Modern information space: manipulations, existing analysis methods and the model of integral analysis*

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Abstract

The paper explores methods for analyzing information sources in social networks with a focus on Telegram channels, which became the dominant news platform in Ukraine after the full-scale Russian invasion in February 2022. The mechanisms of information manipulation are analyzed and their common characteristics are identified. Existing analytical approaches from early statistical methods to modern hybrid systems are systematized and a systemic gap is identified. Two author's methods for comparing sources are proposed: a method based on frequency vectorization and cosine similarity with parameter optimization, as well as a temporal-semantic influence algorithm. A conceptual model for a comprehensive assessment of the similarity of information sources, which integrates cosine similarity, clustering, TSI and network proximity, is formalized, and a method for building a modular information system for the practical implementation of the model is proposed. The proposed system and integral model, implemented as a linear weighted function of the individual factors, were validated on 23 information sources. The experimental results demonstrated the ability of the model to identify coordinated groups of sources sharing common characteristics.

Keywords

disinformation, clustering, cosine similarity, temporal analysis, analysis system, graph. [1]

1. Introduction

1.1 Modern problems of the information space

The relevance of the study is due to the growing socio-cultural influence of information sources in social networks, which actively shape public opinion, influence behavioral patterns and determine the information agenda, which in conditions of armed conflicts and information wars becomes especially critical. The modern digital environment, devoid of traditional mechanisms of editorial control, creates conditions under which reliable and manipulative information spread at the same speed, and coordinated influence campaigns are disguised as organic activity, which significantly complicates the identification of disinformation sources and the assessment of their impact on the information space.

This problem became particularly acute in Ukraine after Russia's full-scale invasion in February 2022, which caused a radical transformation of media consumption: according to the National Institute for Strategic Studies, Telegram's audience grew from 20% in 2021 to 60% in 2022 [1], and an OPORA survey in May 2022 recorded that 76.6% of the population began to receive news from social networks, ahead of television (66.7%), with Telegram taking the dominant position among platforms with a figure of 65.7% [2]. This transformation has proven to be sustainable: according to

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the sociological group "Rating", in April 2025 Telegram remains the main source of information for 52% of the adult population, exceeding YouTube (32%), the telethon "United News" and Viber chats (25% each) [3-5], and at the beginning of 2024, more than 33 thousand active chats operated in Ukraine. The scale of generated text data makes manual analysis impossible and requires the use of natural language processing (NLP) methods, which allow automating the processes of comparing texts, identifying semantic similarities between sources, classifying rhetorical patterns, and tracking the temporal dynamics of content distribution.

1.2 Purpose of the article

The purpose of this article is to analyze the mechanisms of information manipulation and disinformation campaigns in social networks, systematize existing methods of analyzing information sources with the identification of their limitations, present the author's approaches to comparing sources based on cosine similarity and the temporal-semantic influence (TSI) algorithm, as well as to form a conceptual model of a comprehensive assessment of information sources that integrates semantic, temporal, and network components of analysis using NLP tools .

The object of the study is Telegram as a component of the digital information space. The platform has two main types of communication environments: channels and groups. Channels operate on a one-to-many model – the author publishes and subscribers read. Groups implement a many-to-many model, where participants can discuss content with each other.

The technical features of the platform create an environment favorable for information operations. Telegram does not moderate content, does not detect coordinated influence campaigns, does not limit the spread of unverified information. The cloud architecture with data distribution between different countries complicates legal regulation and monitoring.

The subject of the study is methods for analyzing information sources in social networks. Existing approaches can be grouped into three main areas. The first is analysis of message content. Researchers study the thematic structure of content, emotional coloring of texts, and the presence of manipulative markers. To do this, they use methods for automatically grouping texts by topic, determining positive or negative tone, and assessing the aggressiveness and toxicity of statements. Modern approaches are based on neural networks that convert texts into numerical vectors for further analysis.

The second is analysis of the network structure. Researchers build graphs of connections between channels based on referrals and links. This allows us to identify influential nodes, clusters of related sources, and directions of information dissemination. Network analysis shows that a small proportion of channels generate the majority of content: 6% of users create 90% of forwarded messages.

