DYNAMICS OF AGGRESSIVE DISCOURSE ON UKRAINE AND THE WEST IN THE RUSSIAN PRO-GOVERNMENT MEDIA IN 2000-2022

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Abstract

The aim of this research is a build of a tool that helps to detect latent meanings of Russian propaganda messages. For this purpose, a new approach to building time-aware sentence embeddings was created, using the logic of the word2vec word embeddings model. An array of articles (754,372) from more than 50 Russian news websites for the years 2000–2022 was analyzed. In the dynamics of aggressive discourse towards the West and Ukraine, the key year is 2014 - the year of the beginning of the aggression against Ukraine. But at the same time, Russian propaganda positions it as a struggle for influence with the West, and this perfectly demonstrates the synchronicity of anti-Western and anti-Ukrainian propaganda.

Key words: *Propaganda, Sentence Embedding, BERT, Content Analysis, Cluster Analysis*

INTRODUCTION

Personal experience

Recently, a Belarusian friend of mine, who visited Berlin over the weekend, told me a story from the Berlin metro with admiration and surprise. He met two Ukrainian men there. They spoke loudly to each other in pure Ukrainian. But at the same time, their attention was focused on the phone, where they were watching a recording of the program of Vladimir Solovyov, one of the most famous and popular Russian presenters. They watched it for so long that my friend had to ask them to turn it off. He can't stand Russian TV presenters.

A friend rightly assumed that Ukrainian-speaking Ukrainians were hardly Solovyov's audience. He told me this story because he wanted to understand why these men did it. However, this did not surprise me because there are people in Ukraine who watch the Russian state media to understand the Russian state's intentions toward Ukraine. Calls for military intervention in Ukraine have long been heard on Russian television, but these calls have now been implemented. When the first reports of an increase in Russia's military presence near Ukraine's borders appeared, some of my friends rushed to watch Russian TV to understand the seriousness of their intentions, expecting that the reasons for the invasion would be legalized there. That is why Ukrainians now understand more than anyone else in the world the importance of content analysis, a method of sociology that owes its emergence to another great war.

Need for better technologies in social science

The war in Ukraine is called the first online war. Modern communication technologies make it possible to observe military operations almost in real-time. The world learned about Russia's plans for the attack thanks to high-quality satellite images. It has become possible due to the development of technology. If propaganda is part of military preparations, why not use the latest technology to analyze it?

> *It is the question we asked ourselves before starting this study. We'll just try to create an analog of the MAXAR satellite for content analysis.*

Fig. 1. MAXAR satellite shows Russian military build-up (late 2021)

Motivation

Russia's aggression against Ukraine was previously accompanied by informational preparation to justify the need for military action. The demands of the Russian Federation made before the war also contained provisions on NATO, so part of the preparatory aggressive discourse also concerned Western countries. As this is not Russia's first aggressive campaign, it is essential to look at how aggressive speech has developed throughout Putin's rule since 2000. 2000 is also the year of the emergence of the sites of the largest online media, which are now considered pro-government in Russia - RIA Novosti (known for its article "What do we need to do with Ukraine?") and Komsomolskaya Pravda.

Materials from these publications are helpful information on developing the progovernment discourse on Ukraine and the West. We decided to find out what the dynamics of this discourse were. In particular, we were interested in how this discourse changed synchronously with the beginning of Russia's aggressive actions in 2014 and 2022. It is also important how the dynamics of aggressive discourse about Ukraine differ from the dynamics of aggressive discourse about the West.

Also, it is important to have the ability to analyse a vast amount of texts because of the Russian "Firehose of Falsehood" propaganda model [Paul and Matthews 2017]. The key feature of this model is the huge amount and intensity of propaganda sources and messages (so many that it is impossible to verify their veracity and understand the main message).

Therefore, we need to have a tool to detect the latent meanings of Russian propaganda messages (in general), so the aim of this study is an approach that helps to detect such latent senses of Russian propaganda messages.

1. METHODOLOGY OF RESEARCH

The topic of our research is the study of aggressive discourse on Ukraine and the west in the Russian pro-government media in 2000-2022, although tracking the dynamics with traditional content analysis is an unrealistic task. We need to track semantic dynamics, so we turn to the method of sentence embedding - such a task is difficult in itself. Therefore, the methodology of our research contains two parallel tasks at once - the conceptualization of Russian propaganda messages and the build of a tool for its detection.

1.1. Russian propaganda as a subject of study

The topic of Russian propaganda is not new in scientific studies, so there is no need to justify the subject of research. Researchers focus on such an aggressive practice of Russian propaganda as the open use of social media and media outlets in foreign languages, not only Russian, to destabilize other states and societies from within.

For example, Ch. Wagnsson and C. Barzanje exposed the discursive (harmful) ability of strategic narratives of Russian propaganda using the example of the Russian state-sponsored broadcasting company Sputnik's strategic narrative about Sweden from 2014 to 2018 [Wagnsson, Barzanje 2021]. In France, the Russian-founded media RT and Sputnik are also considered partial or misleading. An example is the Yellow Vests movement, whose members have been accused of being manipulated by Russia and its media. The grouping of those spreading content from international Russian media is based on data collected on Twitter during the first months of the Yellow Vest movement [Gérard, Marotte, Salamatian 2020].

An important case is RT Arabic (formerly Russia Today), which creates a strategic narrative of Russia's participation in the war in Syria, effectively legitimizing its presence. D. Dajani, M. Gillespie and Rh. Crilley attempted to conceptualize "how state-sponsored strategic narratives operate in practice and can be mobilized as a of soft power resource". A qualitative analysis of social media (Facebook, Twitter, YouTube) shows that RT Arabic creates an image of Syria as a non-sovereign, dysfunctional state (a fale state or fake country), vulnerable to invasion by foreign forces competing for power and control in the region, Russia is as "portrayed as coming to the aid of Syrians and Syria, as a benign presence promoting the establishment of good governance and skilfully managing the complex diplomatic relations surrounding the conflict" [Dajani, Gillespie, Crilley 2021]. RT Arabic skillfully uses the narrative strategies of "exposure" and "concealment", while in the case of Sputnik the authors presented three antagonistic narrative strategies of "suppression," "destruction," and "direction" [Wagnsson, Barzanje 2021].

