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

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Abstract

Following the Russian Federation's full-scale 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 of 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 narratives[1].

Introduction

Operations within the Information Environment (OIE) rely crucially on the strategic deployment of information narratives, as outlined in JP3-04, which describes them as *a method to convey or interpret events in a manner that supports a specific perspective or set of values* (ibid. p. I-7). These narratives play a critical role in shaping how audiences perceive events, a challenge that has intensified with the advent of digital dissemination tools like generative AI (Goldstein et al. 2023) and social media platforms. The increasing accessibility and influence of these tools underscore the urgent need for advanced methods capable of effectively tracking and analyzing narratives. Such analysis is vital for unraveling the complexities of how narratives are crafted, evolve, and exert influence across the information landscape.

The ongoing war between Russia and Ukraine epitomizes the critical role of such narratives, with varying claims—from Russia's purported mission to "denazify" Ukraine to allegations of biological weapons labs—significantly influencing public opinion (Volkova et al. 2021). Conventional research methodologies often fall short in capturing the fluid dynamics of narratives, which adapt and transform in response to emerging information and evolving contexts (Saldanha et al. 2024).

To bridge this methodological divide, our study proposes an innovative approach tailored to the dynamic analysis of information narratives. It leverages a two-tiered framework designed to not only identify but also analyze the complexity of narrative constructs across social platforms. This method allows for a comprehensive analysis, from a broad overview of narrative structures to an in-depth examination of individual components, shedding light on narrative evolution—how they emerge, fade, and transform over time.

Applying this methodology, we delve into the narratives propagated within Russian and Ukrainian Telegram communities during the initial phase of the war. Our analysis illuminates stark disparities in narrative engagement and perception between these communities. We explore the predominant themes and the underlying dynamics driving their evolution within each community. Additionally, we investigate the key figures and forces shaping the dissemination and evolution of these narratives, offering a nuanced understanding of their influence and trajectory.

Related Work and Background

The exploration of narrative evolution within online communities, particularly in response to geopolitical events, has been addressed through various methodologies across the fields of computational social science. Prominent among these methodologies are clustering algorithms and topic modeling techniques, each offering unique insights but also exhibiting notable limitations in the context of dynamic narrative analysis.

Narrative Detection

The concept of 'narrative' has been a longstanding subject of study within the discipline of narratology (Smith 1980; 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

[1] repo link here

works on narratives (Hanley, Kumar, and Durumeric 2023b), which utilize the logic of the Event Registry (Leban et al. 2014) idea where collections of documents seek to address the same event or issue (Miranda et al. 2018). Applying this logic, a narrative in our dataset might be ”There are Biological Weapons Laboratories in Ukraine.” This narrative encompasses various stories, each consisting of individual posts. For example, 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 be part of the ”Cover-up and Destruction of Biological Weapon Development” story, which in turn falls under the broader narrative about biological weapons laboratories in Ukraine.

Information Spread and Narrative Evolution

The dynamic nature of online information dissemination underscores the critical need for advanced analytical tools to capture the fluid evolution of narratives. Computational narrative analysis has emerged as a key approach, providing methodologies for dissecting and understanding the complex interplay between narrative structures and their propagation through digital platforms.

Significant contributions, such as Chambers and Jurafsky’s work on narrative event chains, and McIntyre and Lapata’s developments in narrative generation and machine learning, have established a strong foundation for understanding narrative dynamics (Chambers and Jurafsky 2008; McIntyre and Lapata 2009). However, the rapid spread of online narratives often challenges traditional methods, leaving some complex aspects and internal dynamics of narrative evolution unaddressed.

Narrative Dynamics during RU-UA War

These challenges becomes particularly evident in the context of the Russian-Ukrainian war. The strategic deployment of narratives, from claims of ”denazification” to allegations of biological weapons labs, has significantly influenced public perception, both locally and globally (Jowett and O’donnell 2018; Badawy, Ferrara, and Lerman 2019). The marked increase in narrative dissemination through various media channels during this conflict highlights the need for more dynamic and adaptable tools in narrative analysis, capable of tracking the evolution of such narratives in real-time.

