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Identification of Vortex Information. Detection of fake news eruption time

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ABSTRACT

The purpose of this study is to develop and validate a procedure known as the Information Vortex Indicator (IVI) for its effectiveness, designed to detect the timing of information vortex formation in textual data streams. Research has established that the formation of this vortex coincides with the onset of the dissemination of fake news (FN) concerning a particular object (such as a person, organization, company, event, etc.). The primary aim of this detection is to minimize the time required for an appropriate response or defense against the adverse effects of information turbulence caused by the spread of fake news. **Methodology:** The study used Big Data information resources analysis instruments (Gogołek, 2019, 2022), including selected statistical and artificial intelligence techniques and tools, to automatically detect vortex occurrence in real time. Experimental validation of the efficacy of these tools has been conducted, enabling a reliable assessment of the timing of vortex emergence. This assessment is quantified using the V-function, procedure, or test, which formally describes the IVI procedure. The V-function's parameters are derived from the distribution patterns of letter pair clusters within the textual information stream. **Conclusions:** A comparison of manual (reference) and automatic detection of vortex emergence times confirmed an accuracy rate of over 80% in detecting the appearance of fake news. These results underscore the effectiveness of the IVI procedure and the utility of the selected tools for rapidly automating the detection of information vortices, which herald the propagation of fake news. Furthermore, the study demonstrates the applicability of IVI for the continuous monitoring of information with significant media value across multiple multilingual data streams. **Originality:** This research introduces a novel approach utilizing the distribution of letter pair clusters within information streams to detect the onset of information vortices, coinciding with the emergence of fake news. This methodology represents a unique contribution to the field, as prior research on this subject is limited.

KEYWORDS
fake news, harmful information, bigrams (letter pairs), fake news detection, information vortex, Big Data, AI, information refining

The advancement of networked communications, as Gogołek (2010) outlines, especially in the realm of online media, has marked the beginning of an era of unprecedented information dissemination. Social media, in particular, has significantly accelerated and diversified the global exchange of information. However, within this continuous and intense stream of networked information, the emotional nuances of certain content may have a detrimental impact on its audience. This deluge often results in the suppression of critical thinking and a failure to evaluate the reliability of information originating from the virtual world. Consequently, this creates fertile ground for the controlled manipulation of internet users and the effective propagation of disinformation within the virtual community, commonly known as fake news (FN).

Fake news typically manifests in the form of coordinated disinformation campaigns aimed at disseminating information that is either unfriendly or excessively friendly with the intention of discrediting specific entities or engaging in Harmful Internet Use (HIU) across the fields of science, business, and politics (Koczkodaj et al., 2022). Often, fake news triggers social behaviors that have dramatic consequences. This underscores the critical importance of information security, particularly during crises such as the coronavirus pandemic, which has witnessed a surge of false, harmful, and life-threatening information within the virtual sphere.

Fake news can be defined as brief text-based information intentionally or inadvertently disseminated in cyberspace, which contains false or misleading elements, such as false links and manipulated content, or fragments of real information taken out of context, each with the intent to cause harm, damage, or validate the author's theories. Fakes, as components of disinformation, are designed to manipulate perceptions, potentially resulting in public, social, or personal harm, threatening various aspects of society, including democratic processes, national security, the economy, science, education, religion, culture, health, and the environment. Moreover, fakes can include content of a terrorist nature, posing threats to society ("Operation…", 2003). A defining characteristic of fake news, irrespective of its content or intent, is its rapid proliferation.

In addition to the aforementioned definition, it is pertinent to acknowledge that fake news can span a spectrum of emotional tones, ranging from negative to excessively positive messages that deceive their audience. For instance, news pertaining to political figures, COVID-19, or the stock market can all exhibit varying emotional undertones (Gogołek & Jaruga, 2016; Wang, Lu, Chow, & Zhu, 2020). This underlines the critical need to consider the emotional context of not only negative but also positive and neutral news messages, as they too can act as deceptive fakes (Luo & Mu, 2022).

