, Environmental Impact, Anti-Mite Treatment. | ukraina24tv (4.04% / 4.6)<br>spravdi (3.1% / 3.3) |
| Russia is sabotaging Ukrainian humanitarian corridors. | Humanitarian Aid, Evacuations, Corridor Blockades, War Crimes Probes, International Cooperation, Government Actions, International Support. | znua_live (4.1% / 3.3)<br>OP_UA (4.0% / 3.2) |

Table 6: Pro-Russian information narrative and theme analysis.

| Narrative | Narrative Themes Discovered | Top Contributing Authors (Contribution / Std Devs Above Median) |
|---|---|---|
| There are Biological Weapons Laboratories in Ukraine. | Ukrainian Bio-Weapons Labs, Military Activities, Global Involvement, Pathogens, Human Rights Issues, Safety Concerns, Strategic Locations, Information Warfare, Health Threats, Legal Action. | regnum_na (5.8% / 6.2)<br>SolovievLive (4.5% / 4.8) |
| Ukraine must be denazified. | Ukrainian Neo-Nazism, WWII History Revision, Russian Anti-Nazi Stance, Western Support, Leadership Sympathies, Conflict Symbols, Media Propagation, Patriotism, Neo-Nazi Impact, War Crimes, Civilian Effects | SolovievLive (3.6% / 6.0)<br>rus_demiurge (3.2% / 5.3) |
| There was no "Bucha Massacre" committed by Russian troops. | Bucha Event Doubts, Media Manipulation, International Report Challenges, Alternative Narratives, Ukraine's Role Critique, Evidence Credibility, International Response | SolovievLive (4.9% / 5.5)<br>borish_rozhin (3.7% / 4.2) |
| NATO poses a threat to Russia. | NATO Expansion, Military Provocations, Western Aggression, Conflict Escalation, Hypocrisy, Indirect Warfare, Geopolitical Impact, Global Security Threat, Russia's Defense. | rus_demiurge (4.2% / 5.81)<br>SolovievLive (3.1% / 4.2) |

Russian culture," and "the genocide of regions that rebelled against Bandera."[5] Overall, these early themes appear to underscore a consistent message: the portrayal of Nazism as rampant in Ukraine and the framing of Ukraine as needing liberation. As the conflict progressed, these themes gradually shifted to more patriotic ones, lauding Russia's actions against Nazism with claims like "Russia has liberated Kherson from the Nazis, there will be no more Nazis there" and "Kyiv will no longer be able to impose its ugly Nazi policies on our region."

Tables 5 and 6 present top contributing authors to each narrative. We observe that within a narrative, the posting patterns of key contributors frequently correlate with ensuing narrative shifts by others in the community.

[5]https://en.wikipedia.org/wiki/stepan_Bandera

**Contrastive Narrative Analysis** The diverging narratives around the Bucha Massacre, as depicted in Figures 2 and 4, highlight the distinct ways each community perceives the events. From the Ukrainian perspective, the narrative starts unfolding in real-time, with a focus on documenting the atrocities. This emphasis on documentation persists and intensifies over time, becoming crucial to counter the Russian narrative's accusations of fabrication and misinformation (this general shift from on-the-ground coverage to doc-

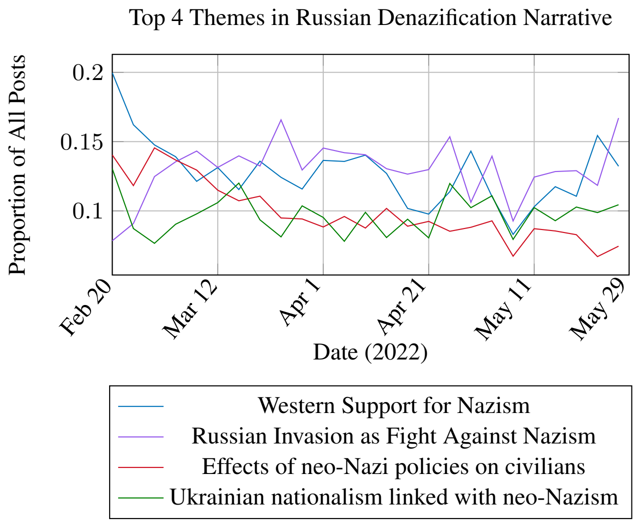


Figure 3: Themes discovered in narratives about Denazifying Ukraine.

umentation is further illustrated in Figure 5). Additionally, this framework of understanding becomes a lens through which the Ukrainian community views and discusses other similar incidents, increasingly comparing other events to the massacre with statements like “the second Bucha is now taking place in the Kherson region,” indicating a broader application of the Bucha narrative to comprehend subsequent events. Contrastingly, the Russian narrative on the Bucha Massacre, emerging predominantly post-Western media coverage, consistently features claims of propaganda and Ukrainian provocation. This emphasis on efforts to “expose the fake about Bucha” and challenge the “demonization of Russia” by Western media intertwines with a persistent theme of Russian victimhood, which we note across other Russian narratives.

