Framing Shifts of the Ukraine Conflict in pro-Russian News Media

Sultan Alzahrani[1(✉)], Nyunsu Kim[1], Mert Ozer[1], Scott W. Ruston[2], Jason Schlachter[3], and Steve R. Corman[2]

[1] School of Computing, Informatics and Decision Systems Engineering, Arizona State University, Tempe, AZ, USA
{ssalzahr,nkim30,mozer}@asu.edu

[2] Hugh Downs School of Human Communication, Arizona State University, Tempe, AZ, USA
{scott.ruston,steve.corman}@asu.edu

[3] Informatics Laboratory, Lockheed Martin Advanced Technology Laboratories, Kennesaw, GA, USA
jason.schlachter@lmco.com

Abstract. An important aspect of information operations (IO) are influence campaigns where a state actor or organizations under its control attempt to shift public opinion by framing information to support a narrative that facilitate their goals. If there is a playbook in operation, then in principle it should be possible to detect its signatures in mainstream media and to potentially provide early warning of malicious intent. This paper describes the results of a proof-of-concept effort where our goal was to detect framing shifts during the Ukraine conflict in pro-Russian news media surrounding the 2014 annexation of Crimea. Our results show significant framing shifts exceeding a smaller peak of 2010, in November 2013, and sharply spiking and trending again in Dec 2013, three-four months ahead of Crimea's annexation by the Russian Federation.

Keywords: Framing analysis · Time series data
Framing shifts detection

1 Introduction

Analysts recognize that the Russian government uses information operations (IO) as a tactic in its strategic efforts to reclaim territory in former Soviet states (it's so-called "near-abroad" [24]). For example, in 2008 Russia sent troops into South Ossetia, Georgia in response to an attack on the semi-autonomous region by Georgian forces. The speed and decisiveness of the Russian invasion and their subsequent extension of the invasion into Georgia proper caught Western leaders by surprise.

R. Thomson et al. (Eds.): SBP-BRiMS 2018, LNCS 10899, pp. 303–314, 2018.
https://doi.org/10.1007/978-3-319-93372-6_34

Russia had promoted ethnic conflict in Georgia to maintain influence there,[1] and provided extensive support to South Ossetian and Abkhazian separatists [17]. Russia also exchanged old Soviet passports for new Russian ones in both South Ossetia and Abkhazia [3] so-called "passportization"- creating a pretext for intervention to protect "Russian citizens," and to take de facto control. Less than six years later, the West was again surprised when Russia used the same techniques to support annexation of Crimea in Ukraine. Joint Chiefs Chairman General Martin Dempsey said of Vladimir Putin, "he's got a playbook that has worked for him now two or three times" [18].[2] What is in this playbook?

> Case officers for the intelligence community operate without official cover, [and] recruit sources and assess the battlefield. Then, small units of special operations forces sneak in, sometimes blending in with the populace, ready to make trouble. Then, special forces units that specialize in "information operations" designed to induce anxiety and outrage among local populations follow a strategy that comes from the top of the government. The idea is to generate genuine indigenous protest movements. Using these protest movements as evidence of "human rights violations," Russia intervenes [16].

It is widely believed that Russia aims to repeat this performance in other ethnically Russian areas, especially the Gaugazia region of Moldova [20]. The Baltics are also a potential target. Three years ago, a Russian Foreign Ministry official echoed playbook tactics when he warned that ethnic discrimination there "may have far-reaching, unfortunate consequences" [21].

If there is a playbook in operation, then in principle it should be possible to detect its IO signature, stimulated by Russian propaganda and other 'gray zone' activities, in mainstream media, to potentially provide early warning of another invasion in other near-abroad states. This paper describes results of a proof-of-concept effort by the ASU's Center for Strategic Communication and Lockheed Martin Advanced Technology Laboratory. Our goal was to detect shifts in framing surrounding the 2014 annexation of Crimea using natural language processing of Russian propaganda articles and machine classifiers trained to recognize framing.

Our corpus comprised of over 100,000 news articles from 372 news sources dated between 2010 and 2017. Our methods and contributions can be summarized as follows:

[1] Archives of the CSCE, Georgia Files, Com. No. 408, Prague, Stockholm, 11 December 1992; Ibid, N.41, Prague, 2 February 1993; Bruce Clark, 'Russian Army blamed for Inflaming Georgian War,' The Times, 6 October 1992; Fiona Hill and Pamela Jewett, 'Back in the USSR: Russia's Intervention in the Internal Aairs of the Former Soviet Republics and the Implications for United States Policy toward Russia,' Cambridge, MA.: Harvard University JFK School of Government, Strengthening Democratic Institutions Project, January 1994.

