Pro-Russian Biases in Anti-Chinese Tweets about the Novel Coronavirus

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Abstract
The recent COVID-19 pandemic, which was first detected in Wuhan, China, has been linked to increased anti-Chinese sentiment in the United States. Recently, Broniatowski et al. found that foreign powers, and especially Russia, were implicated in information operations using public health crises to promote discord – including racial conflict – in American society (Broniatowski et al., 2018). This brief considers the problem of automatically detecting changes in overall attitudes, that may be associated with emerging information operations, via artificial intelligence. Accurate analysis of these emerging topics usually requires laborious, manual analysis by experts to annotate millions of tweets to identify biases in new topics. We introduce extensions of the Word Embedding Association Test from Caliskan et al. to a new domain (Caliskan et al., 2017). This practical and unsupervised method is applied to quantify biases being promoted in information operations. Analyzing historical information operations from Russia’s interference in the 2016 U.S. presidential elections, we quantify biased attitudes for presidential candidates, and sentiment toward Muslim groups. We next apply this method to a corpus of tweets containing anti-Chinese hashtags. We find that roughly 1% of tweets in our corpus reference Russian-funded news sources and use anti-Chinese hashtags and, beyond the expected anti-Chinese attitudes, we find that this corpus as a whole contains pro-Russian attitudes, which are not present in a control Twitter corpus containing general tweets. Additionally, 4% of the users in this corpus were suspended within a week. These findings may indicate the presence of abusive account activity associated with rapid changes in attitudes around the COVID-19 public health crisis, suggesting potential information operations.

The World Health Organization has declared on the Internet surrounding the 2019-nCoV virus to be an “infodemic”, with disinformation widespread throughout multiple social media platforms (WHO, 2020). Concomitant with the spread of unverified information, several governments have expressed concerns (Gabrielle, 2020) that state-sponsored information operations are using this infodemic to sow panic and fear. Russian influence operations have previously used public health issues, such as HIV infection and vaccination (Broniatowski et al., 2018), as wedge issues to promote discord, including racial divisions and a pro-Russian policy agenda (Walter et al., 2020). Here, we find that tweets pertaining to COVID-19 and expressing anti-Chinese sentiment seem to express pro-Russian sentiment. These preliminary findings showcase a novel artificial intelligence (AI) tool, an extension of Word Embedding Association Test (WEAT) (Caliskan et al., 2017), that researchers studying malicious information operations may use to further guide research. Specifically, our findings point to the need for future work to determine whether this pro-Russian sentiment is the result of genuine grassroots attitudes or coordinated inauthentic behavior (e.g., a trolling campaign).

The detection of malicious information operations is complicated by the high velocity and volume of social media posts, since manual identification and annotation of online content requires specialized area expertise and does not scale (Gorwa et al., 2020). Here, we select a practical, unsupervised AI method that identifies biases present in large text corpora and extend it to emerging domains. Specifically, we choose word lists to represent information operation biases that are present in emerging domains that do not have historical samples. Our technique can be applied to new trending topics, including those reflecting suspected information opera-
tions, when annotated data is not readily available. We validate our method by measuring known anti-Muslim negative biases and negative associations with a major presidential candidate during the 2016 U.S. elections, both of which are present in word embeddings trained on corpora generated by a known Russian influence campaign (twi, 2018; Howard et al., 2019). We next collect Twitter data, with tweets containing anti-Chinese hashtags, over the course of one week to investigate potential biased associations present in this public dataset. Since the COVID-19 outbreak originated in Wuhan, China, we expected, and found, indications of expressions of anti-Chinese biases. We further demonstrate that these biases are associated with expressions of panic and negative sentiment. Surprisingly, the same corpus associates Russia with expressions of calm and positive sentiment.

Results

Caliskan et al. show that human-like biases and veridical information are embedded in the statistical regularities of language that are captured by word embeddings (Caliskan et al., 2017). Word embeddings are vector space representations of semantics learned via the distributional hypothesis. Extending Caliskan et al.’s WEAT, we examine biases in word embeddings trained on tweets related to COVID-19. WEAT quantifies human-like biases and cultural stereotypes between two target groups and two sets of polar attributes. Caliskan et al. use these tests in word embeddings to replicate biased associations documented by the Implicit Association Test (IAT) by using word sets in the IAT (Greenwald et al., 1998). We extend the WEAT to our research domain by creating bias tests for political leaders and countries: Calm-Panic, Trustworthy-Untrustworthy, and Pleasant-Unpleasant. Calm-Panic addresses the extent to which text may express panic within a group, whereas Trustworthy-Untrustworthy addresses the extent to which text might frame a group as untrustworthy. Finally, we include the original Pleasant-Unpleasant bias test to measure general negative bias against an opposing group. Kurdi et al. and Werntz et al. provide word sets that represent the polar extremes of trustworthy, untrustworthy, panic, and calm sentiments that we use in our bias tests (Kurdi et al., 2019; Werntz et al., 2016).