Fake news has evolved into a weapon and a new form of warfare, with information warfare being equated with conventional armed warfare as early as 2011 and recognized as a component of hybrid warfare in many countries (Sanger & Bumiller, 2011). Considering the magnitude of contemporary information threats, there is an urgent need to develop effective tools for monitoring fake news and deploying rapid defense mechanisms to counter the impact of hostile information on society (Školkay & Filin, 2019). Early and continuous detection of such threats is paramount, necessitating the development of specific IT tools for quantitatively assessing the nature and intensity of information messages. Constructing tools that facilitate swift and accurate responses is crucial in mitigating the dissemination of socially harmful content before it inflicts significant, often irreversible damage. Thus, the primary functionality of such tools should be the prompt identification of emerging harmful information.

Identification of Fake News (FN) eruption time

It is widely accepted that these harmful texts can be characterized by measurable attributes (Meel & Vishwakarma, 2020, 2021). Machine learning (Huang, 2020), convolutional neural networks, the forms of artificial intelligence tools (Školkay, 2019), are often employed to search for these characteristics. However, these networks require continuous, intensive training on collections of texts, leading to considerable time lags due to their prolonged learning periods (Gomes et al., 2023). This approach significantly extends the detection time for the onset of FN eruptions. In order to expedite this process, an innovative method known as the Information Vortex Indicator (IVI) has been developed for the rapid detection of a characteristic textual feature – the information vortex – using letter pairs (bigrams) instead of whole phrases (Arutyunov, 2016).

This method is analogous to diagnostic procedures in common blood tests, such as those employed to detect Lyme disease caused by the bacteria Borrelia burgdorferi. Similarly, the IVI procedure operates in a manner similar to an ELISA blood test, which does not directly identify the presence of the bacteria but instead detects specific antibodies (IgM and IgG), which are indicative of a Borreliosis infection with high probability.

Likewise, the IVI process for detecting turbulence in the information stream akin to the ELISA blood test, does not directly identify the presence of FN but rather signals a symptom: the emergence of information turbulence. It acts as a proxy, signaling the probable appearance of FN within the information stream, similarly to how ELISA indicates the presence of bacteria in the human body indirectly.

Such an approach significantly reduces the time required to detect the onset of FN eruptions by focusing on identifying indicative textual features rather than relying on comprehensive text analysis.

Informational richness of letter pairs

In seeking a precise method to identify information turbulence within textual data streams – a metaphorical antibody indicative of such turbulence – an established stylometric approach has been employed. This method involves analyzing the density distribution of letter pairs/bigrams within the text, a technique known for decades. It draws from stylometric methods used in the analysis of literary works, which accurately ascertain statistical characteristics of an author's unique writing style (Hirst & Feiguina, 2007). Stylometry has historically been used to determine authorship of designated texts (Hirst & Feiguina, 2007), employing statistical tools like Markov Chains, pioneered by A. A. Markov in 1916 (see Markov, 2006). These tools remain relevant today, even employed in modern applications like automatic speech recognition.

The concept of "stylistic fingerprints", comparable to an author's DNA, was pointed out by Gogołek (2006), with roots tracing back to the early 20th century when Markov successfully confirmed the authorship of Eugene Onegin (Sękiewicz, 2012). Stylometric analysis, particularly in the form of analyzing bigram distributions, has demonstrated remarkable accuracy in identifying the works of various authors, including Hemingway, Poe, Baldwin, Joyce, Shakespeare, Cummings, Washington, and Lincoln (Camps, Clérice, & Pinche, 2021), thereby underscoring the efficacy of stylometry in uncovering textual DNA.

Moreover, the frequency distribution of bigrams in texts helps in (1) the individual assessment of text authors' personalities. It is hypothesized that there are discrepancies in bigram distribution values between FN authors and non-FN text authors (Litvinova, Seredin, & Litvinova, 2015), thus suggesting the informative value of bigrams in identifying texts as FN. Furthermore, research indicates (2) that the analysis of letter pair distributions within texts successfully identifies cyberbullying and hate speech (Shawkat, Simpson, & Saquer, 2022).