[2] A playbook indicates a set of plans, approaches or strategies that aim to be equipped with a play ready catalog stating proposed actions and responses worked out ahead of time.

- We recruited a pair of area experts to classify top 200 news sources as either pro-Russian or other. We were able to train a classifier which achieved 90% F1-score to discriminate between propaganda vs. other articles.
- We worked with subject matter experts (SMEs) from ASU Center for Strategic Communication (CSC) to inductively develop a code book comprising five categories of Russian strategic frames used in Ukraine. Four student coders were trained to map sentences in randomly selected articles to one (or none) of these framing categories. After multiple rounds of training, coders achieved a inter-coder reliability (a.k.a Krippendorff ratio) of $\alpha = 0.83$ [19], which we judged as acceptable.
- We used coded sentences to train a text classifier which achieved 77% F1-score in labeling unseen sentences with the correct frame (or "no frame").
- The propaganda and framing classifiers were used on the news corpus to produce a daily time series of framing density vectors for articles classified as Russian propaganda. We computed Jensen-Shannon [4] divergence between framing density vectors of consecutive days. Results show significant framing shifts exceeding a smaller peak of 2010, in November 2013, and sharply spiking and trending again in Dec 2013, three-four months ahead of Crimea's annexation by the Russian Federation – which took place between 20 February 2014 and 19 March 2014. The war has been ongoing in the Donbass region of Ukraine since 6 April 2014 until the present day.

The rest of the paper is organized as follows. Section 2 presents a review of related works. Section 3 summarizes our data sources and approach. Sections 4 and 5 present the codebook of Russian strategic framing induced from propaganda articles and our sentence coding procedure. Sections 6 and 7 present text classifiers for frame detection, time series analysis of daily framing density vectors and significant framing shifts. Section 8 concludes the presentation with discussions and future work.

2 Related Work

Framing analysis has roots in mass media studies and several frameworks for assisting human identification and coding of frames were developed. Notable works include: Odijk et al. [14] where they developed a two-phase approach: (1) a systematic questionnaire for human coders to evaluate the nature (i.e. conflict, economic consequence, human interest, morality) and aspects of framing, (2) an ensemble of classifiers trained to detect frame presence in text using the coders questionnaire responses. Baumer et al. [9] compared performance effects of different types of features (i.e. lexical, grammatical and manual dictionary-based) for detecting frames in news. Their findings suggest that lexical n-gram features combined with grammatical part-of-speech (POS) tags result in significant improvements in frame detection. We also employed lexical frequent discriminative bi-grams alongside grammatical (subject, verb, object) based generalized triples [11] as features in our framework. Our experiments resulted in an accuracy of 41% average F1-score with bi-grams alone, and an average F1-score of

77% with combined features including bi-grams, generalized triples and other lexical features.

The temporal analyses of framing are also relevant since they can offer indications for detecting framing shifts. Several works were developed for spike detection in noisy time series data based on raw signal smoothing [15] and wavelet transforms [22] for different types of data (e.g. seismic analysis, disease epidemiology, and stock market prediction, etc.). Weng et al. [26] proposed an event detection framework in messages based on detecting correlated bursts of keywords that are expressed during events. To identify related keywords, they apply wavelet transformations on time series of keyword frequencies and measure cross-correlations between keywords and events. Next, they employ modularity-based graph clustering to detect keyword groups signaling events. In our paper, we utilized Jensen-Shannon divergence [4] to measure the daily variations of framing densities in pro-Russian international news. We checked the overlaps of their framing shifts and trends over time with significant phases of the Ukraine crisis to draw our conclusions.

3 Approach

Our analysis is based on detecting strategic framing [13,25] in news articles. Framing is accomplished when a choice of words, phrases, metaphors, images, and other rhetorical devices favor one interpretation of a set of facts, and discourage other interpretations. A special case is adversarial framing, which "is typically competitive, fought between parties or ideological factions, and [where issues] are debated and framed in opposing terms" [12]. A domestic example of adversarial framing is Republicans in the 1990s referring to the US estate tax as a "death tax"- connoting the long arm of the government taxing you even beyond the grave - while their political opponent Democrats referred to the same tax policy conventionally, as an "estate tax" - suggesting that only the super wealthy are subject to the tax.