O. Denkovski and D. Trilling consider the Russian state to be the most innovative in creating false and misleading information (content from RT and Sputnik) and spreading it on social media and news websites to promote alternative socio-political realities. Researchers successfully use computational text analysis to study online disinformation on the example of Serbia [Denkovski, Trilling 2022].

Russian propaganda is aimed at both external and internal audiences. Distorting social and political reality for Russians for decades, the Chekist state legitimizes itself and its illegitimate actions both in domestic politics and in foreign policy. Many narratives are more significant for maintaining the stability of the Russian political course, in particular regarding the annexation of the territories of other states [Golovchenko 2020]. The Chekists of the Russian Federation do not simply ignore public opinion (the leader considers the consideration of citizens' opinion to be a weakness of the politics of Western countries) they shape it through the controlled mass media.

The study of Russian propaganda has a number of other interesting conclusions. Through television, social networks, or websites, Russian propaganda forms narrative strategies depending on the socio-political context and target audience, however, according to S. Radnitz, it succeeds worst (have minimal effects) on those aimed at audience support for conspiracy theories [Radnitz 2022].

S. Alzahrani and others researchers showed that "influence campaigns, in which a state actor or organizations under its control attempt to shift public opinion by framing information to support a narrative that facilitate their goals," precede active action. Researchers studied pro-Russian news media in Ukraine and found "significant framing shifts exceeding a smaller peak of 2010, in November 2013, and sharply spiking and trending again in December 2013, three-four months ahead of Crimea's annexation by the Russian Federation" [Alzahrani et al. 2018].

Recent year Russian propaganda is often the subject of studies, especially after annexation of Crimea in 2014. Such interest on the topic we can explain through unusual way of waging war that got the name as "a hybrid war". Propaganda in Russian government media was an essential part of this strategy. Given the Russian-Ukrainian war, not crisis or conflict, and its implications for the world [Audinet, 2018], the number of publications focusing on Russian media influence actors and the narratives they deploy will increase.

In different studies authors considered various sides of Russian propaganda that resulted in a big variety of the methods applied for this task. I detected the following aspects and features that are inherent for such papers:

- studies on networks of pro-Russian trolls and bots in social media. In such papers scholars analysed in the most cases links between different profiles, and tried to detect some networks, communities most often in Twitter (because of an open API that allows downloading a lot of data from this network). Therefore the main methods of such studies are graph analysis-like community detection approaches (Clauset–Newman–Moore community detection algorithm);
- studies of Russian trolls and bots comments below publications in the West media. In these studies authors tried to detect propaganda stamps and similarity between comments and Russian narratives. In these papers authors rely on text

mining methods that allow to detect linguistic "fingerprints" on Russian bots comments [Helmus et al. 2018];

- studies of the narratives of Russian state media. In these studies researchers rely in the most cases on traditional content analysis strategies trying to detect propaganda-specific categories in the texts and summarise it. Our research belongs to this part of Russian-propaganda studies.

1.2. Analysis of changes in the meaning of words

Language is a changing social product. The meaning of the same words may change over time. For example, the English word "apple" is now primarily associated with the company of the same name, although previously, people used the word only to denote fruit [Yao et al. 2018].

Vector representation of words can quantitatively demonstrate how the meaning of words changes. It is because it represents words to find out their position in the semantic space relative to other words. For example, in the case of the word mentioned above, "apple," the vector representation based on nineteenth-century texts showed its closeness to words related to fruits, trees, and plants. At the same time, the vector representation made on modern texts has placed this word in space next to the words associated with computers, information technology, and corporations. These shifts in the space of meanings are interesting for analysis because they illustrate how, historically, the perception of a particular concept has changed. It is also possible to investigate how the meaning of a concept varies depending on the group context.

Currently, several techniques use word embeddings to analyze the evolution of meanings [Kozlowski et al. 2018]. The easiest way would be to train different vector representations for each period and compare the positions of each word. But the problem is that in each corpus, there are differences in dictionaries (not all words occur in different periods), and the vector representation is calculated purely relative to other words. Hence, it is not the specific coordinates of the word in n-dimensional space but their distance from the coordinates. In other words (simply put, the coordinate systems in different vector representations can differ significantly). Therefore, it is necessary to bring separate vector representations of words to one coordinate system so that we can correctly compare them.

In Dynamic Vector Representations of Words, Bumler and Mandt analyze the evolution of the meaning of words over 150 years from the Google Book Archive using their version of Dynamic Word Embeddings of Words, which is an extension of Mikolov's original skip-gram. This extension is to add to the model a latent time series, which on the one hand, trains a model that would take into account changes in vector meanings of words in space, and on the other hand, implements it by learning just one vector representation instead of a set of models for different periods [Bamler and Mandt 2017].

Zhang, in his dissertation "Dynamic word embeddings for news analysis." Zhang solved the problem of the dynamics of vector representations differently. His algorithm was to train individual vector representations for each period and their subsequent rotation to minimize differences in the coordinates of the same words. He used this approach to analyze the dynamics of the words "Trump" and "Croatia" in the media during 2018 [Zhang 2019].

Yao, Song, Ding, Rao, and Xiong in Dynamic Vector Word Representations for Evolving Semantic Research proposed a version of dynamic word embedding that was also based on rotating spaces to superimpose different vector representations over time. They analyzed nearly 100,000 articles from the New York Times between 1990 and 2016. Their main focus in the analysis was finding equivalent words in the past [Yao et al. 2018].