Clustering and Topic Modeling Limitations

While techniques like K-means, hierarchical clustering, Latent Dirichlet Allocation (LDA), and BERTopic have advanced text grouping and theme identification, they struggle in the dynamic field of narrative analysis due to their need for predetermined cluster numbers (Blei, Ng, and Jordan 2003; Grootendorst 2020). This requirement limits flexibility and fails to adapt to the unpredictable emergence of narratives in response to real-world events (Aggarwal and Zhai 2012; Jain 2010; McInnes, Healy, and Astels 2017).

Additionally, these methods offer only static snapshots, inadequate for monitoring evolving narratives that change with new information and shifts in discourse. Although DBSCAN provides an alternative by not requiring preset cluster numbers, adapting it for real-time, streaming data environments remains a significant challenge. Its focus on data density may also misrepresent the complex structure of narratives, hindering effective analysis in digital contexts.

To address these issues, we propose a novel framework for narrative detection and evolution that adjusts to new information, identifies emerging narratives, and integrates domain expertise for a deeper, more nuanced analysis.

Methodology

This section outlines our method for dynamically clustering textual data over time, designed to adapt to new information. It aims to monitor the evolution of text clusters, aiding in identifying how narratives diverge or converge. This approach supports the organic discovery of narrative structures as they form, making it well-suited for analyzing the fluid information streams of online narratives. An additional analytical layer can further enhance this model by integrating expert interpretation with clustering results, providing deeper narrative analysis. This component, while optional, merges stories into cohesive narratives, enriching the algorithmic insights. While the primary model effectively manages temporal clustering, this integrated methodology is particularly aimed at revealing the complex dynamics within narratives.

Our Model - Clustering Text Across Timesteps

The dynamic nature of analyzing evolving narratives demands a model that not only allows for the inherent interpretability of its processes but also facilitates the dynamic discovery of narrative structures. Hierarchical Agglomerative Clustering (HAC) stands out as our method of choice, given its unique capacity to meet these requirements effectively.

Hierarchical Agglomerative Clustering (HAC) for Dynamic Narrative Analysis HAC is recognized for its adaptability in data analysis, particularly in forming clusters based on similarity without the need for pre-defined cluster numbers. This approach begins with each data point as a separate cluster, iteratively merging the most similar pairs until a specified similarity threshold, such as cosine similarity, is met, ensuring homogeneity within clusters (Müllner 2011). Its inherent ability to uncover data structures naturally positions HAC as a prime clustering candidate for extension for fluid narrative analysis, where the evolving nature of text-based data necessitates flexible and dynamic clustering techniques. Furthermore, HAC’s iterative merging process is apt for online extensions, allowing new data to be integrated efficiently in real-time. This adaptability ensures ongoing narrative analysis remains current, making HAC an exemplary foundation for methodologies aimed at exploring narrative evolution in dynamic environments.

Adapting HAC to Evolving Data To adapt Hierarchical Agglomerative Clustering (HAC) for real-time data analysis, we developed the `OnlineAgglomerative` class, which enhances HAC for dynamic environments. This class is detailed in our GitHub repository **[INSERT GITHUB LINK HERE]**.

Key to this adaptation is the `incremental_fit()` method, which dynamically clusters data and adjusts to new inputs by balancing immediate data integration with long-term cluster evaluation. Initially, clusters are formed using

HAC. The `incremental_fit()` method then uses the class's cluster history to decide at each timestep whether to merge new data into existing clusters or initiate new clustering rounds, based on a predefined similarity threshold.

Additionally, `incremental_fit()` evaluates potential cluster mergers with each data batch using silhouette scores, which measure cluster cohesion and separation, and the pseudo-F index, assessing overall cluster quality. This approach not only ensures immediate data integration but also maintains the structure and coherence of clusters over time.

This method enables effective real-time clustering by making immediate decisions and maintaining complex data structures as new information arrives, thereby helping to discover underlying data patterns in dynamic settings.