Similar techniques are used by Russia with respect to the near abroad countries it threatens. One signature behavior is the framing of an ethnic issue as dealing with "human rights." In May 2014, the Russian Foreign Ministry released a white book detailing what it said were large-scale human rights violations in Ukraine [1], including discrimination against religious and ethnic minorities. In an earlier speech to the Russian Parliament, Vladimir Putin complained, "we hoped that Russian citizens and Russian speakers in Ukraine, especially its southeast and Crimea, would live in a friendly, democratic and civilized state that would protect their rights in line with the norms of international law. However, this is not how the situation developed" [2].

Framing is also undertaken by ethnic groups in the countries where Russian incursions are a threat. In 2012, a Latvian referendum rejected Russian as an official national language. Residents of Eastern regions where Russian is the primary language framed this act as a violation of rights. One such resident was quoted as saying: "[Latvian] society is divided into two classes - one half has full rights and the other half's rights are violated"[5].

Our approach, therefore, sought to identify and detect strategic framing before and after the 2014 invasion of Crimea. To do so we (i) collected mainstream media texts from Russian propaganda sources dealing with Ukrainian ethnic and political issues for the period between 2010–2017, (ii) inductively developed a set of framing categories, (iii) trained human coders to reliably identify sentences invoking these frames in sample texts, (iv) used these coded sentences to train machine classifiers to recognize all other framing instances in the corpus, (v) generated vectors representing the daily densities of these frames in news articles classified as propaganda, and (vi) conducted time-series analysis to identify shifts in framing densities and (vii) locate these shifts within significant phases of the Ukraine conflict.

3.1 News Corpus

This project was supported by Lockheed Martin Advanced Technology Laboratories and used news feeds extracted from Lockheed Martin's ICEWS system. ICEWS is a program of record in the U.S. Department of Defense used by component agencies to track conflict events. During its operation, ICEWS collects and archives English-language and translations of foreign language articles from mainstream media sources and websites worldwide. We queried the ICEWS database for articles between 2010 and 2017, which mentioned Ukraine, and further constrained this dataset to stories which contained keywords believed to be associated with Russian propaganda (i.e. anti-facist, discrimination, second-class citizens, etc.). This resulted in a news corpus containing 103,912 articles.

To focus our analysis on Russian propaganda sources, we recruited two area experts to classify the top 200 sources in our corpus (in terms of article frequency) as either pro-Russian or other. Next we extracted bigrams (i.e. pairs of two consecutive words after text preprocessing) and generalized concepts [11] from these sources and we trained a sparse logistic regression text classifier to discriminate between propaganda vs. other type of articles. A ten-fold cross-validation evaluation showed that the propaganda detection classifier has a an average F1-score of 90% and an F1-score of 86% for the smaller Russian 'propaganda' category. We ran this classifier on the news corpus, yielding 30,845 texts classified as Russian propaganda. These texts formed the basis of our coding and framing analysis.

4 Codebook

A codebook is survey research approach to provide a guide for framing categories and coding responses to the categories definitions. Using the notion of the playbook described in the introduction, we randomly selected articles from our Russian propaganda sources with high counts of discriminative propaganda-related keywords. Two subject matter experts, who are co-authors of this paper, from ASU's Center for Strategic Communication (CSC) read these texts and identified the following five framing categories inductively:

Fascist vs. anti-fascist struggle (denoted by: fascist). There are frequent accusations that leadership/society of a target country support "fascists" or "Nazis," and take actions to harass "anti-fascists" or hinder their efforts to protest and take other actions against the fascists. Essentially, the Nazis/fascists are the "bad guys" from the Russian point of view, and the anti-fascists are the "good guys." Almost any use of "Nazi," "fascist," or "anti-fascist" qualifies as framing, because it interprets the people involved and their actions as part of an ideological struggle between the two sides.

Discrimination against Russian minorities: (denoted by: discrim). This frame addresses discrimination against groups, usually ethnic groups; any such group having its rights trampled on, being marginalized or abused or similar affronts constitutes this frame. Russian information operations seek to convince members of the Russian speaking community in target countries that they are being victimized, discriminated against, and their rights are being violated. This might include references to general or human rights, or specific references to rights like voting, freedom of speech, and political participation. They also claim that there are efforts to stamp-out use of the Russian language, to suppress Russian culture, and to discriminate against Russian speakers in the job market and other domains. Lack of citizenship or denial of citizenship is a form of discrimination.