Di Carlo, Bianchi, and Palmonari, in their article Training TemporalWord Embedding with a Compass, presented an alternative method of training word embeddings that could show semantic dynamics. The main idea of this approach is to train word embedding in two stages. In the first stage, they have trained the general vector representation for texts for all years that they planned to study. Then they train vector representations for periods, which researchers plan to compare. It is necessary to create a space against which changes in values over the years will be measured (the authors call this vector representation a "compass"). However, the values in space for words are calculated relative to their meanings in the "compass." This effect is achieved because each vector representation of words for the period learns not from the beginning but from its values in the vector representation-compass (these values are initialized before learning each new vector representation, which speeds up the model learning process). All the above models are based on the word2vec architecture [Carlo et al. 2019].

Similar studies have already been conducted on the TWEC[1] model [Angelov 2020]. In particular, there was a successful attempt to find out how associations with the police in the Ukrainian mass media have changed over the last 20 years [Kyrychenko 2021], and to study of mediatization of politicians [Salnikova, Kyrychenko 2021]. Therefore, we know the possibilities and limitations of these methods. The critical limit is that many meanings, especially complex ones, are conveyed in whole sentences/texts. Therefore, it would be essential to make coding of entire sentences/texts. It is beneficial to record the dynamics of these embeddings. TVEC allows it, but at the level of words.

1.3. Data

We use an array of articles from the more than 50 Russian news websites for 2000-to 2022 to conduct the study. The total volume of analyzed news pieces is 754,372.

[1] See implementation here: https://github.com/valedica/twec

These are all Russian newspapers, but without so-called "liberal" media like Meduza, tvrain. Some sites have not been fully downloaded due to DDOS attacks on them and blocking.
Below is a table of the top resources from which we take most articles for our analysis.

Table 1: Top-10 news websites by amount of articles

Media	Count
kp.ru	215 731
fedpress.ru	104 417
lenta.ru	92 851
ria.ru	47 099
gazeta.ru	44 570
newsru.com	42 714
life.ru	39 735
vedomosti.ru	37 319
kommersant.ru	30 688
rbc.ru	27 574

Articles were collected using the newspaper package[2] in the Python software environment.

2. RESEARCH MODEL

As you have read above, we need to have a good text encoding method to compare many news pieces. Word embeddings are good, but we need an alternative to compare complete sentences.

2.1. Model to encode complex concepts

In recent years the field of NLP has developed intensively, primarily due to the emergence of the architecture of the model of deep learning Bert [Devlin et al. 2018].
This architecture is characterized by learning to embed the entire input text. It makes it possible to use this model to encode sentences and compare them. However, this requires a correct modification of the model. The classic version of Bert focuses on the tasks of guessing and classifying texts. Embeddings, which the model trains, also focus on this task. However, this architecture is also suitable for paraphrase detection.
For this task, t*he SentenceBert*[3] architecture was created.
We take **Sentence Bert's deep learning model** as the basis of our research method [Reimers and Gurevych 2019]. This model is used for paraphrase detection [Reimers and Gurevych 2020]. To train such a model, you need to prepare a dataset with pairs

[2] See here mode: https://newspaper.readthedocs.io/en/latest/. The code is authored by one of the co-authors of the article, who will also publish his code in the future.

[3] See documentation and code here: https://www.sbert.net/

of sentences and labels (0 or 1), indicating whether the two sentences are the same content.

In our case, we want way more:

- we need to understand the similarity of narratives;
- we need to have links between time and narratives;
- we need to train the model to understand the time relations.

We could use the principle of the TWEC model mentioned above. However, it requires the training of a separate model for each period and one general model. We planned to analyze a huge volume of texts. We also went to get daily details. In this case, we would have to train about 8,000 individual models and then compare them. So we came up with an elegant solution through one model. The key to this solution is the proper preparation of the dataset.

Ideally, we would need to have a large array of marked pairs of things from the Russian media, indicating whether they are similar in content or not.We did not have the resources to do so.

To prepare the dataset, we took the idea that is the basis of **the model of vector representation of words word2vec**. Its training is based on analyzing the proximity of the location of words in a sentence. If the words are close, the model considers them close in meaning. If far - then far [Mikolov et al. 2013]. We decided to label it as zero sentences taken from different pieces. For sentences from one article, we labeled more than 0. Still, not more than one depends on the proximity of sentences in the text (calculated by formula 1/(the number of other sentences between these two sentences in the text +1)).

To evenly present the whole period in the sample, we randomly took five articles from each day and made pairs of them for all sentences. Then we took five new random articles for each day and took one random sentence from them. We randomly chose a different sentence from another text for each sentence. We gave such pairs a score of 0. We have done it to show for models other content in the sentences (although purely by chance, the pair may be similar, the model focuses on generalization, this is not a problem).

It was also essential to create the date embeddings for these texts. Therefore, we also enriched the dataset with data-sentence pairs (if this sentence was in the text for the relevant date, then put a mark of 1, if not - 0) and date-date pairs (we placed marks on the principle of 1/(difference in the days between dates)).We again took five articles for each day and created a pair of sentences for them from the day the article was published.