The third is the analysis of temporal dynamics. Researchers study the speed of message dissemination, the duration of their relevance, and the reaction to external events. It has been found that messages in groups remain active for an average of 105 days, while in channels for only 17 days. News links lose their relevance the fastest, after about 7 days .

2. Mechanisms of information manipulation

The analysis of information sources requires an understanding of the mechanisms of information manipulation, since it is these mechanisms that determine the features by which sources can be identified and classified using natural language processing methods.

The cascade narrative model describes five levels of propaganda messages, each of which covers a wider audience [6]: from the narrative of the "Russian world", which appeals to the cultural identity of Russian-speaking minorities in post-Soviet countries, through the narrative of Slavic unity and nostalgia for the former socialist bloc, to anti-rhetoric of global reach (anti-EU, anti-NATO, anti-immigration) and the broadest level - alternative information addressed to an audience that does not trust traditional media. The mechanism of the pyramid of reinforcement ensures the gradual transformation of disinformation into the perceived public opinion: state media formulate

the initial message, “independent” portals confirm it, and social media users spread it as their own conviction, and at the lower levels of the pyramid the spread occurs mostly unconsciously [6].

The “4D” tactic systematizes four main techniques of information operations [5]: denial (Dismiss) involves discrediting the source of information and declaring the evidence falsified; distortion (Distort) consists in manipulation through selective quoting and changing the context; distraction (Distract) is aimed at switching attention by creating alternative informational pretexts; intimidation (Dismay) creates an atmosphere of fear by demonstrating threats. Empirical analysis of disinformation campaigns confirms the stability of thematic structures: a study of the Telegram channel focused on the Russian-speaking diaspora in Germany revealed seven main thematic trends, and a comparative analysis in eleven European countries confirmed the synchronicity of the emergence of these topics, which indicates centralized coordination [7-8].

The described mechanisms have common characteristics that determine the possibilities and limitations of their detection using NLP methods. First, all the considered models are characterized by the repetition of lexical and thematic structures: coordinated sources use similar vocabulary, reproduce common narrative templates and demonstrate thematic synchronicity. Second, a common feature is the multi-level distribution, in which the message is modified at each level, losing the obvious signs of the initial source, but preserving the semantic core.

Third, the temporal synchronicity of coordinated campaigns creates pronounced temporal patterns that can be formalized through the analysis of the time intervals between the appearance of similar messages in different sources. The adaptability of narratives to different audiences means that the identification of coordinated sources cannot be based solely on direct textual correspondence, but requires the detection of similarities based on non-obvious features.

3. Related works

The task of analyzing information sources in social networks is to determine the role, reliability and relationships between sources based on their content, behavior and structure of connections, which is of practical importance for monitoring the information space, identifying coordinated campaigns and assessing the impact of individual sources on the formation of the information agenda. Existing approaches to solving this problem have developed from isolated statistical methods to integrated systems and can be systematized in three chronological periods.

The early period (2008–2014) was characterized by the adaptation of methods from related fields and a focus on individual aspects of information dissemination. The concept of vector clocks, borrowed from distributed computing, allowed the introduction of the notion of “information latency” – a time distance that measures how outdated the information of one node is relative to another, while an analysis of the e-mail correspondence of a large university (8160 employees, two years of observations) showed that the median latency between pairs of nodes is 7.5 days with a topological distance of only 3 hops [9]. A diffusion regression model built on 22 million tweets from over 3 million users demonstrated that user properties are stronger indicators of information dissemination than characteristics of the messages themselves (the MentionRate correlates up to 0.63 with the diffusion scale), but predicting the speed of dissemination remained a difficult task (R^2 only 0.009–0.067) [10].

Lexical analysis using LIWC (Linguistic Inquiry and Word Count) achieved an F1 of 89% for cascade classification based on 80 psycholinguistic text features, albeit on a limited dataset and without temporal dynamics modeling [11], while time-dependent cascade models (T-BaSIC) showed a 32% improvement in accuracy compared to baseline methods, but systematically underestimated the volume of cascades [12].