In our own investigations into interpreting information whirlwinds as symptoms of FN (Gogołek & Kuczma, 2013), it became evident that turbulence is not exclusive to negative information streams, as it also encompasses streams that convey extremely positive information, often exhibiting characteristics of FN. This finding underscores the utility of IVI in continuously detecting information of significant media value across diverse multilingual data streams. Considering the informative value of letter pair distributions in the text under study, it was assumed that the characteristics of the distribution of letter pairs makes it possible to:

– identify the author of the text,
– assess the strength of the relationship between the distribution of letter pairs in a text and the personality of the author of that text,
– determine the presence of hateful content in the author's texts, and
– content curation (Rohit, 2011) – a continuous search for topics about the harmful information of the texts being analyzed (FN).

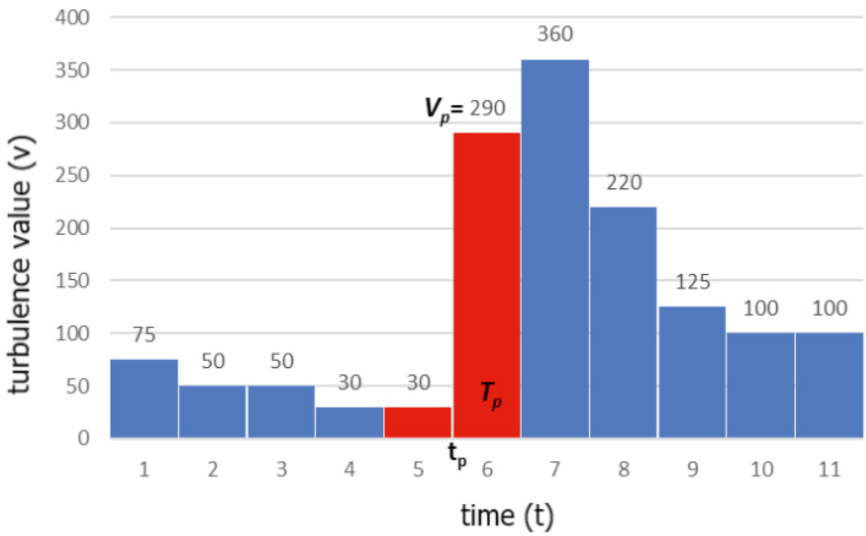
The hypothesis suggests that FN content could shape or reflect the distinctive profile of a virtual Beta author. The Beta author represents all FN distributors, including both creators and propagators, concentrated over time and focused on the designated subject. Beta is characterized by a unique writing style identifiable through bigrams, referred to as the DNA_β writing style. The creator of the remaining analyzed information stream, who possesses a DNA_α style, is known as the Alpha author.

In essence, the assumption is that there are consistently two authors within the analyzed text stream: Alpha and Beta. Each author's texts are distinguished by the value of the function *V*, which represents the turbulence and is indicative of the writing style (bigram distribution) pertaining to the subject under study. The sought-after time of vortex formation, denoted as $t=p$, occurs when the threshold value v_p is exceeded.

Reducing the number of text creators to two – Alpha and Beta – denoted by characteristic values of DNA_α and DNA_β, respectively, enables the quick detection of the moment t_p when Beta texts (fake news) appear within a continuous text stream.

The function *V*'s arguments are the real-time counted values of letter pair frequencies across consecutive n periods from time t to $t+1$, $\{T_t(t,t+1);\ (t,t+1) = (1,2), (2,3), (3,4)\ldots, (n\text{-}1,n)\}$ of the analyzed text. The result of the function *V* is a positive value of v_t, the magnitude of which is directly proportional to the value of the turbulence in the analyzed information stream. The larger the value of v_t, the higher the probability of FN occurrence in the studied fragment/period T_t of the text stream. The values of t and v_t form a time series of the source data: $\{(t,v_t) : t = 1,2,3,\ldots,n\}$.