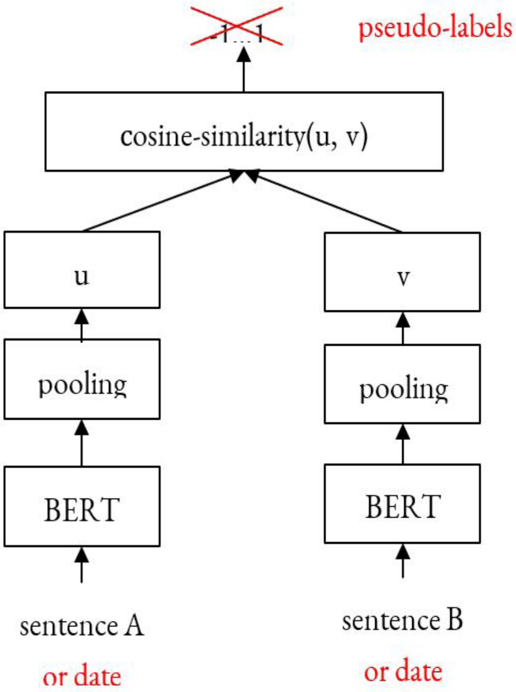
It is also important for the model to understand that there are connections between dates. To do this, we have created 10,000 pairs of random dates between 2000 and 2022. Soon they were assigned as follows:

$$\frac{log\,(2)}{log\,(2+|day_x-day_y|)}.$$

Thus the dataset contained 567,840 pairs of text-text, date-text, and date-date. It allowed us to train a model that could reveal substantive similarities and relate them to the temporal context.

This dataset allowed us to train the embedding model, which can then return a 768-dimensional vector of values for each input of text or date. This vector indicates the position of the text or date in the semantic space of the Russian propaganda media. Using these vectors, we can measure the cosine similarity[4] between texts and dates and thus say which semantic narratives in the Russian media are close and for which dates they are more characteristic.

Fig. 3. Modificated SentenceBert



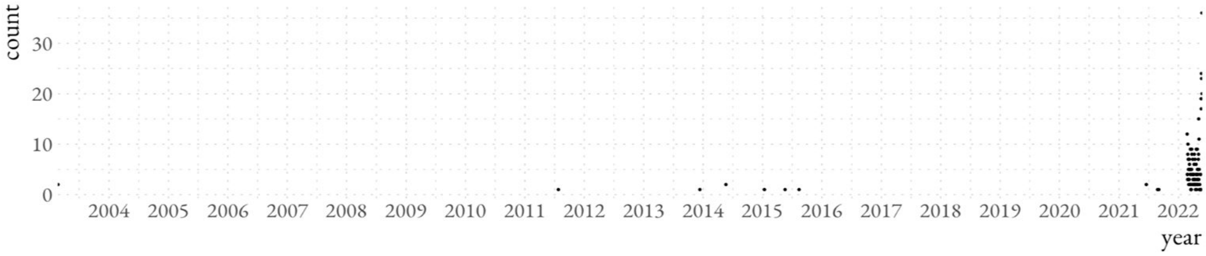
2.2. Challenges

This approach allows for solving many methodological problems related to studying the dynamics of discourse and the possibility of using vector representations for text analysis. The main advantage is that this methodology allows you to quickly and automatically analyze an extensive array of data without manual coding. It is also important that, unlike word embedding models (word2vec already mentioned above), this model makes a vector not for each word individually but for an entire sentence or text. That is, we can use such a **model to encode complex concepts** that are described in a whole sentence. Adding pairs of dates to an array of data also allows

[4] Cosine similarity $= S_G(A, B) := \cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$

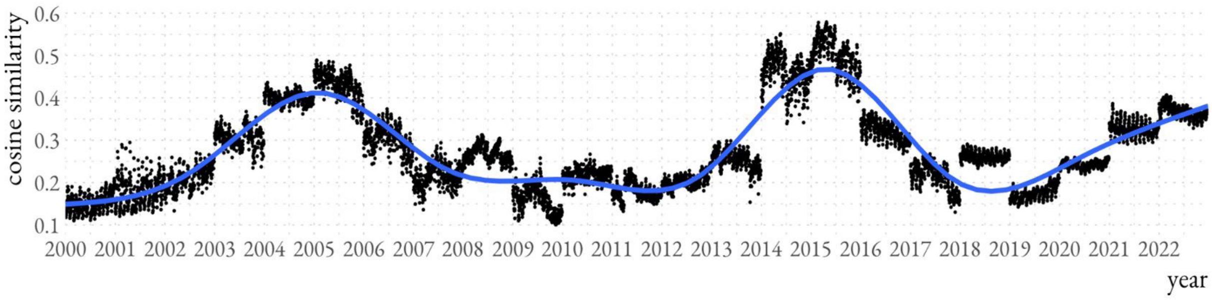
us to identify the proximity of concepts to a specific time, which is the primary tool for determining discourse dynamics.

Fig. 4. Denazification in texts (counts). It seems denazification is a new term



The disadvantage of this approach is that it captures specific changes or fluctuations worse and is highly dependent on the amount of training data. Because of this, the boundaries between the concepts are "blurred". The specificity of the method leads to the fact that similar concepts are recognized, which often appear side by side in one text. Therefore, it is not surprising that the model will not fundamentally distinguish between the concept of "denazification of Ukraine" and "non-admission of Ukraine to NATO" if they are mentioned simultaneously - from the model's point of view, it is one concept.

Fig. 5. Denazification in texts (embedding). That shows denacificatin has existed in Russian media always (but in other linguistic form)



