A Challenging Dataset for Bias Detection: The Case of the Crisis in the Ukraine

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Abstract. The use of disinformation and purposefully biased reportage to sway public opinion has become a serious concern. We present a new dataset related to the Ukrainian Crisis of 2014–2015 which can be used by other researchers to train, test, and compare bias detection algorithms. The dataset comprises 4,538 articles in English related to the crisis from 227 news sources in 43 countries (including the Ukraine) comprising 1.7M words. We manually classified the bias of each article as either *pro-Russian*, *pro-Western*, or *Neutral*, and also aligned each article with a master timeline of 17 major events. When trained on the whole dataset a simple baseline SVM classifier using doc2vec embeddings as features achieves an F_1 score of 0.86. This performance is deceptively high, however, because (1) the model is almost completely unable to correctly classify articles published in the Ukraine (0.07 F_1), and (2) the model performs nearly as well when trained on unrelated geopolitics articles written by the same publishers and tested on the dataset. As has been pointed out by other researchers, these results suggest that models of this type are learning journalistic styles rather than actually modeling bias. This implies that more sophisticated approaches will be necessary for true bias detection and classification, and this dataset can serve as an incisive test of new approaches.

Keywords: Media bias · Machine learning · Natural language processing

1 Introduction

Disinformation is the attempt to willfully deceive and sway public opinion to the benefit of some organization or state [19]. Bias is a more general phenomenon encompassing disinformation, in that bias is not necessarily strategic or deceitful, usually consisting of the articulation of a preference for a particular position on some issue [8]. In this regard, modeling disinformation likely requires modeling bias, and as such we investigate bias classification as a first step toward disinformation detection. Linguistically, the articulation of bias comprises a set of frames, which are combinations of words that seek to "promote a particular interpretation" of some concept or event [2]. Frames can be expressed in

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any number of different ways, including "key-words, stock phrases, stereotype images, ...metaphors, exemplars, catchprases, depictions..." [2, p. 1473], all of which can be used in combination to create an interpretative "package." Thus, language exhibits bias in regard to some action or opinion, and framings are rhetorical tools used to support and express that bias; in other words, the framings of an argument are the surface signifiers for an underlying bias. For example, the frames *pro-choice* and *pro-life* support different biases towards the support for or abolishment of abortion.

Even for people, detecting bias is a difficult task. Recasens *et al.* reported that people achieve only 30% accuracy in identifying the bias-inducing word in a biased sentence (pairwise agreement of 40.73%) [17]. This may be due to the large repertoire of subtle framings available to authors when constructing their rhetoric. Take, for example, an event that took place during the writing of this paper, namely, the President of the United States declaring a national emergency to fund a wall at the U.S.-Mexico border. Examples (1) and (2) ref show headlines on the topic from articles published within hours of each other by left-leaning and right-leaning news outlets[1].

(1) Vox (left): *Trump will declare a national emergency to secure money for his border wall.*[2]
(2) Fox (right): *Trump declares national emergency to build border wall.*[3]

While lexically these sentences are nearly identical, within the context of recent American politics the pronoun *his* in (1) signals an anti-Trump bias. A few months before these articles were published, the President held a televised meeting with two Democratic representatives from the House and Senate. In this meeting, the President stated that he *owned* the controversial government shutdown—brought about by a disagreement over border wall funding—that ended a few weeks before the national emergency declaration. Subsequently Democratic politicians repeatedly referred to both the shutdown and the border wall as belonging to the President, painting both in a negative light. Building a model to automatically detect bias such as this is daunting, requiring not only sophisticated linguistic analysis but also a knowledge base of current events from which to extract the implication of the word *his*. While in this example a lexical model would not be adequate, there is some evidence that frames can be modelled lexically [6], which is the approach we adopt and investigate in our baseline classifier.

The primary contribution of this paper is a dataset that contains biased articles about a shared set of events. In particular, we have collected and annotated a set of 4,538 English language long form news articles from 227 news sources across 43 countries with three broad biases advocating for pro-Russian, Neutral,

[1] As classified by the news media site AllSides, https://www.allsides.com/unbiased-balanced-news.
[2] https://www.vox.com/2019/2/14/18222167/trump-border-security-deal.
[3] http://www.fox5dc.com/news/border-wall-national-emergency-government-funding-trump.