To distinguish between general bias against China and bias against China during the COVID-19 outbreak, we use three sources of Twitter data: i) TWITTER-G, a general large-scale Twitter control corpus that reflects baseline biases, ii) COVID-G, a general public dataset of tweets that mentioned common coronavirus hashtags created from 12 March 2020 until 22 March 2020 (#coronavirus, #coronavirusoutbreak, #coronavirusPandemic, #covid19, #covid_19)(Smith, 2020), and iii) COVID-AC, a set of tweets collected between 11 March and 18 March 2020 that contain hashtags discussing the COVID-19 pandemic and targeting China and Wuhan, many of which expressed anti-Chinese sentiment (#chinavirus, #wuhan, #wuhanvirus, #chinavirusoutbreak, #wuhan coronavirus, #wuhanflu, #wuhaninfluenza, #wuhan sars, #chinacoronavirus, #wuhan2020, #chinaflu, #wuhanquarantine, #chinesepneumonia, #coronachina, #wohan). For TWITTER-G, we use the pre-trained, Global Vectors for Word Representation (GloVe) Twitter word embeddings, which are widely used Twitter word embeddings (Pennington et al., 2014). We used the GloVe Twitter word embeddings with 27 billion tokens and 200-dimensional vectors. The TWITTER-G word embeddings contain similar bias scores to the reported scores by Caliskan et al., showing that they capture known human-like biases and cultural stereotypes (Caliskan et al., 2017). We generate word embeddings using the GloVe algorithm for the COVID-G and COVID-AC corpora since GloVe is known to capture semantics most accurately. In order to validate our methods, we use two Twitter datasets (twi, 2018) with ground truth information on bias associations: i) RU-DISINFO, a corpus that contains Russian information operation tweets released by Twitter in January 2019, and ii) IRA-DISINFO, a Twitter corpus released in October 2018 that contains tweets traced to Russia’s Internet Research Agency (IRA). These tweets were collected by Twitter if they were flagged to be involved with “state-backed information operations”. Consistent with our experimental datasets, we generated word embeddings using the GloVe algorithm for the two validation datasets.

Recently, Broniatowski et al. showed that Russian trolls weaponized health communication to promote discord over Twitter (Broniatowski et al., 2018). Moreover, Russian trolls were responsible for interfering with the 2016 U.S. presidential election (Mueller and Cat, 2019). Given this pre-
vious documentation of Russian information operations, we choose to analyze sentiment towards Russia expressed in these tweets. We implement the Calm-Panic bias test and Pleasant-Unpleasant bias test across the TWITTER-G, COVID-G, and COVID-AC word embeddings to compare results and identify bias shifts. In statistics, our bias score is known as an effect size and is defined by Cohen’s $d$. According to this statistic, an absolute value greater than or equal to 0.80 indicates a high effect size (the statistic can take on values between $-2$ and 2). Accordingly, as shown in Table 1, we identify biases with high effect size ($d \geq 0.80$) that are statistically significant ($P \leq 0.05$), indicating a clear bias in the set of tweets.

We first validated our method using the RU-DISINFO and IRA-DISINFO word embeddings. For the RU-DISINFO word embeddings we implemented the Truthworthy-Untrustworthy bias test to measure the association of the winning presidential candidate, Candidate A, whom U.S. government sources determined was characterized by Russian information operations as more trustworthy than the opposing Candidate B (Mueller and Cat, 2019). Specifically, the Truthworthy-Untrustworthy bias experiment produced an effect size of $d = 1.27$ ($P = 0.023$) using the RU-DISINFO word embeddings consistent with prior research showing that Russian information operations characterized Candidate B as deceitful and untrustworthy (Woolley and Howard, 2018; Bovet and Makse, 2019).