The current period (2021–2025) is characterized by the integration of graph neural networks, natural language processing methods, and attention mechanisms, which has significantly expanded the analytical coverage. The DLIC (Deep Learning Information Cascades) model combines a graph attention network (GAT) for learning spatial features of users with recurrent neural networks (GRU) for encoding temporal sequences of cascades, while the attention mechanism with temporal

decay assigns different weights to time intervals, which improved the results by 2.2% according to the HITS@100 metric, although the model worked on a relatively small data set (12.6 thousand users) and did not take into account the content of messages [13].

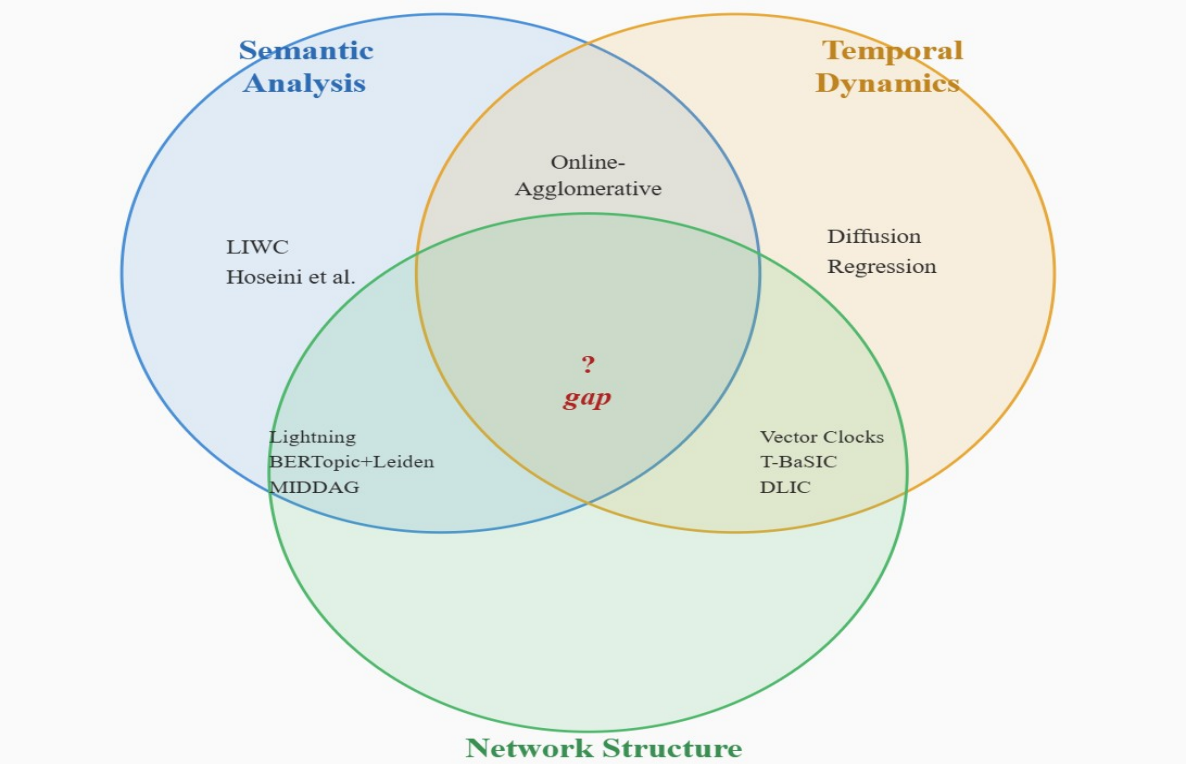

Figure 1: Coverage of analysis components by various methods.