or pro-Western interests in the context of the 2014–2015 Ukrainian Crisis. All the articles report on one or more of a set of 17 events that occured during the crisis. We manually extracted a set of frames related to each event for each of the three biases, and then used these frames to determine what bias each article articulates. We created a simple supervised classification model (an SVM) with lexical features that is able to classify the bias of articles outside of the Ukraine, though fails when applied to articles from within the Ukraine. These results suggest that while some aspects of bias can be captured by lexical models, it seems that the lexicon of similar biases (say, pro-Russian from Russia vs. pro-Russian from Ukraine)—and thus their frames—vary across contexts. Further, the same model achieves comparable, though lower, performance when trained on an unrelated set of political articles and tested on the dataset, suggesting that it is actually capturing writing style more than it captures bias. These results suggest that a deeper level of regional and cultural awareness is necessary to detect and classify bias, and ultimately disinformation.

2 Data

We have collected and manually annotated 4,538 news articles that report on the situation in Ukraine of 2014–2015, with particular focus on the annexation of Crimea by Russia in 2014, the military conflicts in Southeastern Ukraine, and the Maidan protests. It has been noted by many commentators that the use of disinformation was prominent during the conflict [13, for example].

We began collection of the articles by crawling the reference lists of the twelve Wikipedia pages that discuss some facet of the 2014–2015 crisis. We preliminarily categorized the bias of each article based on its country of origin, placing each country into pro-Western, Neutral, or pro-Russian bias classes on the basis of known geopolitical alliances. As described below in Sect. 2.1 we developed a bias classification scheme using these same three classes. Our initial country-based categorization revealed that we had a disproportionate number of pro-Western articles, and therefore we augmented the dataset with more pro-Russian articles by crawling the Sputnik news website[4] and retrieving every article classified by Sputnik as dealing with the crisis.

The second author[5] manually annotated the bias of each article. After manually classifying the bias the dataset was still significantly imbalanced, though with a large number of both pro-Russian and pro-Western sources, as was our primary interest. Given the time consuming nature of identifying and classifying news articles, further balancing the dataset remains for future work. A final manual classification task involved classifying every Sputnik article into one of the events as described by one of our twelve Wikipedia pages on the Ukrainian Crisis. Similarly to Wikipedia, Sputnik organized the Ukrainian articles by event[6],

[4] https://sputniknews.com/.

[5] The second author is an undergraduate researcher majoring in International Relations and specializing in Russia.

[6] Sputnik uses the word “Topics” to refer to their article categories, though these serve the same organizing purpose as Wikipedia’s events.

some of which aligned with the Wikipedia events. In order to merge these two event lists, we manually classified the Sputnik articles into one of the Wikipedia events. Those Sputnik articles that did not match any of the Wikipedia events resulted in a new Sputnik-only event in our timeline. This merging resulted in a total of 17 events. Therefore, at the end of the two annotation tasks, each article is classified by both bias and event. Table 1 shows a chronological list of the events, a breakdown of the number of articles that fall into each bias class and each major event, and the average and total word counts. Table 2 lists the number of articles for each of the top three publishers for each bias class.

Table 1. Breakdown of number of articles for each bias and event, in chronological order. Src ≡ Source of the category: Wikipedia (Wk) or Sputnik (Sp); N ≡ Number of articles in the category; $\overline{|W|}$ ≡ Average number of words per article in the category; $|W|$ ≡ Total number of words in the category. Some articles are classified into multiple categories.