As a further validation, we examined how this known Russian trolling operation characterized Muslims, since a significant body of prior work analyzing Russian information operations (Woolley and Howard, 2018; Hindman and Barash, 2018; Del Vicario et al., 2016; Lazer et al., 2018; Bovet and Makse, 2019) have indicated that these campaigns express anti-Muslim sentiment. We found that the IRA-DISINFO word embeddings associated Muslim words with calm and anti-Muslim words with panic. Here, the Calm-Panic bias experiment produced an effect size $d = 1.22$ ($P = 0.026$). Thus, our validation experiments demonstrate that our unsupervised method generates results consistent with expectations.

We next examined anti-Chinese and pro-Russian biases in the COVID-AC corpus. We find a strong pro-Russian and anti-Chinese bias in the Calm-Panic bias test with an effect size of $d = 1.31$ ($P < 10^{-2}$) using the COVID-AC word embeddings. The COVID-G word embeddings also contain a significant, but smaller effect $d = 0.85$ ($P = 0.045$). Finally, in the TWITTER-G word embeddings, bias drastically moves to the opposite direction to $d = -0.86$ ($P = 0.047$). In this control dataset, Russia is associated with panic whereas China is associated with calm.

We find that at least 1% of tweets in our corpus reference Russian-funded news sources and use anti-Chinese hashtags. Additionally, 4% of the users in this corpus were suspended one week after data collection. In order to investigate the scope of pro-Russian biases, we ran Calm-Panic and Pleasant-Unpleasant WEAT tests for numerous countries (country-$x$) on COVID-AC. These Russia vs. country-$x$ WEAT tests indicated positive pro-Russian biases associating Russia with calm and positive valence. Some of these results were not statistically significant since we were not able to identify 8 words to represent many countries accurately for the WEAT test. COVID-AC embeddings are trained on a small corpus thus identifying 8 neutral words in COVID-AC’s dictionary to represent countries such as Bulgaria, Greece, Singapore, and Taiwan accurately is a challenging task. Aforementioned countries were not affected by the COVID-19 outbreak as intensely compared to Russia during our data collection period. Nevertheless, observing consistent results.

\begin{table} 
\centering 
\begin{tabular}{|c|c|c|c|c|c|c|c|} 
\hline 
\textbf{Embeddings} & \textbf{Categories} & \textbf{Attributes} & \textbf{$d^*$} & \textbf{$P^*$} \\
\hline 
COVID-AC & Russia & Pleasant & 1.04 & 0.016 \\
& China & Unpleasant & & \\
\hline 
COVID-AC & Russia & Calm & 1.31 & \textless{} 10^{-2} \\
& China & Panic & & \\
\hline 
COVID-G & Russia & Pleasant & 1.17 & \textless{} 10^{-2} \\
& China & Unpleasant & & \\
\hline 
COVID-G & Russia & Calm & 0.85 & 0.045 \\
& China & Panic & & \\
\hline 
TWITTER-G & Russia & Pleasant & -0.92 & 0.031 \\
& China & Unpleasant & & \\
\hline 
TWITTER-G & Russia & Calm & -0.86 & 0.047 \\
& China & Panic & & \\
\hline 
RU-DISINFO & Candidate A & Trustworthy & 1.27 & 0.023 \\
& Candidate B & Untrustworthy & & \\
\hline 
IRA-DISINFO & Muslim & Calm & 1.22 & 0.026 \\
& anti-Muslim & Panic & & \\
\hline 
\end{tabular} 
\caption{WEAT Results: Bias in Word Embeddings} 
\end{table} 

*We report the effect sizes ($d^*$, rounded down) and $P$ values ($P^*$, rounded up) to emphasize the statistical and substantive significance of these results.
pro-Russian biases across all of our experiments suggests further investigation into information operations might provide useful insights.

**Methods**

Our practical, unsupervised method used to detect and measure implicit biases in text corpora is an implementation of the WEAT (Caliskan et al., 2017). Given a text corpus from a domain of interest, we generate word embeddings to automatically discover implicit associations by extending WEAT. WEAT produces a normalized bias score (effect size $d$) by measuring the relative association of two social groups with two polar attributes in any input word embeddings. The association is quantified by cosine similarity. Then the one-sided permutation test ($P$-value) measures the unlikelihood of the null hypothesis which is the probability that a random permutation of the attribute words would produce the observed difference in sample means.