## Ethical Considerations

Our study utilized a dataset sourced from publicly accessible Telegram channels managed by widely recognized ”warbloggers.” Alongside this paper, we are also releasing the `OnlineAgglomerative` class and instructional Jupyter notebooks to aid others in narrative analysis[6]. Nonetheless, we recognize that our work could potentially be misapplied, particularly in the context of narrative detection involving at-risk or vulnerable populations. We have taken careful measures to ensure our research is conducted and shared with a strong sense of responsibility and ethical awareness.

## Limitations

Our analysis is confined to data from Telegram; while this platform is recognized as a major source of information for Ukrainians and Russians alike, it may not fully represent the perspectives found on other platforms, and leaves room for future work. Furthermore, our study did not investigate the potential enhancements in story clustering that could be achieved by applying modern contrastive learning techniques (Gao, Yao, and Chen 2022) to our specific dataset. Such methods might offer significant benefits in other research areas. Additionally, our research centers on highly polarized communities engaged in discussions about war, which may limit the applicability of our findings to less contentious or more neutral contexts.

[6] https://patrikgerard.github.io/online-hierarchical-agglo/

## Summary and Future Work

In this work we develop and validate a novel methodology for tracking and understanding information narrative evolution online. To demonstrate our framework, we performed a comparative analysis on the Ukrainian and Russian communities on Telegram during the initial three months of Russia-Ukraine war, evaluating what stories capture their attention, the inner-mechanisms of narratives, and key contributors driving these these narratives. The comparative analysis between Russian and Ukrainian communities highlights not only the difference in perceptions between the communities, but also the fluid nature of narratives, which appeared to adapt differently to new information and influential ideas over time.

While our analysis primarily addresses the differing perceptions of the Russo-Ukrainian war, it also unveils general patterns in narrative fluidity and evolution, relevant beyond this specific conflict. This broader understanding is further enriched by our novel dynamic clustering model, which opens new pathways for studying narrative development.

This proposed technology enables real-time insight into the information environment, allowing for the tracking of dynamics and the analysis of narrative impacts on audiences. It also improves operational planning by providing a comprehensive global narrative overview, supporting Joint Intelligence Preparation of the Operational Environment (JIPOE), and enabling automation across different platforms and languages. Additionally, it facilitates both human and automated decision-making through improved collaboration and efficient management of knowledge and information.

## References

Barthes, R.; and Duisit, L. 1975. An introduction to the structural analysis of narrative. *New literary history*, 6(2): 237–272.

Chakrabarti, D.; Kumar, R.; and Tomkins, A. 2006. Evolutionary Clustering. In *Proceedings of the 12th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD ’06, 554–560. New York, NY, USA: Association for Computing Machinery. ISBN 1595933395.

Chatman, S. 1990. What can we learn from contextualist narratology? *Poetics Today*, 11(2): 309–328.

Gao, T.; Yao, X.; and Chen, D. 2022. SimCSE: Simple Contrastive Learning of Sentence Embeddings. arXiv:2104.08821.

Garza, S. E.; and Schaeffer, S. E. 2019. Community detection with the label propagation algorithm: a survey. *Physica A: Statistical Mechanics and its Applications*, 534: 122058.

