Supplementary Materials for

Content-based features predict social media influence operations

Meysam Alizadeh*, Jacob N. Shapiro, Cody Buntain, Joshua A. Tucker

*Corresponding author. Email: alizadeh@princeton.edu

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S1 Related Work

Previous research has shown how the IRA engaged in politically contentious discourse around a wide range of political issues in the U.S., from amplifying both sides of the debate on police shootings and #BlackLivesMatter movement [9, 31] and vaccines [7], to pushing both to targeting Facebook users in battleground states [12], to pushing different narratives to spread enmity between liberals and conservatives [10]. Work related to ours covers: (1) applying machine learning models to characterize the spread of content; (2) the general problem of detecting automated activity; (3) characterizing specific past campaigns; and (4) detecting IRA trolls based on the textual features for a fixed period.

Much of the related previous work focused on the prediction of emerging social media content such as hashtags [32], images [33], or topics [34]. Other work extended such measurement approaches to understand how certain social media platforms implicitly support “toxic technocultures” [35] or developed tools to detect cyberbullying incidents on social media (e.g. [36]). [19] was the first study to take promoted campaigns on social media as a unit of analysis and tried to predict them. Using a variety of temporal, content, sentiment, and user features they trained a classifier to detect trending memes at early stages, and achieved AUC score of 0.75 for early detection and greater than 0.95 after trending.

There is a growing related literature on identifying automated social media activity, commonly referred to as bot detection [17, 18]. This literature is different from characterizing and detecting coordinated influence operations because many participating accounts in such campaigns are manually operated. Recent reports suggest that in most cases these accounts are human-operated (See e.g. the U.S. Department of Justice indictment of IRA operatives and criminal complaint against Elena Alekseevna Khusya Ynova).

In the context of coordinated online influence campaigns, which is the focus of this paper, [10] was the first study we are aware of which characterized IRA troll content. They used
natural language processing and machine learning to assess whether IRA trolls were creating unique content. Comparing the syntactic patterns of IRA trolls’ tweets to those written by a sample of random English-speaking Twitter users revealed clear differences. They interpret this as an indicator that there was no serious attempt to obfuscate the non-nativity of IRA content. The authors did not test the predictive value of that content distinction.

A related effort to use publicly available Facebook, Reddit, and Twitter data of IRA trolls and a conflict-oriented events data to test hypotheses on temporal dynamics of IRA activities, found that “IRA Reddit activity granger caused IRA Twitter activity within a one-week lag”, but that there were no similar relationships with Facebook activity [23]. In addition, the author found no similar Granger relationship between IRA activity and (1) Russian threat or military posturing toward U.S., (2) U.S. threat or military posturing toward Russia, and (3) approval of Donald Trump.

Recent work closer to ours has approached classification in a more static manner. One study used a network analysis approach to study the South Korean National Information Service (NIS)’s coordinated campaign during the 2012 presidential election in South Korea [4]. The authors construct retweet, co-tweet, and co-retweet networks of the NIS and a sample of other random South Korean Twitter users to identify a set of potential NIS suspects. Then they used temporal and content similarities to detect new NIS trolls. Notably, this study links management techniques identified in court documents about the NIS activity to observable patterns in NIS-troll activity (e.g. the tendency to post identical content multiple times in a short period is attributed to fact that mid-level managers used output-based performance metrics such as number of tweets sent).

Another recent study focused on troll detection. The authors first develop a machine learning classifier to predict whether a Twitter account was one of the IRA accounts identified by Twitter and then use it to identify current active IRA accounts on Twitter, relying on human coders to determine whether the candidate troll accounts look like IRA trolls [22].
The model is trained on data which combine the most-recent 200 posts by the first set of IRA accounts released by Twitter on October 2018, 3,841 accounts, with the most-recent 200 posts of 171,291 random American Twitter users. Using a combination of user- and content-level features they obtain 10-fold cross-validation precision of 78.5% at the account level with a logistic regression model. While similar in spirit to our analysis, this approach relies on historical behavioral data of users over a long time-period, and does not show variation in performance of the approach over time. In addition, the study uses a random sample of American users as control data, which is potentially an easier classification task compared to distinguishing coordinated information campaign content from that of politically-engaged users. In real-world practice, troll posts continue circulating even after their accounts are removed. Therefore, troll detection systems may not be an efficient tool for situations in which there is a need to identify all potential content spread by them.

More recently [21] trained various classifiers to detect IRA trolls based on their tweets. The authors use textual features representing thematic information such as emotions, stance and bias cues, and morality, and profile traits including native language identification and stylistic features. The positive cases are the first set of IRA accounts released by Twitter, and the negative cases are a random sample of American users who posted at least 5 election-related tweets between August 1, 2016 and December 31, 2016. The final dataset is highly imbalanced with IRA users being only 2% of users. Their Logistic Regression classifier yielded a macro weighted F1 score of 0.94 on cross-validation data. This work is closest to ours in approach. However, it does not study the performance of the classifier on unseen, out-of-sample data and does not assess performance of the classification approach over time.
S2 How Twitter Detects and Handles Coordinated Influence Operations

This section provides background information on Twitter’s encounters with foreign influence efforts (FIEs) on their platform, how many suspicious accounts were identified, and the company’s proposed policy changes to increase security and prevent future FIEs. This is followed by a review of what is publicly known about Twitter’s process on identifying and classifying suspicious accounts, concluding with an external review on the process.