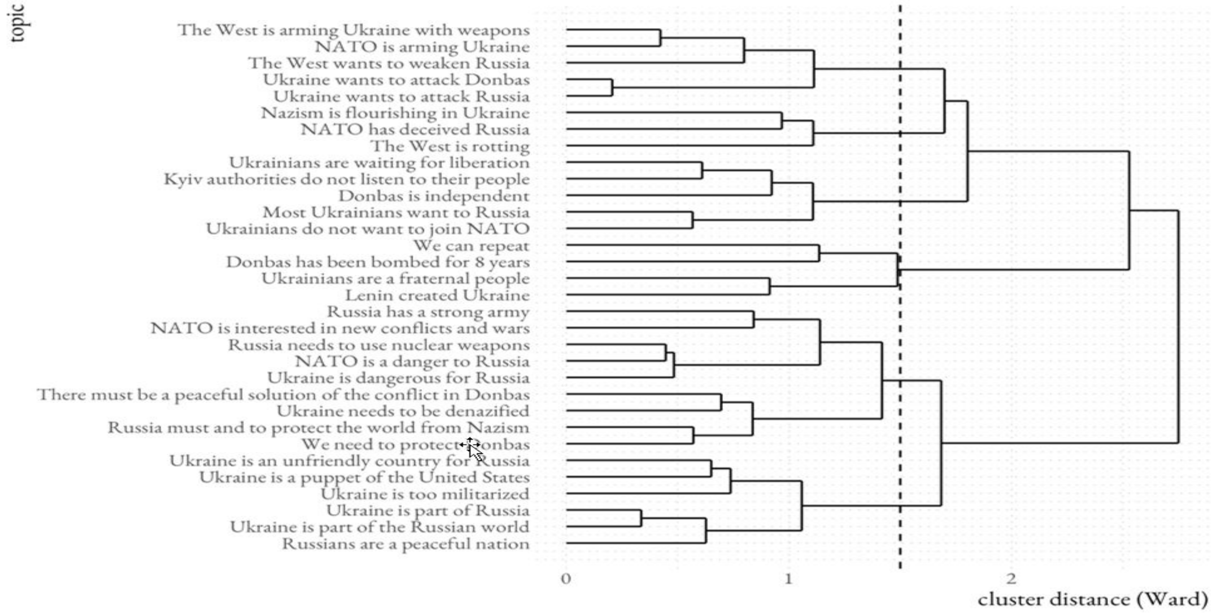
3. RESEARCH RESULTS AND DISCUSSION

Our analysis is based on a study of a set of propaganda statements. We obtained the embedding for each of them, which we compare with the embedding of each day between 2000 and 2022. But for the convenience of analysis, we first conducted a cluster analysis of these statements. It needs to be clarified so that we have an idea of the topics the propaganda raises simultaneously.

3.1. Hierarchical clustering on topics

We performed a simple hierarchical clustering analysis using the Ward's method. In the dendrogram below, we have identified six main topics we analyze below.

Fig. 6. Hierarchical Clustering of propaganda topics



The presence of topics in one cluster means that the cosine similarity of their vectors from the SentenceBert model is more similar than to other topics. Not every cluster was easy to interpret because, in general, all propaganda statements have a relatively high level of similarity.

Table 2: Cluster description

Cluster	Topic
Aggressive Ukraine and West	NATO is arming Ukraine; The West is arming Ukraine with weapons; The West wants to weaken Russia; Ukraine wants to attack Russia; Ukraine wants to attack Donbas
Crisis of the world order	NATO has deceived Russia; Nazism is flourishing in Ukraine; The West is rotting
Distortion of history	Lenin created Ukraine; Donbas has been bombed for 8 years; Ukrainians are a fraternal people; We can repeat
Justification of military actions	NATO is a danger to Russia; NATO is interested in new conflicts and wars; Ukraine needs to be denazified; Russia has a strong army; There must be a peaceful solution of the conflict in Donbas; Russia needs to use nuclear weapons; Ukraine is dangerous for Russia; We need to protect Donbas; Russia must and to protect the world from Nazism
Narratives against the central government	Kyiv authorities do not listen to their people; Ukrainians are waiting for liberation; Ukrainians do not want to join NATO; Most Ukrainians want to Russia; Donbas is independent

Ukraine is a fake country	Ukraine is part of the Russian world; Ukraine is part of Russia; Ukraine is a puppet of the United States; Ukraine is too militarized; Ukraine is an unfriendly country for Russia; Russians are a peaceful nation

We provide below an explanation of cluster names.

3.2. Keypoints before you go to analysis

Following the trained model, we made embeddings for several narrative phrases typical of Russian propaganda about Ukraine and NATO and examined their dynamics. To do this, we measured its cosine distance with the year vector for each phrase and mapped values on the graphs.
But for a good understanding of the trends that will be evident from the graphs, we have recorded critical historical dates that may be related to our findings.