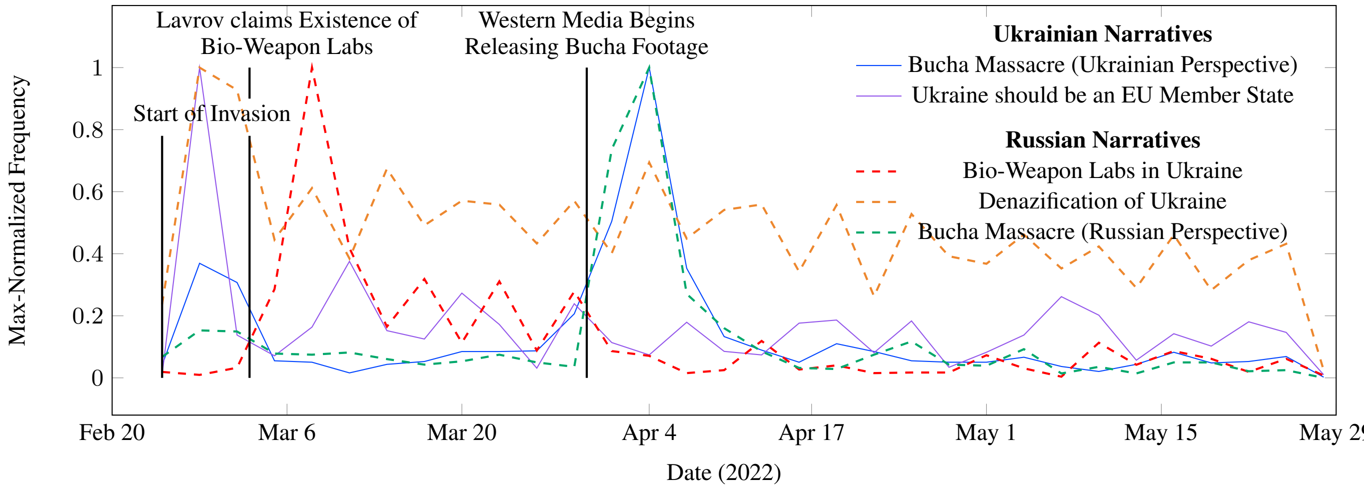


Figure 4: Information narrative evolution shown using max-normalized frequency of posts in key narratives within Ukrainian and Russian communities over time (summed over 3-day time-periods for clarity), where max-normalization adjusts frequency counts relative to each narrative's peak activity for comparative clarity.

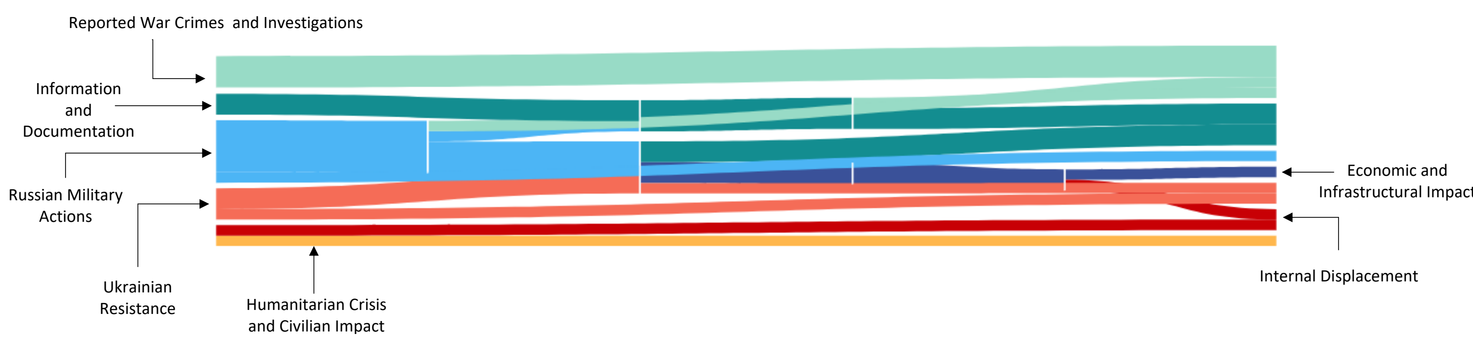


Figure 5: Information narrative evolution of dominant theme distribution of story clusters focused on Russian atrocities. To make this we look at the top 2 dominant themes in top 5 most populated story clusters; then, we aggregate this at a monthly timeframe (thus, having 4 points for potential pivoting) to understand general flow of these themes.

Table 7: Summaries of monthly information narratives in observed pro-Ukrainian and pro-Russian communities.