Fig. 1. Time and value of vortex appearance in the information stream



t – time
v_p – threshold value of the turbulence magnitude
T_p – period of identification of the threshold value of the turbulence magnitude
t_p – time of appearance of the vortex (beginning of T_p)

Assumptions

1. Information Streams and Chronological Packets: Information streams are organized into chronologically ordered packets, each with a fixed duration period T_t. These packets are timestamped and relate to a specific object or topic. This structure enables the simultaneous analysis of multiple streams from various sources.
2. Definition of Bigram: Bigrams, sequences of two adjacent letters, are defined within the analyzed entries of the information streams. These bigrams play a crucial role in pattern analysis and anomaly detection within the text.
3. Information Vortex (Vortex): The concept of an information vortex denotes the presence of fake news within the information stream. Detection is based on characteristic changes in the frequency distribution of letter pairs (bigrams). These alterations, indicative of recipient emotional engagement, align with the definition of fake news. The appearance time of these vortices, t_p, signals the potential presence of fake news.
4. Application to ORLEN: The assumptions involve using source materials from Piotr Wierzbicki about the large Polish company ORLEN, to illustrate the procedure or IVI test. This implies the IVI test's applicability for identifying fake news associated with specific companies or entities.

This methodology involves analyzing textual information streams focusing particularly on monitoring changes of bigram frequencies for detecting the presence of fake news, specifically applied to ORLEN in this context.

Hypothesis

Implementing the IVI procedure accurately identifies the emergence time of an information vortex, represented as {time – t_p, value – v_p}, assuming a certain probability of error. The values of t_p and v_p represent the automatic identification of information vortices, significantly assessing the time t_p of fake news emergence and the corresponding value of v_p.

Procedure for identifying information vortices – IVI test

The IVI test automates the identification and calculation of V values representing information turbulence within a discretized information stream divided into fixed periods T_t (refer to Fig. 1). An example study illustrates how the IVI test signals information vortices (time t_p and value v_p) within segments of a text stream during the period T_p. The time t_p marks the emergence of the vortex, triggered when the V value exceeds the threshold v_p, marking the onset and spread of fake news.

In this example study, a constant stream of letter pair frequencies $\{f(l);\ l=l_{aa},\ l_{ab}, \ldots l_{ba}, \ldots, l_{żż}\}$ assumed a priori, was used for periods shorter than 12 hours, with t representing the time/date of each period's initiation in the analyzed information stream. Each period is characterized by its v_t value, which indicates the relative frequencies of letter pair occurrences. For instance, the relative frequency value $f(t,l_{aa})$ for the pair aa at time t = March 1, 2020, is 0.002637312 (the sum of relative frequencies for each successive period and all pairs equals 1).

Normalizing relative frequency values helps eliminate seasonal fluctuations within the analyzed bigram information stream, thus minimizing the influence of extraneous factors on the assessment of changes in bigram frequency distributions over the studied time interval T_t.

Table 1. A fragment of the results obtained from measuring the relative frequency values f(l) of letter pairs within the information stream pertaining to the ORLEN company

Number of pairs	8721	22418	11495	13147
Time (t)	01.03.2020	02.03.2020	03.03.2020	04.03.2020
f(l=aa)	0,002637312	0,003435	0,002522836	0,001978
f(l=aą)	0	0	0	0
f(l=ab)	0,000687994	0,000937	0,001826881	0,001217
f(l=ac)	0,005503956	0,004773	0,003914746	0,00464
f(l=ać)	0,00160532	0,000803	0,001739887	0,001445

The study focused on the frequency of letter pairs, selecting those with a relative frequency exceeding 0.0009% within each period (T). For example, the least common pair 'ży' had an average frequency of 0.0009173 over the period. Results were obtained for L = 1086 pairs.