The Lightning system has made a significant step in integrating network analysis with content processing, combining GraphSAGE or GAT for network representation with the Longformer model for encoding text content into 768-dimensional vectors and achieving 86.83% AUC on 640 million tweets, although the temporal component is only represented by dividing the data into time slices without modeling dynamics [14-15]. For the analysis of narrative evolution, a streaming clustering called OnlineAgglomerative was developed, which tracks narrative changes in real time without a predetermined number of clusters and achieves 93.2% accuracy by combining automatic clustering with expert validation [14]. To analyze disinformation campaigns, approaches have been developed that combine BERTopic topic modeling with Leiden community network analysis and sentiment analysis, which allowed us to identify differences in the network structures of English-speaking and Russian-speaking audiences on the basis of more than 6 million tweets [8]. A large-scale analysis of Telegram communities with a volume of more than 138 million messages from 9024 channels and groups using BERTopic, RoBERTa, and Google Perspective API found that 6% of users generate 90% of the forwarded content [4]. The MIDDAG system combines information path prediction, audience susceptibility assessment, and public opinion analysis, achieving 86.83% AUC and 86.28% F1 on multiplatform data [16-20].

It should be recognized that modern methods have achieved significant results in certain aspects of analysis: graph neural networks (GAT, GraphSAGE) provide high-quality modeling of network structures, transformer models (Longformer, RoBERTa) demonstrate high accuracy of semantic analysis, and streaming clustering allows tracking the evolution of narratives in real time. However, a comparison of these methods (see Figure 1) reveals a systemic gap: none of the analyzed approaches provides simultaneous coverage of the semantic, temporal, and network components of the analysis.

4. Proposed techniques

4.1 Cosine similarity for source comparison

For quantitative comparison of information sources by lexical characteristics, an approach based on vectorization of texts and calculation of cosine similarity between the obtained vector representations has been developed. To measure the similarity between sources, the cosine similarity between the vector representations of sources is calculated:

$$\mathrm{sim}(A,B)=(A\cdot B)/(|\mathrm{A}|\times|\mathrm{B}|) \quad (1)$$

Theoretically, cosine similarity (1) takes values from -1 to 1, but since frequency vectors contain only non-negative values, in practice the result is always in the range from 0 to 1.

4.2 Timed-Semantic Influence (TSI)

Comparison of information sources based on cosine similarity allows us to assess the degree of lexical proximity between them, but does not take into account the direction of information influence, that is, it does not allow us to determine which source disseminates information first and which one picks it up. To overcome this limitation, the Timed Semantic Influence (TSI) algorithm was developed, which integrates the analysis of semantic similarity of messages with the analysis of time intervals between their publications.

The TSI algorithm is based on the assumption that the influence of one source on another is manifested in the appearance of a semantically similar message on the second channel after a relatively short period of time after the first. For each message M from channel A, an array of N messages from channel B published within a given time horizon (parameter horizon_hours), after which message M is compared using the selected similarity function with each message from the array N, and a pair with maximum similarity is selected provided that the threshold value is exceeded (parameter similarity_threshold). The TSI coefficient (2) for each selected pair is calculated using the exponential decay formula:

$$TSI=\mathrm{sim}(m_a,m_b)\times\exp(-\alpha\times(\Delta t/60)) \quad (2)$$

where $\mathrm{sim}(m_a, m_b)$ is the similarity value between messages, Δt is the absolute time difference in minutes between publications, and α is a coefficient that adjusts the weight of the time component in the formula.

5. Proposed conceptual model for comprehensive source assessment

As shown in Section 3 and visualized in the diagram (see Figure 1), none of the existing approaches provides a simultaneous combination of semantic, temporal and network analysis for a comprehensive assessment of information sources, leaving the central area of intersection of the three analytical components unfilled. This limitation is fundamental, since the reliability and impact of an information source are determined by the combined action of all three factors, and the isolated application of any of them gives an incomplete picture. Based on analyzed paper [21], to overcome this gap, a model of a comprehensive assessment of the similarity between two information sources a and b (3) is proposed, which integrates the results of the methods described in Section 4 and supplements them with a network component:

$$score(a,b)=f(\mathrm{sim}(a,b),TSI(a,b),network(a,b)) \quad (3)$$

The sim(a, b) component is responsible for assessing the lexical similarity of sources and is based on the frequency vectorization method described in subsection 4.1. The TSI(a, b) component

is responsible for assessing the temporal-semantic influence between sources and is based on the algorithm described in subsection 4.2. The net(a, b) component characterizes the network proximity of sources in the information flow graph, built on the basis of directed influence graphs and Telegram message metadata, taking into account the presence and intensity of direct connections through forwarding and links, common contacts, and belonging to the same network community.