Table 3: Important dates

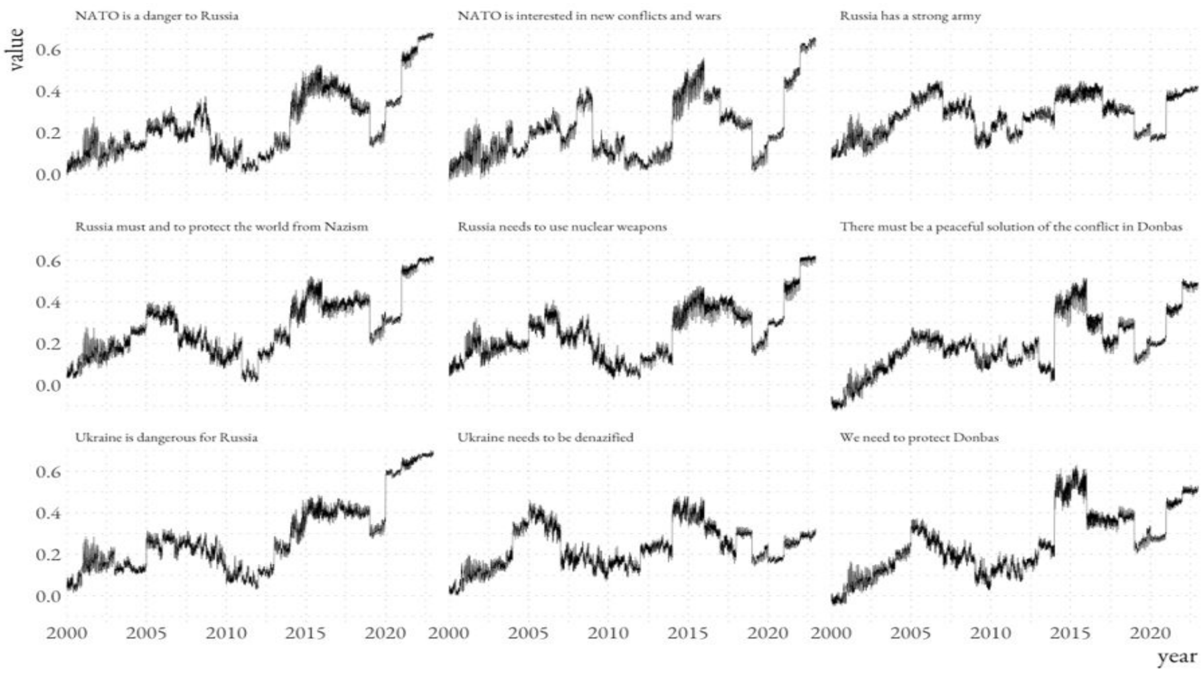
Years	Event
2004-2005	the Orange Revolution in Ukraine, the defeat of the pro-Russian presidential candidate, the victory of the pro-European
2008	active attempts by Ukraine to obtain an action plan for NATO membership, Russia's war against Georgia
2010-2013	pro-Russian president in Ukraine
2013-2014	pro-European revolution of dignity in Ukraine, the establishment of a pro-Western government in the country
2014-2022	Russian hybrid invasion of Ukraine, annexation of Crimea, the war in the Donbas
2019	presidential elections in Ukraine, the new president's efforts to restore diplomatic efforts to achieve peace in the Donbas
2021-...	preparation and the further full-scale Russian invasion of Ukraine

These dates will further help us understand the peaks in the graphs.

3.3. Justification of military actions

From a practical point of view, this group of theses interested us the most from the very beginning. The preface states that Ukraine is most interested in this.
This cluster includes allegations of Russia's threat from other states, the strength of its army, and the need to protect something.

Fig. 7. Justification of military actions



We estimated that the peaks of these allegations fell during the three years in which Russia carried out aggressive actions - 2008, 2014, and 2022. The decline in the intensity of these narratives is due to the pro-Russian president of Ukraine and Russia's expectations of the positive consequences of the Ukrainian presidential election in 2019.

The most exciting thing is that these events coincide with the negative connotations against NATO. However, Russia has never been at war with NATO.

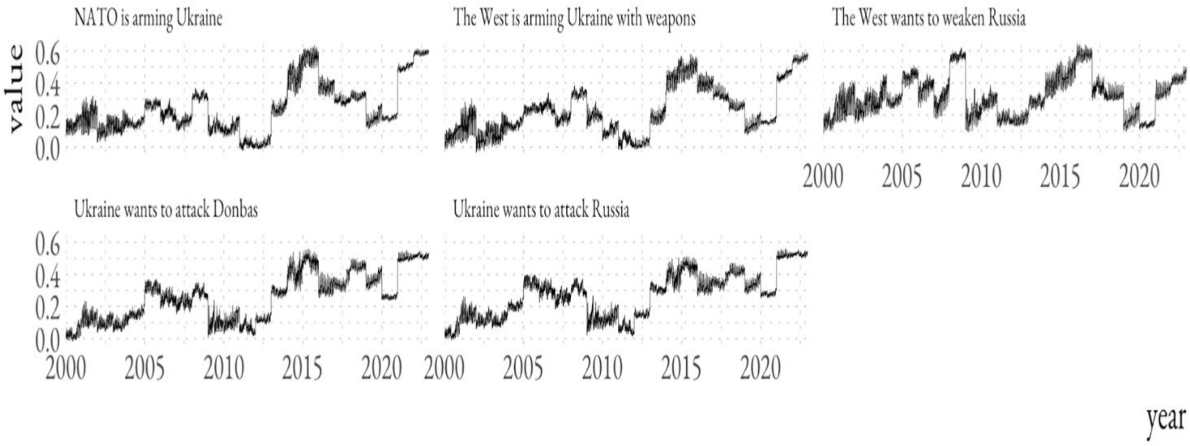
Russia's desire to fight Nazism coincides somewhat less. For example, the peak of denazification fell during both pro-Western revolutions in Ukraine.

If we talk about current events, the most noticeable feature of the new conflict is that in 2014 there were more narratives about the threat of Donbas from Ukraine, while from 2020, the idea of the threat to Russia (from Ukraine and NATO) is developing more actively. At the same time, threats to use nuclear weapons are also more pronounced. It is not surprising, given the scale of the 2022 war. However, it is crucial to understand that according to this analysis, Ukraine began to threaten Russia in 2020. Other propaganda narratives grew in 2021. The information campaign preceded the start of hostilities and did not accompany them ex post facto.

3.4. Aggresive Ukraine and West

This group of narratives is quite similar to the first. However, it places a key emphasis on the threats and hostility of Ukraine and the West. And here, the last growth was also observed in 2021, long before the full-scale invasion of the Russian army on the territory of Ukraine on February 24, 2022. So, the information field about aggressive 'neighbors' was prepared in advance.

Fig. 8. Aggresive Ukraine and West



The main difference between these narratives is that they are at the same level of intensity in 2021-2022 as in 2014-2015.

In both cases - justification of military actions, the attitude of Ukraine and the West - Russia acts as in the case of Syria, portraying a favorable image of Russia as defenders or victims, and threatening and aggressive images of Ukraine, the West and NATO.

3.5. Crisis of the world order

Ironically, Russian media has not strongly developed the topic of the decline of the West since 2005.