To demonstrate IVI's effectiveness we present a sample study on the automatic identification of vortices in a news stream including 99,625 tweets about ORLEN from March 1, 2020, to April 16, 2021, over 411 days. IVI's efficacy was confirmed by comparing automatically obtained results (t_p time and v_p value) with expert manual labeling of vortices in the examined information stream of ORLEN.

The IVI test aims to detect the phenomenon associating information vortices with changes in the frequency of letter pairs within the time series of the text stream. To achieve this, a three-dimensional matrix was created, with f_l representing consecutive values for each letter pair l $(l=1,2 \ldots L)$; in the study (L=1086) in the examined information stream, represented as: $A1 = [l_1, l_2, \ldots l_L; f_1, f_2, \ldots f_L; t_1, t_2 \ldots t_n]$.

As mentioned, to minimize estimation error, seasonality factors (including cyclical, random, seasonal fluctuations, trends, etc.) were eliminated a from the series of f_l values. In the study, this operation was conducted by calculating relative f_l values for each t.

Determination of turbulence value

To compute the turbulence value v_t and quantify turbulence within the defined period T_t of the information stream, pairwise frequencies for each t are reduced to a single value f_t. This reduces the dimensions of the source data space (matrix A1), reducing each pair's frequency *f(t,l)* to a single value *k(t)* for each *t*. Consequently, the source data can be represented as a two-dimensional matrix: $A2 = [t_1, t_2...t_n; k_1, k_2,...k_n]$.

This involves calculating a controlled number of clusters in the pair frequency distribution (e.g., t-SNE) for each *t*. Experimentally, it was stipulated that the maximum number of clusters per pair and per *t* should not exceed 20. Subsequently, the cluster numbers were condensed to a single positive value *k(t)* for each *t*.

K(t)'s value reflects the intensity and speed of turbulence changes. It serves as the argument of the function *V*, with *v(t)* being the measure of vortex magnitude. A vortex is identified when *v(t)* surpasses an experimentally determined threshold value *v(t)*. The parameters adopted by the function *V* ensure that a stable increase of *v(t)* above v_p does not continuously trigger new vortex signals. To avoid 'turbulence echoes,' as termed by P. Wierzbicki, power arguments are considered, thus maintaining the accurate detection time of the vortex.

Arguments and value of the *V* function

1. The value of *k(t)* reflects the magnitude and speed of turbulence changes. It is the first argument of the *V* function, with *v(t)* measuring vortex size.
2. The second argument, assessing vortex value, is vortex strength *m(t)*, which comprises the sum of successive vortices 'semivortices' following the identification of a vortex formation at time t_p. Referred to as turbulence echoes by P. Wierzbicki, semivortices are consecutive vortices identified until a new vortex emerges, typically through a dedicated machine learning (Zhou, 2022) model. These semivortices do not trigger signals regarding the emergence of new vortex formations within the system. Ignoring semivortices as true vortices reduces the risk of mistaking mere echoes for actual vortices.
3. The third argument, evaluating vortex value, measures the sentiment towards the object under scrutiny – denoted as *s(o,t)*. Sentiment measures the emotional message's saturation with an arbitrary tone. The sought-after value of *s(o,t)* is determined by the function of the difference between positive and negative sentiments. A corpus comprising both types of sentiment is created individually for each subject under study (e.g., politics). Experience shows targeted sentiments have a limited lifespan, highlighting the need for continuous updates.

$$V(t) = f[k(t),m(t),s(o,t)]$$

k(t) – power of changes in the value of the turbulence
m(t) – vortex strength
s(o,t) – value of difference of positive and negative sentiments

Experimental research procedure for identifying information vortices

The procedure for identifying turbulence has been streamlined. It utilizes the *V* function with a single fundamental variable *k(t)* specific to the object under study: *V(t) = f[k(t)]*.