The function f determines the method of aggregation of components and can take different forms depending on the specific analytical task: weighted sum, product or trained function. The choice of a specific form of aggregation and determination of optimal weight coefficients is the subject of further research, requiring empirical verification on labeled data with known connections between sources.

The model is extensible due to its modular structure, which allows adding new components without restructuring the overall architecture, in particular, promising areas of addition are tonality analysis for comparing the emotional coloring of the content of two sources, recognition of named entities for identifying common persons and organizations, analysis of toxicity and stylistic markers characteristic of certain types of information operations.

6. Proposed system: architecture of analysis system

The practical implementation of the proposed conceptual model requires the creation of an information system capable of providing a full processing cycle. The designed system must meet several functional and non-functional requirements: the ability to add new information sources for processing and analysis, access to basic statistical information about each source, construction and viewing of cosine similarity matrices and TSI between all sources, as well as a mode of periodic data update at least daily or weekly. The system architecture (see Figure 2) is proposed as modular, consisting of several key components, each of which is responsible for a separate stage of the analytical pipeline.

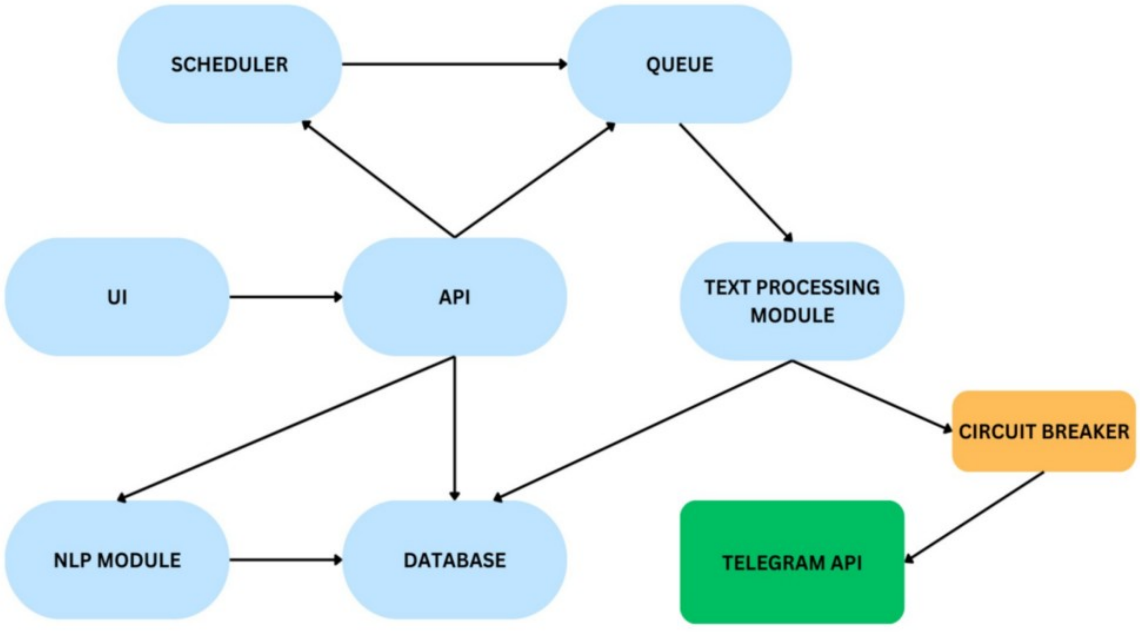

Figure 2: System Asrchitecture Module diagram.

The user interface (UI) plays the role of the main point of interaction between the user and the analytical system. The API level serves as a connecting component between the user interface and all system modules, ensuring the call of basic functions.

The task queue is implemented on the basis of the Kafka message broker, which allows you to scale information processing by dividing large tasks into smaller subtasks and ensuring their stable execution. The data processing module (Processing Handler) is responsible for converting raw messages from information sources into structured data suitable for further analysis, and functions as an asynchronous unit. Since the Telegram API does not guarantee a stable connection, the Circuit Breaker pattern is used to avoid overload during failures. Processing each message includes a sequence of parsing operations, extracting key fields, determining the language, and cleaning the text from unnecessary words.