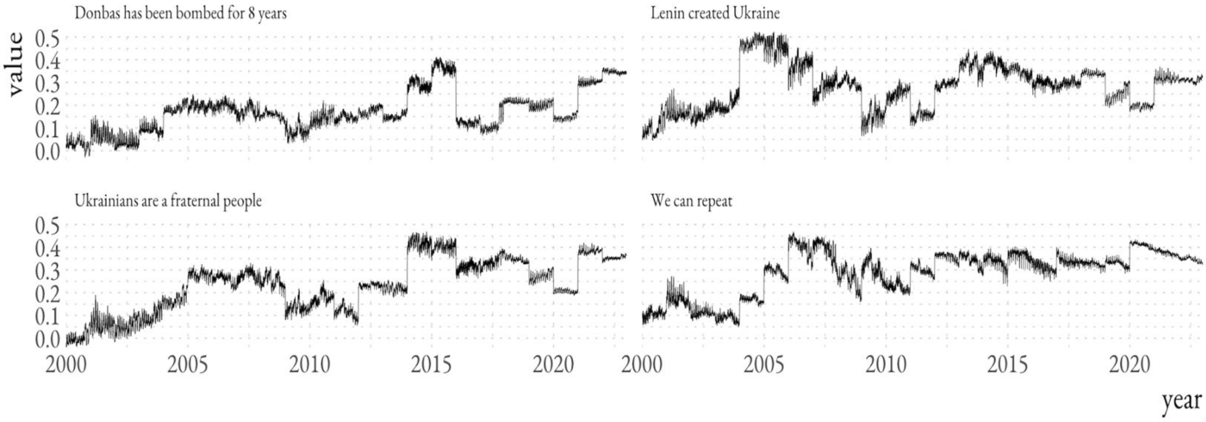
Fig. 9. Crisis of the world order

Therefore, the conclusions of S. Radnitz about the minimal influence of Russian propaganda, aimed at the support of the population of post-Soviet countries for narratives in the context of conspiracy theories [Radnitz 2022], are also confirmed within the framework of this study. He believed that the rejection of such narratives depends on the support of the government by the population as well. So we can already assume that the propaganda directed against the Ukrainian authorities was also not particularly successful. This is true (see 3.8).

3.6. Distortion of history

This group of statements contains references to history. Three of them are references to the shared history of Russia and Ukraine, mostly related to the Soviet Union. Mostly these are myths that Russia is actively trying to spread.

Fig. 10. Distortion of history

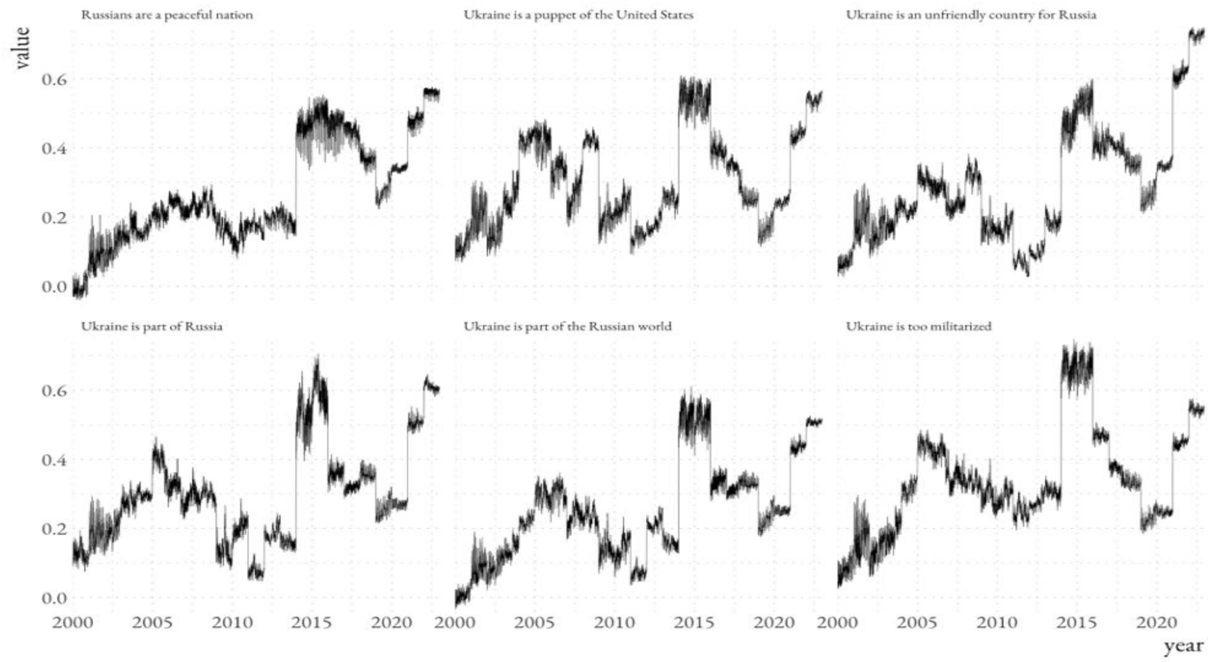


They were not used more action before the start of hostilities, although they were widely present throughout the study period in most cases.

3.7. Ukraine is a fake country

This group of theses includes statements about Ukraine as an object and not a subject of international politics. Moreover, this contains ideas on the dependence on the United States and the thesis that Ukraine is part of the Russian world.