IVI's primary function is the continuous, real-time measurement of turbulence values v_{t-1} and v_t in the information stream, for each consecutive period pair $\{T_{t-1}, T_t\}$. The current value v_{t-1} serves as the reference point (relative value) for determining the presence or absence of a vortex v_t between periods $\{T_{t-1}, T_t\}$. To achieve this, a function detects sharp *V(t)* changes between periods, resembling a 'V' shape, hence the name of the IVI procedure.

A decrease in turbulence value *v(t-1)* at time *t-1* (the left arm of the 'V') is followed by an increment in turbulence *v(t)* at time *t* (the right arm of the 'V'). This increment's magnitude is calculated using time series analysis techniques is computed using time series analysis techniques, such as the weighted sum of cosine functions or the slope of the regression line. This complements seasonality elimination from the text stream analysis.

An increment exceeding the threshold v_p signifies vortex emergence. Conversely, the absence of an increase above the threshold value v_t relative to v_{t-1} indicates that a vortex has not occurred. The outcome of this functionality is depicted in Figure 2.

Surpassing the threshold vp marks the critical value v_p marks the sought-after time t_p which distinguishes text stream segments unaffected by fake news T_{t-1}, authored by virtual author Alpha, from segments at time T_t containing fake news authored by virtual author Beta. This achievement fulfills the study's objective: detecting the appearance time of texts authored by the Beta author, constituting an information vortex.

Fig. 2. Illustrates the values of turbulence measures v(t) in a fragment of the tested information stream of texts

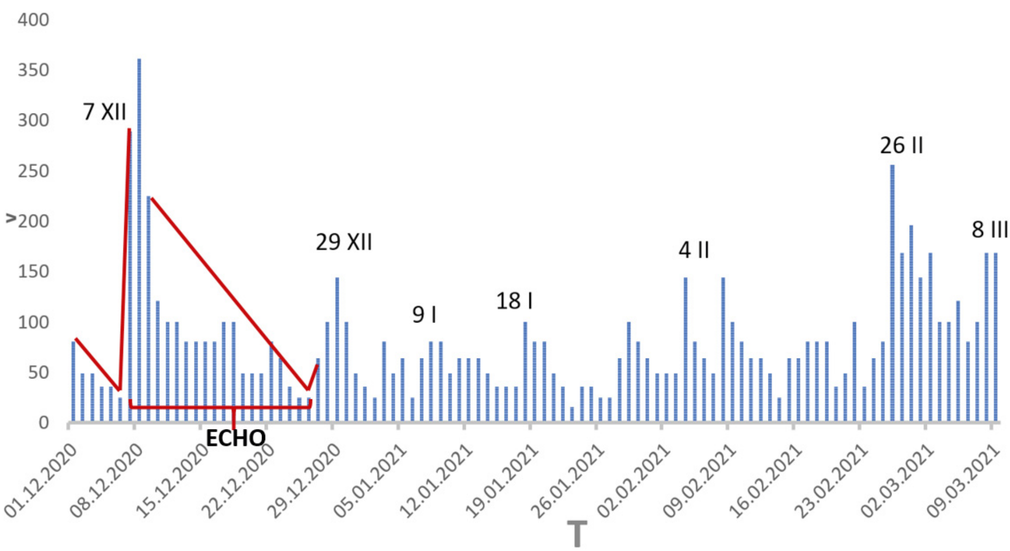


Figure 2 displays the time series of $V_t(t)$ values for all *T* periods, automatically calculated by the IVI procedure, the dates of information turbulence, manually identified by an expert, are also plotted. Sharp increases in v_t values, indicating information turbulence eruptions, align with the expert's manual indications. Expert comments in Table 1, marking the dates of information turbulence appearances, further evidence this alignment.

Table 2. Evaluation of information turbulence regarding ORLEN from December 1, 2020 to March 9, 2021

No. of vortex	Start of vortex	End of vortex	Strength/type
1.	December 7, 2020	December 9, 2020	strong
2.	December 10, 2020	December 18, 2020	echoing vortex
3.	December 29, 2020	December 30, 2020	moderate
4.	February 26, 2021	March 4, 2021	strong
5.	March 8, 2021	March 20, 2021	strong

Source: Wierzbicki (2022).