The natural language processing module (NLP module) is the central part of the analytical core of the system and is responsible for calculating high-level metrics based on pre-prepared data. Each analytical operation is implemented as a separate submodule.

The task scheduler automates the start of data processing, regularly initiating information updates from sources and adding the corresponding tasks to the Kafka queue.

7. Results

Based on the proposed system and the integral model, 23 information sources were analyzed for Q4 2025. The first comparison factor is the cosine similarity between sources. Figure 3 presents the results of their pairwise comparison in the form of a clustered matrix. he higher the similarity between two sources, the more intense the red color at their intersection in the matrix. For clarity, pairs with a similarity below 0.4 were filtered out, and as a result, three distinct clusters of sources emerged.

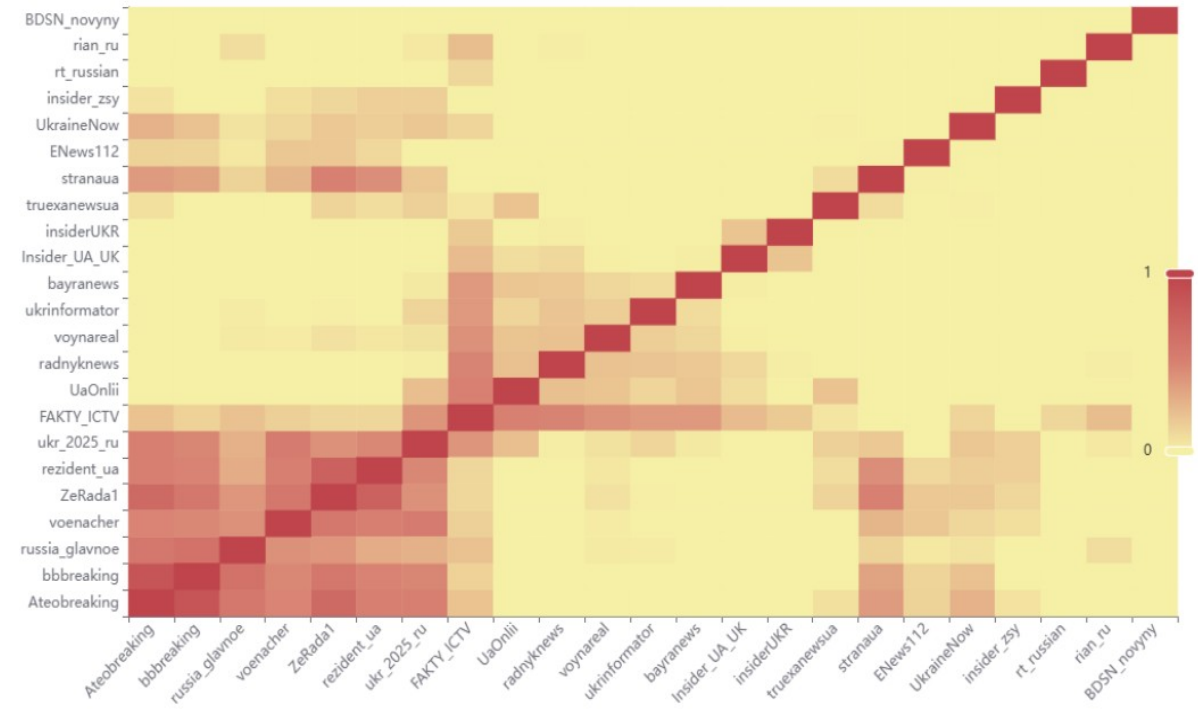

Figure 3: Heat map: cosine similarity of vocabulary usage between 23 sources.

The second factor is the TSI indicator, which reflects the overall strength of influence produced by one source on another (see Figure 4). The stronger the overall influence of one source on another, the more intense the red color at their intersection. For pairs of sources with no detected interaction, the intersection remains white.