| Time Period (2022) | Summary of Top Trending Stories | |
|---|---|---|
| | Ukrainian | Russian |
| February | Troop landings, martial law, Kyiv's mayor appeals, real-time conflict updates; repetitive air raid alerts in Kyiv; Ukraine's EU candidacy, European Parliament approval; strong advocacy for Ukraine's urgent EU accession, national pride, European integration sentiment. | Russian dialogue conditions, military operations in Kyiv, European Parliament's EU candidacy recommendation for Ukraine, Russian State Duma's legislation on military "fakes," narrative control, diplomatic maneuvers at the Ukrainian-Belarusian border. |
| March | Russian attacks on Ukraine, Belarus; humanitarian corridors; Kuleba-Lavrov talks; European PMs visit Kyiv; Russia ousted from Council of Europe; Ukraine-Russia prisoner swap; "Orsk" ship destruction; Istanbul negotiations; Russian troop withdrawal. | Ukraine bioweapons claims; Russian crackdown on Meta; Ovsyannikova's protest; Donetsk missile attack; U.S.-China-Russia Ukraine diplomacy; Russia's ruble-for-gas demand; Poland-Ukraine tension; South Ossetia's Russia referendum; Putin's gas ruble decree; Bucha narrative conflicts. |
| April | Bucha atrocity reports, Russian denial; "Moskva" cruiser sunk by Ukraine; chemical weapon fears in Mariupol; Ukraine's military aviation aid; Starlink's Ukraine expansion; U.S. lend-lease law for Ukraine; Kyiv monument dismantling. | Peskov's communication role, Russia suspended from the corrupt Human Rights Council, Medvedchuk arrest reactions, "Moskva" cruiser sinking, Zelensky's POW exchange proposal, Tinkov criticizes Russia, Putin's Mariupol strategy, Russia tests "Sarmat" missile, Moldova's geopolitical tensions, Gazprom's gas halt over ruble dispute. |
| May | Shariy's Spain detention, Lavrov's comments controversy, U.S. $40 billion aid to Ukraine, Russian ambassador paint attack, Ukraine-Poland solidarity, Azovstal soldier evacuation, Medvedchuk's Poroshenko allegations, Dodon's Moldova arrest. | Detention of Ukrainian blogger in Spain, 2014 Odessa tragedy remembrance, Kherson's Russian integration plans, attack on Russian Ambassador in Poland, Turkey's opposition to NATO expansion, McDonald's Russian exit, Poland's potential Ukraine involvement, Russian citizenship decree for Zaporozhye, Kherson. |

Ghasiya, P.; and Sasahara, K. 2023. Messaging Strategies of Ukraine and Russia on Telegram during the 2022 Russian invasion of Ukraine. *First Monday*.

Goldstein, J. A.; Sastry, G.; Musser, M.; DiResta, R.; Gentzel, M.; and Sedova, K. 2023. Generative language models and automated influence operations: Emerging threats and potential mitigations. *arXiv preprint arXiv:2301.04246*.

Hanley, H. W. A.; and Durumeric, Z. 2023. Partial Mobilization: Tracking Multilingual Information Flows Amongst Russian Media Outlets and Telegram. arXiv:2301.10856.

Hanley, H. W. A.; Kumar, D.; and Durumeric, Z. 2023a. Happenstance: Utilizing Semantic Search to Track Russian State Media Narratives about the Russo-Ukrainian War On Reddit. arXiv:2205.14484.

Hanley, H. W. A.; Kumar, D.; and Durumeric, Z. 2023b. Specious Sites: Tracking the Spread and Sway of Spurious News Stories at Scale. arXiv:2308.02068.

He, P.; Gao, J.; and Chen, W. 2023. DeBERTaV3: Improving DeBERTa using ELECTRA-Style Pre-Training with Gradient-Disentangled Embedding Sharing. arXiv:2111.09543.

Hruschka, E. R.; Campello, R. J. G. B.; Freitas, A. A.; and Ponce Leon F. de Carvalho, A. C. 2009. A Survey of Evolutionary Algorithms for Clustering. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 39(2): 133–155.

Labov, W. 2013. *The language of life and death: The transformation of experience in oral narrative*. Cambridge University Press.

Leban, G.; Fortuna, B.; Brank, J.; and Grobelnik, M. 2014. Event Registry: Learning about World Events from News. In *Proceedings of the 23rd International Conference on World Wide Web*, WWW '14 Companion, 107–110. New York, NY, USA: Association for Computing Machinery. ISBN 9781450327459.

Lukasová, A. 1979. Hierarchical agglomerative clustering procedure. *Pattern Recognition*, 11(5-6): 365–381.

Metaxas, P.; Mustafaraj, E.; Wong, K.; Zeng, L.; O'Keefe, M.; and Finn, S. 2015. What do retweets indicate? Results from user survey and meta-review of research. In *Proceedings of the international AAAI conference on web and social media*, volume 9, 658–661.

Miranda, S.; Znotiņš, A.; Cohen, S. B.; and Barzdins, G. 2018. Multilingual Clustering of Streaming News. In Riloff, E.; Chiang, D.; Hockenmaier, J.; and Tsujii, J., eds., *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, 4535–4544. Brussels, Belgium: Association for Computational Linguistics.