Identification of the vortex

The IVI functionality enables real-time tracking by editors/users of dynamic changes in the turbulence measure *v(t)* to confirm vortex eruption times or interpret vortices' echoes, such as successive decreasing vortices (e.g., 10–18 December 2020, Fig. 2). This involves measuring a vortex's power by its size and the number of successive vortices from 10 December, 2020.

Editors can automatically evaluate turbulence values with the option for unlimited verifying previews at manually selected periods T_t in the information stream.

Similar to confirming borreliosis with an LTT test, in the IVI procedure, editors resolve doubts, akin to the role of antibodies in diagnostics.

Discussion/Conclusions

The results obtained from detecting the timing of fake news (FN) appearance using the IVI test, which involves automatic identification of information turbulence, showed a correspondence between the occurrence of information vortex and the onset of fake news publication. Further research in this domain confirmed the reliability of the results and the rapid detection of vortex eruption, with a detection delay of less than 12 hours. The detection delay time is affected by the efficiency and abundance of the controlled information stream regarding the studied object, as well as an experimentally determined minimum duration and value of turbulence.

It is noteworthy that the IVI procedure, through the normalization of source data (relative values), mitigates conventional seasonal fluctuations in bigram numbers within the information stream, thus enhancing its reliability. IVI exhibits characteristics of a procedure for identifying the nature and significance of content, particularly in distinguishing fake news based on their time of appearance.

An important extension to the IVI procedure involves the utilization of additional detection tools, such as:

1. A tool for detecting turbulence in the concentration of the number of complete words (after lemmatization and/or tokenization) in the analyzed information stream.
2. Detection of unique pairs of letters in texts related to the studied object, which are characteristic of fake news.
3. Specific sentiment analysis tailored to the sentiment corpus of the studied object.

The investigative power of the IVI procedure, coupled with standard Big Data tools (Gogołek, Jarzyńska, Żukowski, Wierzbicki, & Durlak, 2022), has been validated through numerous studies, demonstrating its accuracy in assessing emotional tones in analyzed texts and indicating political preferences. Access to multiple information streams regarding the studied object improves the effectiveness of automatically identifying fake news outbreaks.

Considering the simulations conducted thus far and the insights gained during the procedure development, there is value in exploring the potential of convolutional neural networks (CNNs), t-distributed Stochastic Neighbor Embedding (t-SNE), and similar tools to develop a comprehensive model for identifying the time of appearance of fake news "antibodies."

Integrating IVI with tools for assessing post concentration, analyzing unique bigrams specific to the adopted research object regarding fake news, and custom sentiment analysis dedicated to the object, will undoubtedly improve the accuracy and speed of identification the time of fake news appearance in the studied information stream. Moreover, the versatility of IVI extends further, facilitating continuous detection of significantly valuable media information across multiple multilingual information streams (Gogołek, 2022).

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List of abbreviations and designations

DNA_{α}	– ALFA author's conventional style of writing
DNA_{β}	– BETA author's conventional style of writing
f	– the frequency of occurrence of a pair of letters in period T
FN	– Fake News
HIU	– Harmful Internet Use
IVI	– Identification of Vortex Information
k	– the number of clusters of letter pairs in a certain time
L	– quantity of all pairs of letters in period T
l	– number of the letter pair
m	– vortex strength
n	– the number of the period of counting pairs of letters
o	– ID of the object
p	– the time of formation of the information vortex
s	– value of difference of positive and negative sentiments
t	– time of the beginning of the period of counting pairs of letters
t-SNE	– Distributed Stochastic Neighbor Embedding – a dimensionality reduction technique
T	– the period of counting pairs of letters
v	– turbulence value
V	– function of calculating the value of v

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