Exploiting Online Data Integration Building on this foundation, the `OnlineAgglomerative` class then enhances our ability to exploit online data integration effectively. Through the `incremental_fit()` method, it tracks each cluster's centroid and size history, offering insights into cluster evolution. This tracking reveals patterns of development, merging, or separation, allowing us to decode the evolving landscape of data and offering a window into the complex mechanisms that drive the data's evolution.

Complementing Our Model - MacroNarrative Class

To enhance our model, we then introduce the `MacroNarrative` Class, an additional layer atop the `OnlineAgglomerative` curated clusters. This optional augmentation allows domain experts to weave together these clusters into a coherent narrative framework. We find this to be especially vital given the inherently fragmented landscape of narrative frameworks (demonstrated in our data analysis), allowing for a synthesized, expert-informed view of the narrative's progression and thematic undercurrents.

How the Macro-Narrative Class Works

After tracking story clusters using the `OnlineAgglomerative` class, we then use these as "story clusters" and employ the `MacroNarrative` class to infuse expert knowledge and examine how these story clusters form larger narrative clusters.

Discovery and Refinement of Narrative Seed Stories To begin our formation of narrative clusters, we start with a single 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 Upon identifying an initial potential seed cluster, our next step involves seeking additional seed clusters to guide the development and progression of a *Narrative Cluster*. This procedure harmonizes automated discovery with human-in-the-loop (HITL) refinement, engaging domain experts to ensure a balanced approach. Initially, we employ a queue-based system for temporal evaluation of the seed. At each timestep, story clusters falling within a predefined similarity threshold—typically between 0.7 and 0.8 cosine similarity, as determined effective for our narratives—are queued for further analysis and simultaneously earmarked for human review. This method, reminiscent of a breadth-first search (BFS), ensures a comprehensive and *robust* selection of potential seed stories for additional refinement by human analysts. These analysts then evaluate a representative sample, chosen randomly (in our scenario, 20 points from each cluster), at every timestep. The analysts then save clusters that retain ongoing *relevance* and *alignment* with the intended narrative direction. These are used as the "seed clusters" whose positions in the embedding space will guide the resulting Narrative Cluster throughout time.

Macro-Narrative Class and Narrative Centroid Expanding from the curated seed clusters, the `MacroCluster` class constructs a 'Narrative Centroid' that dynamically navigates through time alongside its seed clusters. This evolving centroid adjusts in real-time to the development of seed story clusters, enabling the narrative cluster to reflect the narrative's fluidity over time. By applying similarity thresholds, the `MacroCluster` class then integrates other story clusters into the narrative at various points in time, offering an adaptive perspective on narrative evolution.

An example of this adaptive narrative tracking is our analysis of the Bucha Massacre narrative within the Ukrainian context. In examining the Bucha Massacre narrative within the Ukrainian community, we observed 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.

Data Analysis: Russo-Ukrainian War

Applying our `OnlineAgglomerative` and `MacroNarrative` classes, we then delve into the narratives emerging from the Russo-Ukrainian War. This conflict, known for its complex and evolving narratives, provides a fertile testing ground for our methodology. It challenges our model to adeptly cluster and track these shifting narratives, offering a robust validation of our approach in a context filled with a rich tapestry of political and human interest stories.

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 the first three months of the war (from February 20, 2022 through through May 28, 2022), in which we track 568 channels (comprising distinct "Russian-leaning" and "Ukrainian-leaning" communities) and approximately 2 million posts.

Telegram Telegram, a messaging app that facilitates both user interactions in private and public groups and one-way broadcasts via channels, is seen as a bastion of a "free" Internet in Russia, evading bans that affect other platforms like Facebook and TikTok since 2020 (Oleinik 2024). It has emerged as a vital platform for military bloggers and a primary information source on the Russo-Ukrainian war, with approximately 39% of Ukrainians and 19% of Russians relying on it for news, ranking it highly in information sourcing in both countries (Oleinik 2024). This positions Telegram as a crucial subject for analyzing discourse and narrative evolution regarding the conflict.

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. Overall, there are 243 Ukrainian-leaning channels with a median of 71K posts per timestep (and a total of 4.2 million posts) and 325 Russian-leaning channels with a median of 77k posts per timestep (and a total of 4.4 million posts).