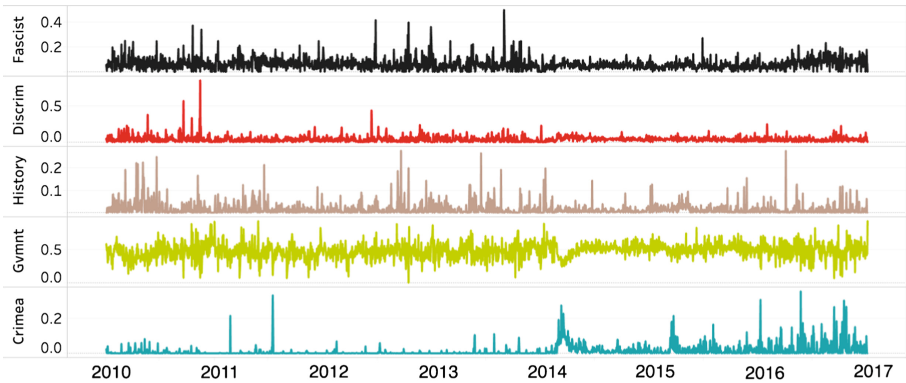
Assault on Soviet history (denoted by: history). Russian information operations seek to condemn the subversion or suppression of Soviet history. This can take the form of complaining about the removal of statues and memorials commemorating the Soviet role in World War II, changing names of Soviet-era streets and other geographical landmarks, or trying to change the historical narrative about the Union of Soviet Socialist Republics (USSR) and its role in former Soviet states.

Criticism of government (denoted by: gvmnt). Russian information operations seek to criticize the governments of target countries, in terms of functioning, procedures, and results (including economic results), as well as corruption among government officials. The frame implies that government is ineffective, not functioning properly, and acting in ways that are detrimental to good governance. The "government" includes legislative, executive and judicial branches at the national, provincial and municipal levels; it includes the police; it includes semi-synonymous terms like "the authorities". The frame applies when the national, provincial or municipal government of a target country is criticized (such as Ukraine, Latvia, Georgia, Lithuania, Estonia, Moldova, Poland, etc.)

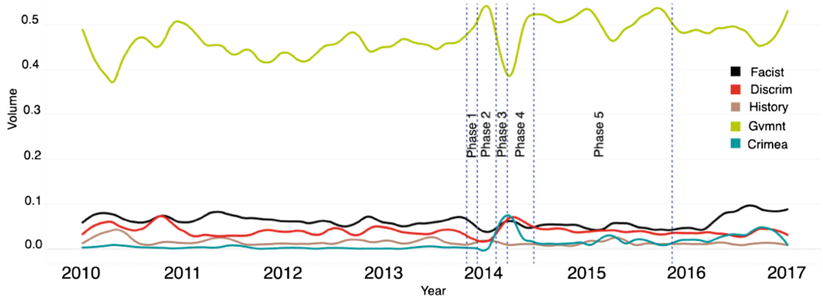
Invasion of Crimea (denoted by: crimea). Russian information operations seek to justify and create support for their annexation of Crimea. This can involve discussions of sovereignty, discussion of the area's future, and statements supporting the annexation. The annexation is often framed as a moral imperative or a righteous act, and subsequent opposition by Ukraine, EU, and the international community are immoral, hypocritical, etc. Select this frame when the annexation of Crimea is clearly the context of some sort of justification, not when it could be the subject of the justification.

5 Frame Coding

Computer-aided techniques of frame coding essentially use two approaches: (I) dictionary/keyword lists based (e.g. [10]) or supervised learning approaches (e.g. [23]) trained with human coded sentences. In this project four student coders were trained to assign sentences in randomly selected propaganda texts to one (or none) of the five framing categories described above. Coders would first work independently, assigning each sentence to one (or none) of the coding categories. We would then calculate reliability, and identify disagreements between coders. Coders would then discuss these disagreements as a group, and we would refine category definitions in the codebook as necessary. After seven rounds of training, coders achieved a inter-coder reliability (a.k.a Krippendorff ratio) of $\alpha = 0.83$ [19], which we judged acceptable. Subsequent coding was performed by two randomly assigned coders per text, who discussed and resolved disagreements to arrive at a final set of codes. They coded texts until we had a large enough set of coded sentences, where adding more coded sentences no longer significantly boosted the overall accuracy of the best text classifier model. The final number of coded sentences in each category was: *crimea*, 162; *discrim*, 196; *fascist*, 307; *gvmnt*, 334; *history*, 187, and those sentences were used as the labeled training dataset.