We list the word sets used in experiments to extend the WEAT methodology in Table 2 in the appendix. We systematically selected neutral words to represent Russia and China as social groups, using a representative word and the corresponding hashtag of the word. The calm, panic, pleasant, unpleasant, trustworthy, and untrustworthy attribute sets are selected from prior work in social psychology (Greenwald et al., 1998; Kurdi et al., 2019; Werntz et al., 2016).

When word embeddings are trained on a small corpus, or the word sets are considerably small (less than 8 words), the bias score may be insignificant. Adding more words to the category and attribute sets increases the significance of the WEAT’s results. Both calm and panic were represented with 4 words in prior work (Werntz et al., 2016). Since some of those words were not present in our word embeddings, we added synonyms and antonyms to represent each attribute set with 5 words. TWITTER-G’s dictionary did not contain many of the hashtags we used in the COVID-19 domain. Consequently, we excluded the hashtags while representing Russia and China in WEAT for TWITTER-G. Instead, we added four random major city names from Russia and China to enhance the representation.

The word lists used in all experiments, our source code, and word embeddings will be made available on our public GitHub project page.

**Datasets**

We collected 852,955 tweets related to COVID-19 with hashtags listed in the results section that were deemed as potentially spreading anti-Chinese sentiment on Twitter. The dataset was collected between 11 March and 18 March 2020 to generate case-insensitive COVID-ACembeddings. Case-insensitive COVID-G embeddings were trained on a general public dataset of tweets that mentioned common coronavirus hashtags. Case-insensitive RU-DISINFO and IRA-DISINFO embeddings were trained on datasets with tweets linked to Russia and IRA. These datasets are available in Twitter’s transparency report on information operations (twi, 2018). Case-insensitive TWITTER-G embeddings were trained on 2 billion random tweets. Therefore, we used TWITTER-G to obtain control results that are highly likely to reflect the baseline biases (Caliskan et al., 2017).

**Conclusion**

We examined a set of tweets containing anti-Chinese hashtags pertaining to COVID-19, COVID-AC, to determine if these tweets contained any hallmarks of potential malicious information operations. Using an unsupervised AI method to quantify biases expressed on Twitter, our novel approach allows for real-time bias analysis of a given text corpus, without requiring expert annotated data. Generating word embeddings, we are able to implement an extended WEAT to measure bias associations for Calm-Panic and Trustworthy-Untrustworthy, which may indicate the presence of information operations used to cause confusion and distrust in targeted groups. We validate our method on Twitter data linked to known Russian and IRA information operations, selecting word sets that represent targeted information campaigns during the 2016 U.S. presidential election. We quantify biases towards political candidates and Muslims in these prior information operations. We quantify pro-Russian and anti-Chinese biases in addition to associations of China with fear and panic in recent COVID-19 related public Twitter data. Various domains can apply this practical method by selecting the desired opposing groups (e.g., Russia vs. China) to discover and measure the present biases. These methods could be used to characterize attitudes on several different social media platforms in advance of major world events,
such as the upcoming U.S. presidential election, or the quickly evolving COVID-19 outbreak, by automatically identifying emerging biases. If unexpected biases are detected, researchers might then examine whether these could be artificially and deliberately introduced to the public sphere.

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## A Appendices

Table 2: Word Lists for WEAT Bias Experiments

| Embeddings | Topic     | Word Set                                      |
|------------|-----------|-----------------------------------------------|
| COVID-G&19 | China     | beijing, china, chinese, wuhan, #beijing, #china, #chinese, #wuhan |
| COVID-G&19 | Russia    | moscow, russia, russian, russians, #moscow, #russia, #russian, #russians |
| TWITTER-G  | China     | beijing, chengdu, china, chinese, shanghai, shenzhen, tianjin, wuhan |
| TWITTER-G  | Russia    | moscow, novosibirsk, petersburg, russia, russian, russians, volgograd, yekaterinburg |
| All Embeddings | Pleasant | glorious, happy, joy, laughter, love, pleasure, peace, wonderful |
| All Embeddings | Unpleasant | agony, awful, evil, failure, horrible, hurt, nasty, terrible |
| All Embeddings | Calm     | calm, peaceful, quiet, relaxed, tranquil* |
| All Embeddings | Panic    | anxious, fear, frightened*, panicked, scared |

*The word ‘tranquil’ was not present in IRA-DisINFO’s dictionary. As a result, the word ‘tranquil’ from calm attributes, and the word ‘frightened’ (chosen at random) from panic attributes were deleted while running WEAT on IRA-DisINFO.*