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[2]. 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 Euclidean 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).

Data Analysis and Validation

Following our data preparation, we then employ our `OnlineAgglomerative` and `MacroCluster` to uncover and dissect narratives from the Russian and Ukrainian online communities. First , we segregate stories using the `OnlineAgglomerative` class for clustering. Then, infusing domain expert insight, we form narrative clusters using the `MacroCluster` class, capturing both predetermined and newly identified narratives through trend analysis. Finally, we distill key themes from these narratives and monitoring their progression over time.

Story Cluster Discovery First, we dynamically cluster the data of either community

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

using the `OnlineAgglomerative` class's `incremental_fit()` method.

Story Cluster Validation To ensure the validity of the evolving clusters, we must ensure 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. 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.

Trending Stories Discovery Following the `OnlineAgglomerative` clustering, our methodology includes a key process for spotting emerging trends within story clusters, utilizing the `analyze_micro_cluster_trends()` function, included in our code repository. This approach evaluates the expansion or reduction of story clusters at each timestep by tracking the change in data volume compared to the preceding period. More than just pinpointing the largest clusters at any given time (which often reflected persistent themes rather than trending topics) our strategy focuses on identifying fluctuations that signal shifting interests or concerns within the community; this method proved particularly effective in highlighting stories gaining traction and capturing the community's engagement with unfolding events. These insights revealed not only what topics are currently engaging the community but also serve as indicators for potential overarching narratives, laying the groundwork for deeper narrative analysis.

Trending Stories Validation Our analysis focused on the 5 top-trending clusters each week, revealing that approximately 93.2% of the time, these clusters directly matched significant, unfolding external events documented in the accompanying sheet. This underscores our model's proficiency in identifying relevant topics. Notably, our dynamic methodology—leveraging information from the previous timestep to inform the current one—demonstrated superior performance compared to static approaches that correlate trendiness solely with cluster size within the same timestep. Detailed findings are further elaborated in the provided sheet.

Narrative Cluster Formation Next, collaborating with a topic expert, we formed narrative clusters using the `MacroCluster` framework for both Pro-Russian and Pro-Ukrainian communities. These narratives are shown in tables 4 and 5. We note that while most of the narratives we sought to study were predetermined (for example, "Russian troops committed a massacre in Bucha"), others were only discovered by evaluating the trending story clusters (for example, "Russia is engaging in chemical warfare" and "Russia is sabotaging Ukrainian humanitarian corridors").

Narrative Cluster Validation To validate our narrative clusters, we cross-referenced the emerging and predetermined narratives against external sources and expert opinions. This process ensured that the clusters accurately reflected the evolving discourse within the targeted communities.

Further Analysis: Narrative Theme Extraction 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[3]

Narrative Theme Extraction To assess theme representation across messages in a narrative, we employ an off-the-shelf SOTA 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 because we found that some texts can indeed represent more than one theme effectively. Then the model then returns a list of corresponding model scores and confidences for each label.

Narrative Theme Extraction Validation We aim to distill narrative themes that provide both broad *coverage* and detailed *nuance*. The process begins by generating 15 theme dictionaries through analyzing story clusters within the similarity thresholds of narrative centroids. We initialize an empty map to track the emergence of each theme. The Llama2 model, supplied with data points closest to each cluster's centroid and any previously generated themes, identifies new themes or refines existing ones. Each theme and its emergence timestep are recorded in this map. The process is thoroughly documented in our repository.

We then evaluate each theme dictionary using a classification model to calculate a Theme Coverage Score (TCS), which measures the percentage of texts exceeding a set threshold for at least one theme, summed across all timesteps. A higher TCS indicates better theme recognition, suggesting a more comprehensive and representative set of themes. After comparing TCS values, we select the dictionary with the highest score, ensuring our narrative analysis is effective and representative. While TCS scores are generally consistent, variations occur mainly in the number of themes and their phrasing. The validation of the classification model's scoring mechanism was conducted both prior to and during the theme extraction process.