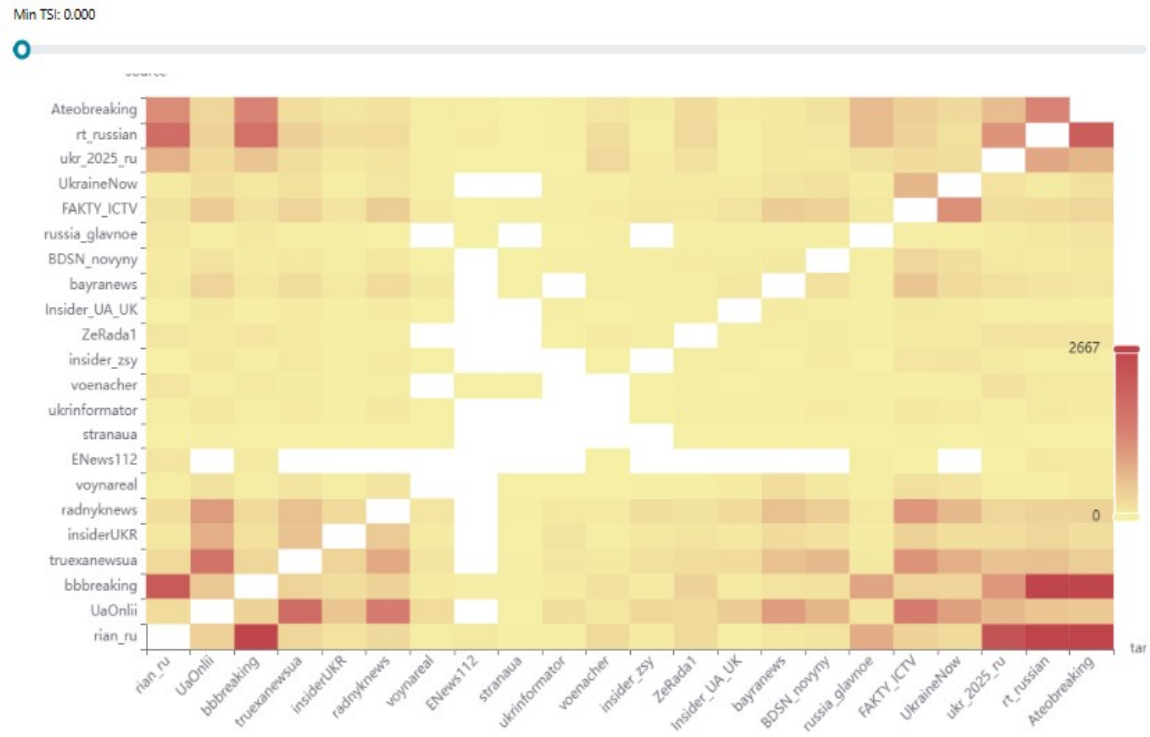

Figure 4: Heatmap of TSI Scores between 23 sources .

Using integral formula (3), the integral matrix of mutual influence among the sources was computed, as shown in Figure 5. The integral model is a linear weighted function of the individual factors. In this example, the following weights were assigned: cosine similarity - 0.45, TSI - 0.43, and graph-based features - 0.12. Three distinct regions can be identified in the resulting matrix, corresponding to groups of sources that share common characteristics and can therefore be assessed as coordinated groups of sources.