Fig. 11. Ukraine is a fake country

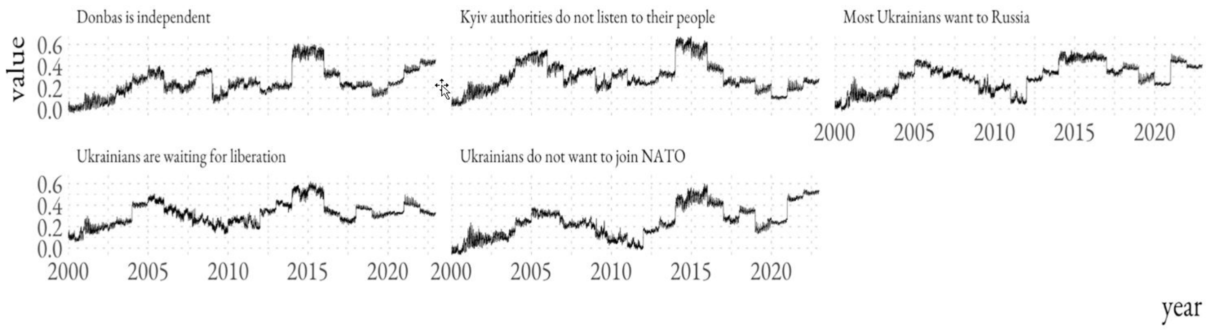


The most significant emphasis before the war of 2022 was on Ukraine's hostility to Russia. Other theses experienced the most significant peak in 2014-2015.
It is known that the main Chekist of Russia publicly declared the fakeness of Ukraine as a state; in 2000, the World Bank report used the phrase "state capture" in relation to Ukraine [Hellman et al. 2000]. Society's reaction to the merger of power and business was the alienation of society from the state [Salnikova 2014]. Hence, obviously, there are constant narratives of Russian propaganda about the non-acceptance of their power by Ukrainians and the fakeness of state institutions. Russia's mistake is that it considered such a situation in Ukraine to be static, but it turned out to be dynamic: since 2000, the situation in Ukraine has gradually changed. Revolutions in Ukraine are not about Ukrainians not accepting their state institutions; it is about the desire to change.

3.8. Narratives against the central government

These narratives include allegations of anti-people power in Ukraine. This power makes ordinary citizens either want to secede into a separate state or wait for Russian power to come because they do not support the government's pro-Western course.

Fig. 12. Narratives against the central government



Interestingly, this group of theses has the most pronounced peaks in 2004-2005. Then the first pro-Western president seized power in Ukraine. At the same time, the thesis about the separation of the eastern regions of Ukraine was loudly raised for the first time. There was no military campaign after that. However, the pro-Russian forces in Ukraine became powerful. They took revenge in the 2006 parliamentary elections. After that, the power in Ukraine, according to Russian media, became more popular.

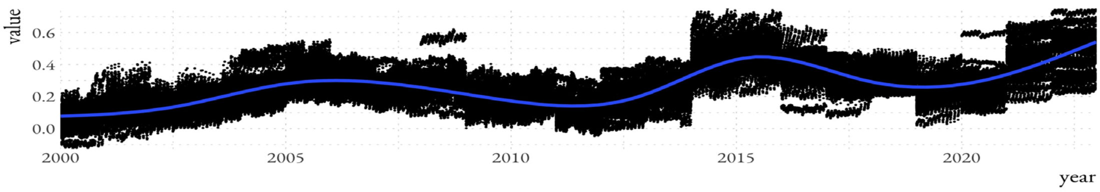
3.9. General trends of narratives

Our analysis shows that most narratives have similar dynamics. The key to this dynamic is 2014, in which the intensity of anti-Western and anti-Ukrainian rhetoric increased sharply. It confirms our hypothesis about the synchronicity of this rhetoric in the Russian propaganda media. At the same time, we cannot say that the rhetoric was much ahead of the start of hostilities.

Until 2014, there was no significant increase in anti-NATO narratives in the Russian media. Since 2014, the dynamics of such narratives have constantly been growing, which we can interpret as Russia's informational preparation for a confrontation with the bloc.

Anti-Ukrainian narratives first intensified in 2004-2005, during the Orange Revolution. But then, this strengthening was not as substantial as in 2014. Paradoxically, in 2014-2015 there was a peak in the narrative about "brotherly peoples." After this period it continued to decline. It is also noteworthy that the strengthening of anti-Ukrainian narratives also took place in 2020, which we can see as the beginning of preparations for a new round of aggression against Ukraine.

Fig. 13. General trends



CONCLUSIONS AND PERSPECTIVES

This paper aims to build a system that allows us to analyse huge amounts of media content (more than 1 million news pieces) without reading it. This article presents the way for the automated content analysis of media through sentence embeddings (in other words, we build latent representations of the main statements in the texts). We use that to detect changes in aggressive Russian discourse against Ukraine and the West. In order to do that, we created a new approach to building time-aware sentence embeddings using the logic of the word2vec word embeddings model (We use cooccurrences of statements in one text as the sign of the similarity of meaning). The model is based on SentenceBert transformer neural network architecture. Our modification of this model is able to encode text statements to 768-dimensional numeric vectors (latent representation), estimate the similarity of different statements, and the propriety of the statement for a specific time point. We use latent representation also to make cluster analysis to detect the main narratives in Russian-state media. In general, it allows us to speed up the content analysis of news and conduct such a significant comparative study. The main conclusions are that in the dynamics of aggressive discourse towards the West and Ukraine, the key year is 2014 - the year of the beginning of the aggression against Ukraine. But at the same time, Russian propaganda positions it as a struggle for influence with the West, and this perfectly demonstrates the synchronicity of anti-Western and anti-Ukrainian propaganda.

Russian propaganda positions it as a struggle for influence with the West, which perfectly demonstrates the synchronicity of anti-Western and anti-Ukrainian propaganda. To test the hypothesis of the precedence of informational preparation for aggression, we need to gather a larger array of data that would allow us to make a daily dynamics of narratives. Aggregating data for up to a year does not allow it to do so (only if this training has taken years). We plan to improve this analysis in future publications.

However, this analysis shows the great potential of using neural networks in sociology. We were able to find an effective solution to identify the dynamics of narratives by rethinking the model of deep learning used for another non-sociological task. However, we need to continue this work.

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