Narrative Theme Classification In the final step of our analysis, we use the final colleciton of extracted themes and applied the classification model to assign thematic labels to

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

each message within the narrative. For a message to be classified under a specific theme, it had to meet or exceed a predetermined confidence threshold (outlined in the subsequent paragraph), ensuring that our thematic categorization was both precise and meaningful.

Narrative Theme 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.

Key Findings

We apply this pipeline to the Russian and Ukrainian communities. Then we first evaluate both communities separately, inspecting them at the macro (narrative) level and the micro (story) level before then performing a contrastive analysis using the Bucha Massacre as an example.

Story Cluster Analysis

To understand how both communities discuss the events during the war, we extract and analyze trending 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. As indicated earlier, we release these summaries, along with news articles related to that summary, in our repo.

Communities React Quickly Both communities react very quickly and consistently to events. Illustrated in this **INSERT SHEET** sheet, in each timeframe examined, the majority of the leading story clusters were closely linked to external events.

Contrasting Focuses 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 1.

Table 1: 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%**

Table 1 reveals significant differences in the primary concerns of each community, particularly within the realm of international politics. Ukrainian narratives often emphasize foreign aid and movements towards EU and NATO integration, while Russian narratives typically highlight economic strategies and portray Russia as subjected to biased international critique.

For instance, in the week following March 6, 2022, after a suspected Russian airstrike intended to draw Belarus[4] into the conflict, Ukrainian discourse focused on the event and its implications, contrasting sharply with Russian discourse which largely overlooked the airstrike. Instead, Russia emphasized allegations of US-backed biological warfare in Ukraine and the exit of Western businesses from Russia, illustrating distinct narrative priorities.

Moreover, when addressing shared topics, the communities exhibit markedly different viewpoints. The Bucha Massacre's coverage showcases this divergence; Ukrainian discussions revolved around exposing Russian crimes and debunking misinformation, whereas Russian discourse framed the coverage as biased, attributing it to Ukrainian provocation. This stark contrast in perspectives, especially evident in the Bucha case, underscores the ongoing narrative division, as depicted in Figure 1.

Narrative Analysis

We conduct an in-depth analysis of four major narratives from each community (shown in tables 4 and 5) evaluating the narratives at both the story level and the summary (theme) level; we examine their persistence, the micro-narratives they encompass, their summaries, and the key authors involved.

Story Makeup Varies 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[5], the Russian narrative about bio-weapon 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."

Themes Persist Across Stories 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

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

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

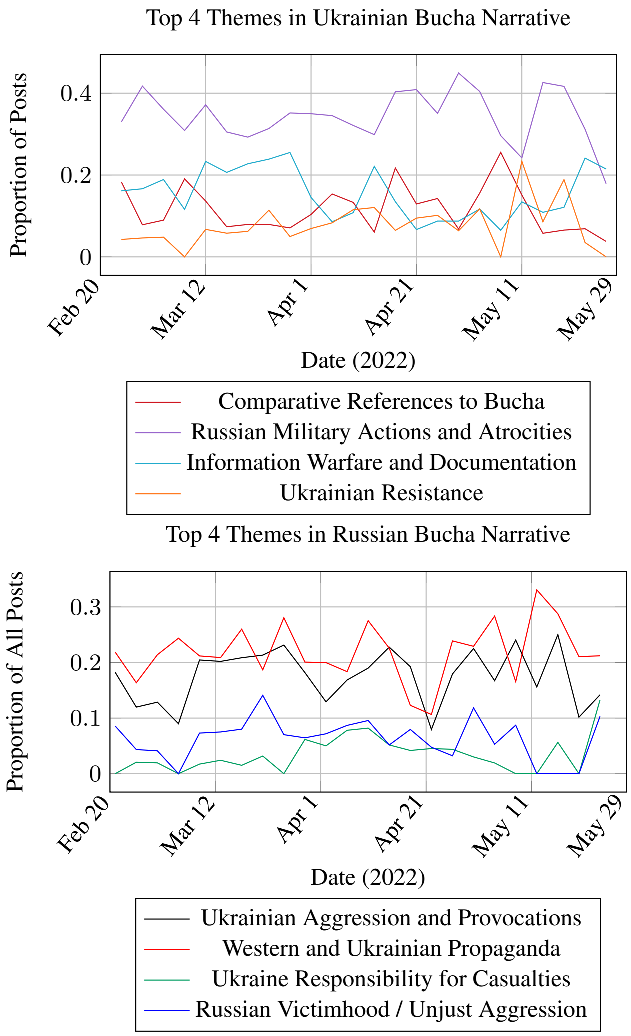

Figure 1: Contrasting information narratives surrounding the Bucha Massacre across Russian and Ukranian communities.