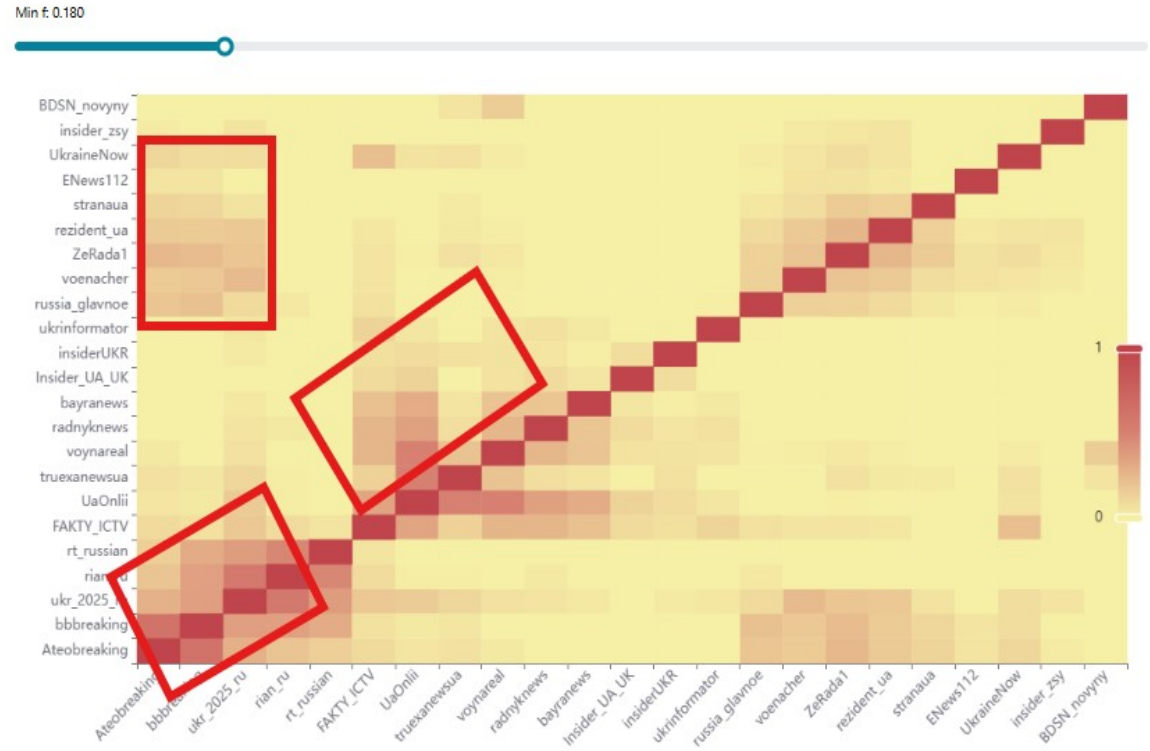

Figure 5: Integral scores between 23 sources

8. Conclusion

The paper analyzes the mechanisms of information manipulation in social networks, in particular, cascading narrative systems, the pyramid of amplification, and the "4D" tactic, which are characterized by common features. It is established that Telegram plays a special role as a platform for the implementation of these mechanisms due to the lack of content moderation, cloud architecture, and pronounced asymmetry of information flows, while providing a convenient software interface for automated collection of research data.

The systematization of existing methods for analyzing information sources revealed a systemic gap: none of the analyzed approaches provides simultaneous coverage of the semantic, temporal, and network components of the analysis, and existing methods do not form a comprehensive assessment of the similarity between information sources based on the totality of their characteristics.

A method based on frequency vectorization and cosine similarity with optimization of the minimum token frequency parameter according to the criterion of maximizing the variance of the similarity matrix, as well as the Timed Semantic Influence (TSI) algorithm, which integrates the semantic similarity of messages with the analysis of time intervals between publications and allows determining not only the degree of similarity, but also the direction of information influence between sources. Based on these methods, a conceptual model of a comprehensive assessment of the similarity of information sources (similarity_score) was formalized, which integrates four components - cosine similarity, clustering, TSI and network proximity - and is extensible due to the modular structure, which allows adding new analytical components without restructuring the overall architecture. For the practical implementation of the model, a method for building a modular full-cycle information system based on Telegram as the main platform, including asynchronous processing via Kafka, pre-processing with support for bilingual content, and an NLP module with separate submodules for each analytical operation, is proposed.

Therefore, based on experiment results, the proposed approach can serve as an effective tool for detecting coordinated information influence campaigns based on the combined analysis of source similarity and mutual influence.

The practical value is determined by the possibility of forming a comprehensive assessment of an information source, which is not achieved by any of the individual metrics. Such an assessment can be used to monitor the information space, identify coordinated information operations, support decision-making in the field of information security and develop content verification systems.

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Declaration on Generative AI

During the preparation of this work, the author(s) used SemanticScoolar, ChatGPT-5 and Grammarly in order to: Grammar and spelling check and as a smart Search Engine to find related works based on context of conversation. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the publication's content.

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