Müllner, D. 2011. Modern hierarchical, agglomerative clustering algorithms. *arXiv preprint arXiv:1109.2378*.

Oleinik, A. 2024. Telegram channels covering Russia's invasion of Ukraine: a comparative analysis of large multilingual corpora. *Journal of Computational Social Science*, 1–24.

Piktus, A.; Petroni, F.; Karpukhin, V.; Okhonko, D.; Broscheit, S.; Izacard, G.; Lewis, P.; Oğuz, B.; Grave, E.; tau Yih, W.; and Riedel, S. 2022. The Web Is Your Oyster - Knowledge-Intensive NLP against a Very Large Web Corpus. arXiv:2112.09924.

Rahutomo, F.; Kitasuka, T.; and Aritsugi, M. 2012. Semantic cosine similarity. In *The 7th international student conference on advanced science and technology ICAST*, volume 4, 1.

Rossetti, G.; and Cazabet, R. 2018. Community Discovery in Dynamic Networks: A Survey. *ACM Computing Surveys*, 51(2): 1–37.

Saldanha, E.; Acharya, A.; Ocal, M.; Glenski, M.; and Volkova, S. 2024. *Detecting and Summarizing Narratives in the Information Environment: A Case Study of Misinformation and Disinformation Campaigns*.

Shahsavari, S.; Holur, P.; Wang, T.; Tangherlini, T.; and Roychowdhury, V. 2020. Conspiracy in the time of corona: automatic detection of emerging COVID-19 conspiracy theories in social media and the news. *Journal of Computational Social Science*, 3.

Smith, B. H. 1980. Narrative versions, narrative theories. *Critical inquiry*, 7(1): 213–236.

Song, K.; Tan, X.; Qin, T.; Lu, J.; and Liu, T.-Y. 2020. Mpnet: Masked and permuted pre-training for language understanding. *Advances in Neural Information Processing Systems*, 33: 16857–16867.

Theisen, W.; Cedre, D. G.; Carmichael, Z.; Moreira, D.; Weninger, T.; and Scheirer, W. 2022. Motif Mining: Finding and Summarizing Remixed Image Content. arXiv:2203.08327.

Todorov, T.; and Weinstein, A. 1969. Structural analysis of narrative. In *Novel: a forum on fiction*, volume 3, 70–76. JSTOR.

Touvron, H.; Martin, L.; Stone, K.; Albert, P.; Almahairi, A.; Babaei, Y.; Bashlykov, N.; Batra, S.; Bhargava, P.; Bhosale, S.; Bikel, D.; Blecher, L.; Ferrer, C. C.; Chen, M.; Cucurull, G.; Esiobu, D.; Fernandes, J.; Fu, J.; Fu, W.; Fuller, B.; Gao, C.; Goswami, V.; Goyal, N.; Hartshorn, A.; Hosseini, S.; Hou, R.; Inan, H.; Kardas, M.; Kerkez, V.; Khabsa, M.; Kloumann, I.; Korenev, A.; Koura, P. S.; Lachaux, M.-A.; Lavril, T.; Lee, J.; Liskovich, D.; Lu, Y.; Mao, Y.; Martinet, X.; Mihaylov, T.; Mishra, P.; Molybog, I.; Nie, Y.; Poulton, A.; Reizenstein, J.; Rungta, R.; Saladi, K.; Schelten, A.; Silva, R.; Smith, E. M.; Subramanian, R.; Tan, X. E.; Tang, B.; Taylor, R.; Williams, A.; Kuan, J. X.; Xu, P.; Yan, Z.; Zarov, I.; Zhang, Y.; Fan, A.; Kambadur, M.; Narang, S.; Rodriguez, A.; Stojnic, R.; Edunov, S.; and Scialom, T. 2023. Llama 2: Open Foundation and Fine-Tuned Chat Models. arXiv:2307.09288.

Volkova, S.; Glenski, M.; Ayton, E.; Saldanha, E.; Mendoza, J.; Arendt, D.; Shaw, Z.; Cronk, K.; Smith, S.; and Greaves, M. 2021. Machine Intelligence to Detect, Characterise, and Defend against Influence Operations in the Information Environment. *Journal of Information Warfare*, 20(2): 42–66.

Wang, W.; Zheng, V. W.; Yu, H.; and Miao, C. 2019. A survey of zero-shot learning: Settings, methods, and applications. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 10(2): 1–37.