"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).

Narrative Focuses May Correlate with Key Contributors 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 2 and 3. 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 community discourse.

Table 2: 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

Narratives Adapt in Quantity and Makeup Narratives appear to adapt to external influences, showing changes in both post volume and thematic content. This adaptation is evident in how narratives respond to events, incorporating both the frequency of posts and their evolving themes.

The Bucha Massacre serves as a distinct example of this phenomenon. The Ukrainian community's narrative was characterized by active reporting on the event, focusing on civilian harm and military defense, as shown in the increase of posts during this time. Conversely, the Russian community initially minimized discussion, later shifting to claims of "provocation" and misinformation as the event gained international attention. This divergence in response and strategy between communities is starkly illustrated in the aftermath of Bucha, emphasizing the narratives' dynamic nature.

The evolution of narrative themes further demonstrates their responsiveness. Initially, Russia's narrative centered on "denazification," highlighting issues like language suppression and cultural genocide, as referenced in early statements[6]. However, as the conflict progressed, the narrative pivoted to patriotic themes, celebrating Russia's actions against perceived Nazism, as depicted in Figure 2. This shift from focusing on the "Nazification of Ukraine" to lauding "liberation" efforts showcases the narratives' capacity to adapt to evolving contexts and external perceptions.

Russian and Ukrainian Communities' Perceptions Differ Strikingly: Bucha Massacre Case Study The diverging narratives around the Bucha Massacre, as depicted in

[6] https://en.wikipedia.org/wiki/Stepan_Bandera

Table 3: 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 4: 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) 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) 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) 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) OP_UA (4.0% / 3.2)

Table 5: 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) 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) 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) 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) SolovievLive (3.1% / 4.2)

Figures 1 and 3, 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 documentation is further illustrated in Figure 4). 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.

Discussion

Our exploration into the narratives of Russian and Ukrainian online communities during the early stages of their conflict sheds light on the dynamic and contrasting ways these

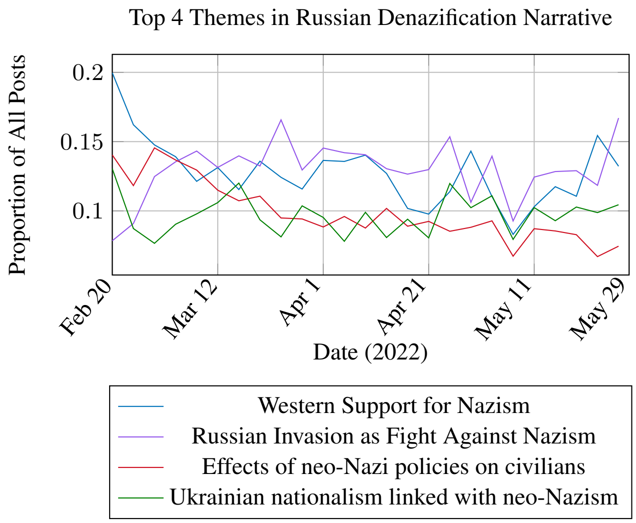

Figure 2: Themes discovered in narratives about Denazifying Ukraine.

groups perceive and respond to unfolding events. By applying a dynamic clustering model, we sought to capture these evolving narratives, revealing both the rapidity of their responses and the distinct focuses that characterize each community.