(a) Daily averaged framing densities.



(b) Smoothed daily averaged framing densities.

Fig. 1. Daily averaged framing and Smoothed densities.

6 Frame Detection Model

We used coded sentences described above alongside a random collection of sentences that were not mapped to any framing category from coded articles to train five classifiers - one classifier for each frame category. We used one-vs.-all (OvA) strategy which involves training a single classifier per frame, with the samples of that frame as positive samples and all other samples as negatives. We extracted four sets of features from each sentence: keywords, frequent bigrams, whether the sentence contained a quote, and its matching generalized semantic triplets. Generalized semantic triplets (GST) are merged collections of subjects, verbs, and objects that co-occur together in similar contexts. The details of the GST features can be found in an earlier paper [7,8]. We evaluated several text classifiers using ten-fold cross-validation. The best overall performance was obtained with a linear SVC (L1) classifier yielding the following F1-scores: history, 74%; crimea, 87%; discrim, 76%; fascist, 75%; gvmnt, 73%; average, 77%. The rest of the results are shown in Table 1.

Table 1. Frame detection accuracies

Classifier	Frame														
	fascist			discrim			history			gvmnt			crimea		
	Pr	Re	F1	Pr	Re	F1	Pr	Re	F1	Pr	Re	F1	Pr	Re	F1
Ridge classifier	.82	.68	.74	.78	.67	.72	.83	.62	.71	.73	.63	.68	.87	.8	.83
Perceptron	.78	.65	.71	.71	.77	.74	.77	.73	**.75**	.76	.62	.68	.84	.86	.85
Passive-aggressive	.8	.65	.72	.79	.69	.74	.81	.67	.73	.75	.71	**.73**	.89	.8	.84
LinearSVC (L2)	.79	.68	.73	.76	.68	.72	.83	.67	.74	.74	.69	.72	.89	.78	.83
SGDClassifier (L2)	.8	.69	.74	.71	.69	.7	.79	.67	.73	.72	.64	.68	.88	.86	**.87**
LinearSVC (L1)	.79	.71	**.75**	.81	.71	**.76**	.8	.7	**.75**	.72	.74	**.73**	.85	.79	.82
SGDClassifier (L1)	.75	.65	.7	.73	.67	.7	.78	.72	**.75**	.7	.65	.68	.85	.82	.84
SGDClassifier (Elastic-Net)	.73	.65	.69	.75	.58	.66	.79	.71	.74	.78	.63	.7	.84	.83	.84

7 Time Series Analysis of Daily Framing Densities

The set of frame classifiers were applied to each sentence to produce real-valued confidence scores. The classifier which reported the highest confidence score was considered to be the dominant frame category for each sentence. We applied this technique to all sentences in each article one-by-one in order to produce a vector of framing density values for each article. These vectors were averaged daily to yield a vector of daily averaged frame densities shown in Fig. 1. Since the time series were noisy, first we performed Gaussian smoothing, shown in Eqs. 1 and 2 (where σ, w are $2, 10$ respectively, acting as low-pass filter) to remove high frequency noise. The smoothed time series are shown in Fig. 1. Next, in order to reveal framing shifts, we computed Jensen-Shannon [4] divergence, a statistical distance measure, between the daily framing density vectors of consecutive days. The resulting divergence plot is shown in Fig. 2.

$$N(x; \mu = 0, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-x^2}{-2\sigma^2}} \tag{1}$$

$$S(t) = \sum_{i=t-w/2}^{t+w/2} O(i)N(t-i) \tag{2}$$

Knowing that KL is the Kullback-Leibler divergence $KL(p;q) = p_i \ln \frac{p_i}{q_i}$, Jensen-Shannon divergence can be expressed in term of KL as follows

$$JS(v_1, v_2) = KL(v_1, \frac{v_1 + v_2}{2}) + KL(v_2, \frac{v_1 + v_2}{2}) \tag{3}$$