Event		Src	pro-Russian			Neutral			pro-Western			Total		
			N	$\overline{\lvert W\rvert}$	$\lvert W\rvert$	N	$\overline{\lvert W\rvert}$	$\lvert W\rvert$	N	$\overline{\lvert W\rvert}$	$\lvert W\rvert$	N	$\overline{\lvert W\rvert}$	$\lvert W\rvert$
1	Ukraine-EU Association Agreement	Wk	**0**	0	0	**10**	310	3,098	**36**	610	21,958	**46**	545	25,056
2	Russia-Ukraine Gas Conflict	Wk	**289**	259	74,809	**2**	209	418	**1**	294	294	**292**	259	75,521
3	Euromaidan	Wk	**1,302**	275	357,595	**84**	247	20,764	**126**	641	80,813	**1,512**	304	459,172
4	Russian Photographer Stenin Killed	Sp	**119**	322	38,284	**0**	0	0	**0**	0	0	**119**	322	38,284
5	Annexation of Crimea	Wk	**362**	320	115,808	**32**	521	16,670	**143**	842	120,352	**537**	471	252,830
6	Crimea: New Life for Russia's Historic Resort	Sp	**25**	273	6,820	**0**	0	0	**0**	0	0	**25**	273	6,820
7	2014 Hrushevskoho Street Riots	Wk	**0**	0	0	**15**	232	3,478	**30**	577	17,312	**45**	462	20,790
8	Euromaidan (Post)	Sp	**1,045**	199	207,861	**0**	0	0	**0**	0	0	**1,045**	199	207,861
9	Russian Military Intervention	Wk	**5**	5,656	28,279	**41**	751	30,807	**229**	967	221,350	**275**	1,020	280,436
10	2014 Pro-Russian Unrest in Ukraine	Wk	**14**	1,809	25,322	**30**	560	16,794	**128**	879	112,479	**172**	899	154,595
11	International Sanctions During Ukrainian Crisis	Wk	**3**	125	376	**6**	469	2,813	**43**	584	25,092	**52**	544	28,281
12	War in Donbass	Wk	**14**	135	1,896	**40**	384	15,359	**225**	818	184,090	**279**	722	201,345
13	2014 Ukrainian Presidential Election	Wk	**2**	122	243	**4**	268	1,071	**6**	718	4,311	**12**	469	5,625
14	Russian Humanitarian Aid Convoys	Sp	**281**	234	65,792	**0**	0	0	**0**	0	0	**281**	234	65,792
15	2014 Donbass General Elections	Wk	**6**	485	2,909	**3**	392	1,175	**10**	782	7,821	**19**	627	11,905
16	2014 Ukrainian Parliamentary Election	Wk	**7**	501	3,507	**1**	730	730	**0**	0	0	**8**	530	4,237
17	2015 Ukrainian Local Elections	Wk	**1**	676	676	**0**	0	0	**1**	860	860	**2**	768	1,536
	Total Unique Articles or Total Tokens		**3,372**	255	860,212	**258**	420	108,453	**908**	804	729,965	**4,538**	374	1,698,630

Table 2. Top three publishers per bias

	pro-Russian	Neutral	pro-Western	Total
Sputnik	**3,308**	3	0	3,311
TASS	**36**	1	0	37
Voice of Russia	**17**	0	0	17
Interfax	0	**73**	30	103
Euronews	0	**20**	11	31
OSCE	0	**18**	1	19
BBC News	0	9	**162**	171
Reuters	0	6	**125**	131
The Guardian	0	4	**74**	78

2.1 Bias Annotation Scheme

In order to lay the groundwork for validating the annotation on the data, the second author drew on her knowledge of the Ukrainian Crisis and Russian politics to identify sets of frames present in the dataset. We randomly selected a sample of 150 articles (roughly six per event) and she identified all of the frames she could, partitioning them by bias, resulting in a total of 51 sets of frames—one for each bias in each of the seventeen events. She then used these frames to manually classify every article in the dataset. As an example, the following frames are used in the *Annexation of Crimea* event:

pro-Russia: Crimea coming home; Russia welcomes Crimea; Crimea's accession to Russia; Russia welcomes Crimea; Admission of Crimea into Russia; Ukraine took over Crimea; Crimea wants to go back to its roots in Russia; Referendum website hit by cyber-attack; The U.S. plans to supply weapons to Ukraine.

pro-Western: Russia stealing land from a sovereign nation; Russian Separatists; Annexation by Moscow; Russia stages coup; Russia took over Crimea; Russia does not fear the West; Crimea has been isolated by Russia; Putin admits Russian actions to take over Crimea; Putin refuses to rule out intervention in Donetsk.

Neutral: Mention frames from both sides equally, reporting facts, or offer explanation for both pro-Russian and pro-Western frames. State factual information without any emotional, political or ideological charge.

2.2 Content Extraction

We archived all the articles and processed them into raw text using a tool which we specially built for this purpose called WART—the Web ARchiving Tool. While most web browsers have a function to archive webpages, the process often does not save a faithful snapshot of the page, nor do they automatically identify and extract the textual content. Webpages differ dramatically in how they are structured internally and there is no standard for identifying the text of a news article. Further, we wanted the ability to batch download articles, because manually saving thousands of web pages using browser functionality is inconvenient and inefficient. WART uses the `wget` [16] archiver on the backend to take an exact snapshot of a webpage and package it into a compressed archive. WART also provides the ability to batch download pages, view a page saved in an WART archive file, and automatically identify the content. For content extraction, we began with the Dragnet tool [15] and fixed a bug which improved content extraction F_1 score from 0.84 to 0.90.