This analysis has illuminated the quick adaptation of online communities to external events, underscoring the fluid nature of digital narratives. For instance, the divergent focuses on military actions, political movements, and humanitarian efforts between Russian and Ukrainian narratives not only reflect differing priorities but also highlight the influence of narrative framing on public engagement and perception. Moreover, the contrasting reactions to events like the Bucha Massacre, as well as the varying emphasis on themes such as "denazification" and "bioweapon labs," suggest a complex interplay of information, misinformation, and narrative strategy. These findings point to the importance of nuanced, dynamic approaches in narrative analysis—approaches that consider the rapid shifts in online discourse and the multifaceted nature of narrative construction and evolution.

Furthermore, our study's insights into the narrative dynamics within these communities underscore the significant role of key contributors in shaping and shifting these narratives. This observation prompts a deeper reflection on the mechanisms of influence and control within digital spaces, where certain voices or perspectives can significantly impact collective understanding and response.

Finally, analysing the broader implications of our findings, it becomes evident that the challenge of narrative analysis in the digital age lies not only in tracking these fluid narratives but also in understanding their genesis, evolution, and impact. The adaptability and responsiveness of narratives to external events call for a continuous refinement of analysis tools and methodologies that can keep pace with the ever-changing digital discourse. Our study presents a dynamic clustering model tailored for analyzing textual data over time, designed to grasp the evolving narratives in online spaces. This stands in contrast to traditional narrative analysis methods, which often remain static, not fully capturing the narratives' fluidity, especially in the digital media context.

Ethical Considerations

Our study utilized a dataset sourced from publicly accessible Telegram channels managed by widely recognized "war-bloggers." Alongside this paper, we are also releasing the `OnlineAgglomerative` class and instructional Jupyter notebooks to aid others in narrative analysis[7]. 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

This study introduces a methodology designed to dynamically track and analyze information narratives within digital platforms, but it has limitations that are crucial for future research and methodological improvements. A primary limitation is the reliance on data solely from war bloggers on Telegram. While Telegram is a key channel for information among Ukrainian and Russian communities, its focused use may not capture the wide range of perspectives across the broader social media landscape, raising concerns about the generalizability of our findings and highlighting the need for comparative studies across different platforms.

Moreover, our methodology's effectiveness depends on similarity metrics derived from text embeddings for clustering narratives. The performance of these metrics is tied to the training and capabilities of the embedding models, which may not perform well with contexts different from their training data or with lengthy texts, potentially biasing clustering outcomes. We've made our approach modular to allow the integration of alternative embedding models that could better capture the nuances of specific contexts or datasets (Devlin et al. 2018; Reimers and Gurevych 2019; Gao, Yao, and Chen 2022). Additionally, our study, focusing on the initial three months of the Russia-Ukraine conflict, provided a rich dataset but may not reflect the long-term evolution of narratives. Extending the observation period could yield deeper insights into the dynamic processes of narrative evolution, enhancing our understanding of their life cycles.

Summary and Future Work

Our study introduces a novel methodology tailored for dynamic analysis of online narratives, which proved effective during the initial stages of the Russia-Ukraine conflict. It demonstrated the ability to capture and understand narrative evolution within Ukrainian and Russian online communities, emphasizing its utility and potential for broader application in various digital contexts. The insights from our case study highlight the method's effectiveness in identifying narrative strategies and adaptations, showcasing its importance