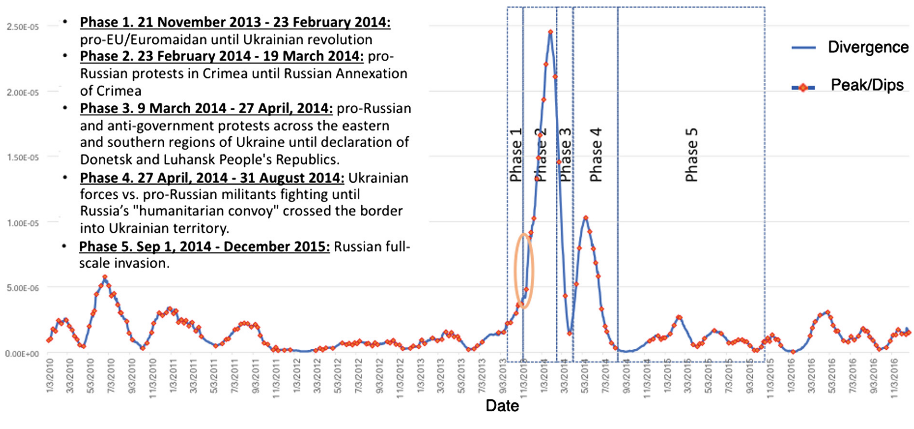


Fig. 2. Daily Jensen-Shannon divergence-vertical lines demarcating the significant phases of the Ukraine conflict timeline determined by the CSIS (CCIS: Center For http://ukraine.csis.org/)

Prior to Phase 1, corresponding to the period between pro-EU Euromaidan protests until the Ukrainian revolution, divergence remains at relatively low levels, except for some small peaks during 2010–2011. As the pro-EU/Euromaidan protests begun in November 2013, the divergence signal begins to rise, exceeding all previous highs in November 2013, followed by a sharp rise in Dec 2013. Divergence increases sharply during the pro-Russian protests well into the midst of Phase 2 which terminates with the annexation of Crimea by the Russian Federation on March 19, 2014. Following that, divergence sharply falls to its baseline levels. During Phase 3, the signal spikes once again as pro-Russian and anti-government protests took place across the eastern and southern regions of Ukraine until the declaration of Donetsk and Luhansk People's Republics. The signal declines again in Phase 4 which marks the Ukrainian forces vs. pro-Russian militants fighting a war. The signal meets zero-line during the initial days of Phase 5 marking the Russian full-scale invasion which was framed as an "humanitarian convoy" crossing into the Ukrainian territory. Following that, the signal remains at its baseline levels with no more major breakouts.

8 Discussions and Future Work

A question arises: could Russian propaganda framing shifts forecast the onset of hostilities leading to an invasion? In the Ukraine case, the divergence signal's early rise, exceeding all previous highs in Nov. 2013 followed by the sharp rise in Dec 2013 provides a signal of interest three-four months ahead of Crimea's annexation. If the premise is accepted that information operations are intended to "soften-up" the target area and provide a pretext for active conflict, then shifts in strategic framing might provide an early warning before the onset of pro-Russian protests, militant action and invasion under the guise of an "humanitarian convoy".

Our future work involves various tasks. Since our classifiers achieved an average 77% F1-score only, we plan to experiment with additional syntactic and semantic (framenet, wordnet, verbnet, LIWC18)[3] features, and other features such as named entity types to improve performance.

Next, we believe it might be possible to automatically surface framing categories to help spot newly emerging framing categories. We aim to synthesize narrative graphs incorporating co-occurrence patterns [11] of discriminant bi-grams, their adverbs, adjectives, named entities (i.e. people, places, organizations and locations) and apply dynamic graph clustering algorithms [6] to detect newly emerging clusters for SME's attention. Our initial experiments indicate that we can surface expert induced framing categories developed in the Ukraine codebook with a Normalized Mutual Information (NMI) score of 56% and purity of 68%.

Finally, we plan to evaluate this framework in other historical contexts; such as the Transnistria War in November 1990 between Moldovan troops and pro-Transnistria forces supported by elements of the Russian Army and the Russo-Georgian War between Georgia, Russia and the Russian-backed self-proclaimed republics of South Ossetia and Abkhazia in August 2008.

Acknowledgements. The authors would like to thank Kristin Fleischer, Madison Roselle, Sean West, and Zebulon Stampfler who participated in sentence coding support.

[3] https://framenet.icsi.berkeley.edu/, https://wordnet.princeton.edu/, https://verbs.colorado.edu/verbnet/, https://liwc.wpengine.com/.