3 Bias Classification

3.1 Preprocessing

We extracted the main content of each article using WART, and then tokenized the text with `nltk` [3], also removing capitalization. We also removed all mention of each article's publisher to ensure our model is not simply learning to relate publishers to biases.

3.2 Classifier

We trained a 1-vs-1 Support Vector Machine (SVM) with a linear kernel [14] with a 250-dimensional doc2vec model trained on our dataset [12]. Our decision to use document embeddings (rather than word or sentence embeddings) was motivated by various factors. From a performance standpoint, doc2vec has been shown to achieve state-of-the-art results in several tasks, including, specifically, text classification (of which bias detection can be thought of as a variant) [12]. From the standpoint of semantic richness of document representations, doc2vec embedding models capture quite a bit of semantic similarity between texts that are otherwise syntactically different; this is one main advantage of embeddings in general over, for example, bag of words approaches.

In addition to SVM, we also tested LDA and QDA, Multilayer Perceptron, k-Nearest Neighbors, and Random Forests [10]. The linear kernel SVM performed best on our dataset and as such we report on this model's performance. Importantly, all models performed similarly across all experiments.

To test the effectiveness of the embeddings, we carried out a retrieval test of embedding effectiveness. In this test, we computed an embedding for each document treating the document as previously unseen. We then used that computed embedding to find the closest embedding vector over all documents. This retrieval returned the original document 98% of the time, confirming a suitable doc2vec representation of our corpus.

4 Results and Analysis

We ran seven different experiments on our data. All experiments used 5-fold cross validation and were run twice through our data—once with the entire dataset and then using oversampling to compensate for the minority class imbalance in the dataset (the minority class was usually the Neutral bias, but in a few instances it was pro-Western or pro-Russian). We performed oversampling using the Borderline-SMOTE technique, which augments the minority class in the training data by generating synthetic samples near those minority samples closest to samples from other classes. This helps the model find a more general decision boundary less prone to overfitting to the majority classes [5,9]. We first split the data into one of the five fold-splits, performed oversampling on the training set, and then tested on the test set which was unseen by the SMOTE oversampling algorithm. In this way we ensured that the synthetic SMOTE interpolations were not seen by our model during both training and testing, providing a more realistic measure of performance. Table 3 shows the results of the experiments, along with the broad questions we were seeking to answer in each.

The first experiment, $\mathbf{A} \rightarrow \mathbf{A}$, seems to confirm that indeed a simple model can be used to model bias on news articles sampled from different countries. This is similar to the result in experiment $\{\mathbf{A}–\mathbf{U}\} \rightarrow \{\mathbf{A}–\mathbf{U}\}$, where the slight performance increase seems to suggest that the Ukrainian articles are more diffi-

Table 3. Experiments, results, and relevant questions. $\mathbf{A} \equiv$ *All articles from all countries;* $\mathbf{U} \equiv$ *All articles from Ukraine;* $\mathbf{WC}_{\bar{\mu}} \equiv$ *The average of train/test within a country over all countries;* $\mathbf{Aux} \equiv$ *Auxilliary dataset of non-Ukraine-Crisis geopolitical articles from Reuters and Sputnik*

Train	Test	F_1 Full Corpus	F_1 Over-sampled	Question
A	**A**	0.86	0.76	Naive experiment. Can a lexical model capture bias?
A–U	**A–U**	0.89	0.81	Given the domain of our data, is it easier to model bias outside of Ukraine, the central country?
U	**U**	0.57	0.57	Can our model capture bias only within Ukrainian articles?
A–U	**U**	0.07	0.34	Does bias generalize from non-Ukrainian to Ukrainian articles?
U	**A–U**	0.05	0.06	Does bias generalize from Ukrainian articles to non-Ukrainian articles?
$\mathbf{WC}_{\bar{\mu}}$	$\mathbf{WC}_{\bar{\mu}}$	0.74	-	Is bias more easily classified when trained and tested within a single country?
Aux	**A**	0.76	-	Is our model actually learning regional journalistic style?

cult to classify than the non-Ukrainian articles. The drop in performance on the third experiment, **U** → **U** suggests that the bias lexicon in Ukrainian articles is more difficult to learn, which is a reasonable interpretation given that Ukraine is the central country in the conflict (as well as the only country with articles classified into each of the three different biases). This seems to be supported by the penultimate experiment, $\mathbf{WC}_{\bar{\mu}} \rightarrow \mathbf{WC}_{\bar{\mu}}$, where we see a less significant drop in performance from **A** → **A** but an improvement over **U** → **U**, suggesting that indeed modeling bias within the Ukraine is more difficult (at least with its smaller set of articles). The striking performance drops in experiments **{A-U}** → **U** and **U** → **{A-U}** suggest that, at the very least, our lexical model does not generalize from the rest of the world to the Ukraine. The slightly higher performance in the oversampled **{A-U}** → **U** experiment suggests that the larger sample size of the non-Ukrainian articles offers a richer lexicon for the Ukrainian articles than the other way around, as is to be expected.