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

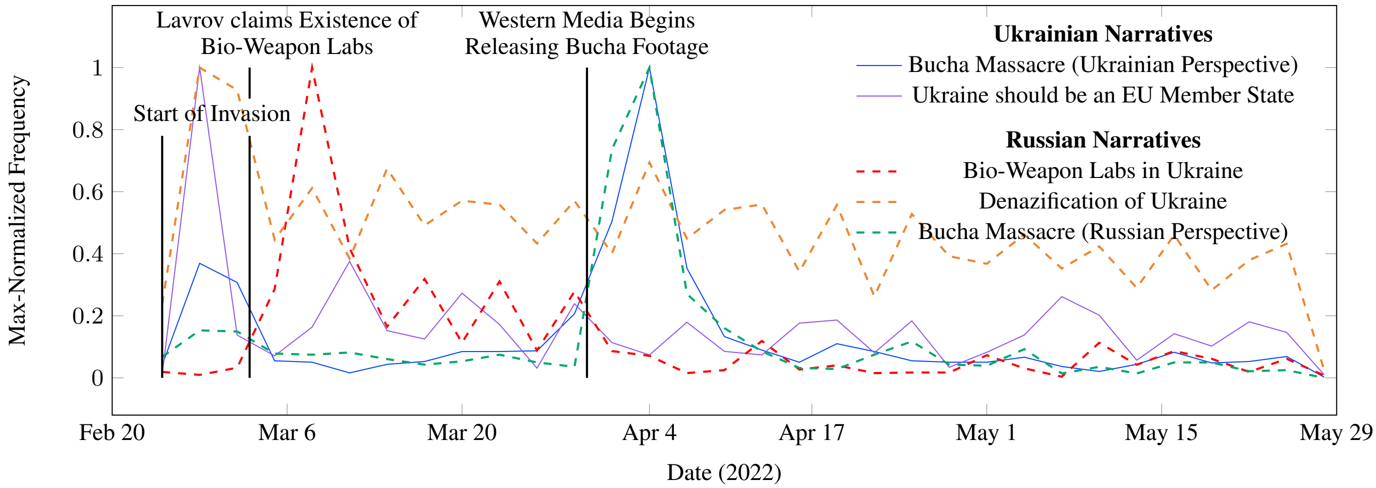

Figure 3: Information narrative evolution shown using max-normalized frequency of posts in key narratives within Ukrainian and Russian communities over time (summed over 3-day time-periods for clarity), where max-normalization adjusts frequency counts relative to each narrative's peak activity for comparative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

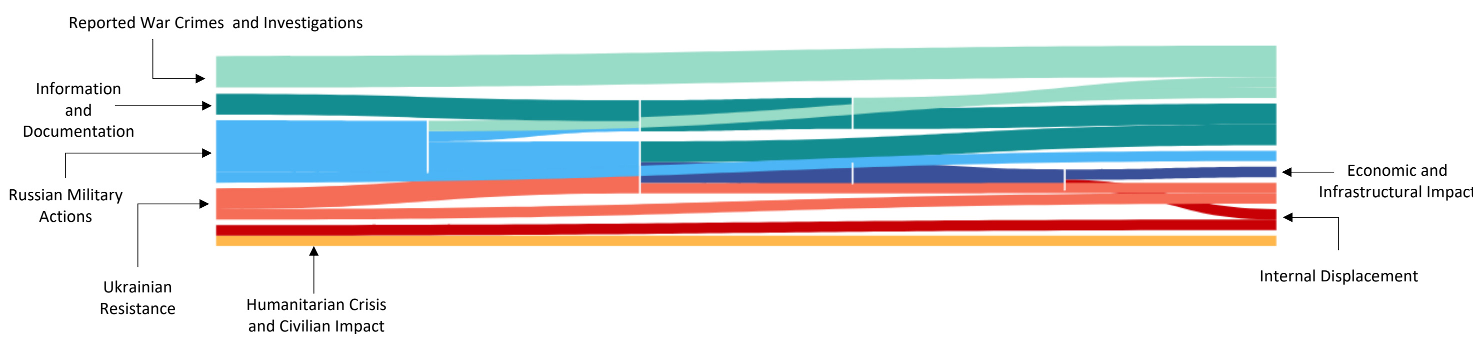

Figure 4: Information narrative evolution of dominant theme distribution of story clusters focused on Russian atrocities. To make this we look at the top 2 dominant themes in top 5 most populated story clusters; then, we aggregate this at a monthly timeframe (thus, having 4 points for potential pivoting)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

for understanding and shaping public discourse. This approach not only enriches academic research but also benefits Operations in the Information Environment (OIE) by enabling planners and analysts to adapt strategies in real-time, enhancing strategic resource allocation and audience engagement. Future research could expand its use to other platforms and conflicts, refining tools to better understand narrative dynamics and address current limitations by integrating broader data sets, improving clustering algorithms, and incorporating cultural insights. These advancements will enhance the generalizability and depth of narrative analysis, benefiting both researchers and practitioners.

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