References

1. TASS: Russia - Russian Foreign Ministry presents White Book on human rights abuses in Ukraine. http://tass.com/russia/730463
2. Transcript: Putin says Russia will protect the rights of Russians abroad - The Washington Post. https://goo.gl/bacjU5
3. TSG IntelBrief: Russia's Passport Imperialism—The Soufan Group. http://www.soufangroup.com/tsg-intelbrief-russias-passport-imperialism/
4. Jensen-Shannon divergence and Hilbert space embedding. In: 2004 Proceedings of the International Symposium on Information Theory, ISIT 2004 (2004)
5. Latvians reject Russian as official language—World news—The Guardian (2012). https://goo.gl/wXR8K4
6. Aktunc, R., Toroslu, I.H., Ozer, M., Davulcu, H.: A dynamic modularity based community detection algorithm for large-scale networks: DSLM. In: ASONAM, IEEE/ACM (2015)
7. Alashri, S., Alzahrani, S., Tsai, J.-Y., Corman, S.R., Davulcu, H.: "Climate change" frames detection and categorization based on generalized concepts. Int. J. Semant. Comput. **10**(02), 147–166 (2016)
8. Alzahrani, S., Ceran, B., Alashri, S., Ruston, S.W., Corman, S.R., Davulcu, H.: Story forms detection in text through concept-based co-clustering. In: 2016 IEEE SocialCom (2016)
9. Baumer, E.P.S., Elovic, E., Qin, Y.C., Polletta, F., Gay, G.K.: Testing and comparing computational approaches for identifying the language of framing in political news. In: ACL, pp. 1472–1482 (2015)
10. Benoit, K., Laver, M.: Estimating Irish party policy positions using computer wordscoring: the 2002 election. Ir. Polit. Stud. **18**, 97–107 (2003)
11. Ceran, B., Kedia, N., Corman, S.R., Davulcu, H.: Story detection using generalized concepts and relations. In: 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM) (2015)
12. Chong, D., Druckman, J.N.: A theory of framing and opinion formation in competitive elite environments. J. Commun. **57**(1), 99–118 (2007)
13. Entman, R.M.: Framing: toward clarification of a fractured paradigm. J. Commun. **43**(4), 51–58 (1993)
14. Odijk, D., Burscher, B., Vliegenthart, R., de Rijke, M.: Automatic thematic content analysis: finding frames in news. In: Jatowt, A., et al. (eds.) SocInfo 2013. LNCS, vol. 8238, pp. 333–345. Springer, Cham (2013). https://doi.org/10.1007/978-3-319-03260-3_29
15. Tapley, B.D., et al.: GRACE measurements of mass variability in the Earth system. Science **305**(5683), 503–505 (2004)
16. Resneck, J.: In tiny Moldova, Russia is repeating its Ukraine playbook—Public Radio International. https://goo.gl/PQR5XA
17. Graham, J.: Russia and Ethnic Conflict in Georgia - On This Day. https://www.onthisday.com/russia/georgia.php
18. Kifield, J.: How to Prevent War with Russia - POLITICO Magazine. https://goo.gl/ocLo55
19. Krippendorff, K.: Content Analysis: An Introduction to Its Methodology. Sage, Beverly Hills (2004)
20. Ambinder, M.: Russia masters the art of clandestine warfare against Ukraine. https://goo.gl/dG3EzD

21. Seddon, M.: Russia Warns of "Unfortunate Consequences" Over Ethnic Tension in Baltic States. https://goo.gl/rfA39V
22. Zoran, N., Burdick, J.W.: Spike detection using the continuous wavelet transform. IEEE Trans. Biomed. Eng. **52**(1), 74–87 (2005)
23. Quinn, K.M., Monroe, B.L., Colaresi, M., Crespin, M.H., Radev, D.R.: How to analyze political attention with minimal assumptions and costs. Am. J. Polit. Sci. **54**(1), 209–228 (2010)
24. Safire, W.: On Language: The Near Abroad. The New York Times, May 1994
25. Scheufele, D.A., Tewksbury, D.: Framing, agenda setting, and priming: the evolution of three media effects models. J. Commun. **57**, 9–20 (2007)
26. Weng, J., Yao, Y., Leonardi, E., Lee, F.: Event detection in Twitter. Development, pp. 401–408 (2011)