These considerations naturally lead us to question if our model is learning bias at all or if, more likely, the model is simply learning journalistic style. The last experiment in Table 3 (**Aux** → **A**) supports this view. The **Aux** set consists of a balanced dataset of 6,000 articles from Reuters and Sputnik dealing with geopolitics (removing all articles mentioning Ukraine). The articles were crawled from the websites using the publishers' *politics* news tags. We automatically annotated all Reuters articles as pro-Western and all Sputnik articles as pro-Russian, as these publishers are one of the top two majority publishers in our Ukrainian dataset for the pro-Western and pro-Russian biases, respectively (Table 2). The high performance of the model under these conditions, in light of our other experiments, suggests that we cannot be certain if a lexical model is learning bias rather than some other traits—such as regional or publisher style—that are correlated yet not causally linked to bias itself.

5 Related Work

Media bias has long been studied in the social sciences, but has historically received relatively little attention in computer science. Hamborg *et al.* gave a fairly broad history of media bias research both in Computer Science and in the Social Sciences, noting that the conceptual frameworks in Computer Science approaches tend to lack conceptual sophistication [8]. They attempted to bridge the gap between the two perspectives by compiling a sort of taxonomy of the forms of media bias as conceptualized by social scientists and a compilation of modeling frameworks devised to detect parts of the social science taxonomy by computer scientists. Grimmer and Stewart provide a helpful overview of some of the pitfalls in interpreting the results of automatic political text analysis, aligning with the general conclusion of our results [7].

We mention a few relevant computer science works here. Recasens *et al.* deconstructed bias into two components, epistemological bias and framing bias, the latter dealing with statements focusing on the truthfulness of a proposition and the former with subjective words or phrases associated with a particular point of view [17]. They constructed a large dataset of sentences flagged by Wikipedia users as violating the neutral point-of-view (NPOV) Wikipedia requirement, and trained a classifier to predict the bias inducing word in a sentence. They asked humans to perform the experiment and found that performance was surprisingly low, with around 30% prediction accuracy. Baumer *et al.* investigated how humans detect bias by asking annotators to highlight the parts of articles that contain instances of framing, in addition to building a classifier for the task [2]. They used lay annotators as opposed to subject matter experts, raising the important point that framing is only as effective as it is understandable, suggesting the need to study the effects of different framings on different subsets of populations. Field *et al.* studied framing and agenda setting in Russian news, finding that they could predict mentions of the United States in Russian news media by using fluctuations in Russian GDP [6], in addition to building a lexical classifier to predict an article's main frame using the Media Frames Corpus [4]. Krestel *et al.* used a similar lexical approach to detect bias in German Parliament speeches and German news [11].

Recent work in fake news detection consider the role of bias in fake news production, using bias detection as a feature in fake news detection models that tend to include some form of a knowledge database to judge the veracity of a news item [1,18]. While fake news can be seen as a more general form of disinformation—in that fake news does not necessarily have a discernible end goal tied to a state or organization—most fake news detection frameworks assume that bias is a good predictor, and so share a conceptualization similar to ours of the relationship between bias and disinformation.

6 Contributions

We have compiled and annotated a dataset of 4,538 articles from 227 news sources across 43 countries relating to the Ukrainian Crisis of 2014–2015 annotated with bias (pro-Russian, Neutral or pro-Western) and relevant events in the crisis timeline. We investigated the suitability of lexical models to capture bias in this dataset. We found that the lexical approach did not generalize from non-Ukrainian to Ukrainian publishers, suggesting that during the Ukrainian Crisis the lexicon of bias is more complex within the Ukraine itself. Further our results suggest that the lexical model is not in fact learning bias at all, but rather regional journalistic styles which are likely correlated with bias but not indicative of bias itself. Our results point both to the need for more sophisticated NLP techniques in building a general bias detector and simultaneously call into question the premise a general bias detector is possible given that the rhetorical tools used to express bias are so steeped in culture.

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