During the 2016 US presidential election, Twitter identified suspicious coordinated activity and automated accounts which were sending election related content onto their platform. Overall, Twitter identified a total of 3,814 accounts that were later associated with a Russian government-linked organization called the Internet Research Agency (IRA) which sent out 175,993 tweets, of which roughly 8.4% were election related tweets [37]. It also identified over 50,258 automated, Russian-linked accounts which sent out 2.12 million tweets or roughly 1% of all election-related tweets in the time period preceding and during the 2016 election [38]. These accounts were suspended and users who interacted with them (e.g. liked, retweeted, commented, quoted or followed) were duly notified by Twitter [37]. Twitter later released an extensive dataset of the 3,841 IRA affiliated accounts and their contents, allowing external parties to conduct independent research themselves.

In response to these FIEs, Twitter has proposed changes to company policy to combat future attempts of hostile manipulation and disinformation on their platform, whether from state or non-state sponsored actors. Twitter has committed to improving user security and increasing restrictions on developers, creating research partnerships with third parties, and increasing specialized personnel and services to combat FIEs. Daily users will find a greater need to confirm human control of accounts that are being accessed, through reCAPTCHAs
and mandatory email or phone verification for new accounts [38, p. 7]. To mitigate automation and abuse of the service, Twitter has also updated policies for developers and third parties who access data through APIs, prohibiting developers from using data in a manipulative manner or invading user privacy on the platform. The company has also focused on compliance checks to prevent spam-generating applications [38, p. 13].

To prepare for the 2018 U.S. midterm elections, Twitter prioritized hiring additional personnel to a dedicated “cross-functional analytical team” and the creation of a political conversations dashboard to focus on site monitoring and service integrity [38, p. 8]. The cross-functional team processes and detects potentially threatening activity, automated or human-coordinated, in real-time while the dashboard captures sudden changes in sentiment around a specific topic, along with information on groups of linked accounts that may be involved with malicious efforts [38, p. 9].

S2.1 Twitter Forensic Process

Twitter uses a combination of automated and manual reviews, supplemented by user reviews and additional security information from third parties to detect suspicious activity on their platform. The first stage is automated, using machine learning methods and internal technologies to screen accounts for malicious activity. Twitter uses both public (e.g. frequency and timing of tweets, retweets, and likes) and private account metrics (e.g. contact information, login history), along with additional features that are accessible only within the company, to determine whether an account is fake or spam [39, p. 5]. The company has publicly acknowledged some of the signals it uses to find malicious automation, including “inhuman response times and coordinated activities across accounts” [39, p. 37], “exceptionally high-volume tweeting with the same hashtag” or “measuring the same @handle without a reply from the account being addressed” [38, p. 7]. Twitter has stated that automated techniques are not enough to address the issue entirely and rely on internal, manual reviews
conducted by personnel within their process. In addition, user reports supplement the automated and manual reviews and are used to calibrate their detection systems to identify other sources of spam and disinformation [40, p. 18]. This general work structure, including collaboration with industry peers, experts, third party security vendors, and other companies make up the key stages of Twitter’s revision process.

S2.2 Identification of Russian-linked and Election-related Activity

In an open hearing with the US Senate in November 2017, Twitter outlined the steps in its retrospective analysis of the 2016 US presidential election, to identify suspicious accounts. The time period of interest precedes and includes election day, from September 1 to November 15, 2016. First, election-related tweets in this time period were identified and tagged based on Twitter usernames, hashtags, and tweet content. For example, Tweets which mentioned @HillaryClinton, @realDonaldTrump or included #primaries and #feelthebern were tagged as election-related tweets, for a total of 189 million election-related tweets [40, p.9]. Next, Russian-linked accounts were identified based on the following criteria:

“...whether the account was created in Russia or the user registered the account with a Russian phone carrier or email address, whether the username associated with the account contained Cyrillic characters, whether the user frequently tweets in Russian, and whether the user logged in from any Russian IP address even once.”

Accounts were classified as Russian-linked if they satisfied any one of these criteria. Overall, a high concentration of the automated content creation came from data centers and users who accessed the website via virtual private networks with 12% of tweets during the time period that was studied coming from accounts with unknown locations [40].
S2.3  Timeline of Suspicious Activity Detection

IRA-linked Accounts

- September 1 - November 15, 2016: Preceding and during election day
  → 2,752 accounts

- January 2018: Update on 2016 Midterm Elections Twitter blog post [37].
  → 1,062 additional accounts

- Total of 3,814 IRA-linked accounts (228 of these were mistakenly identified as Russian-linked, but later determined to be Venezuelan-linked)

- Sent out 175,993 tweets during the election period [6, p. 3].

Automated and Russian-linked Accounts

- November 2017: Open Hearing to the US Senate [40, p. 9].
  → 36,746 accounts

- January 2018: Update on 2016 Midterm Elections Twitter blog post [37].
  → 13,512 additional accounts

- Total of 50,258 automated, Russian-linked accounts

- Sent out 2.12 million tweets, constituting 1% of all activity on the website [37].

S2.4  Disclosed Account Level Features for Detecting Suspicious Activity

1. Publicly accessible account features
• Frequency and timing of tweets, retweets, and likes [39, p. 8]
• Tweet and follow counts, language usage [39, p.5]

2. Privately accessible account features

• Contact information, including emails and mobile phone numbers, and login history [39, p. 9]
• Monitoring and reviewing unsolicited targeting of accounts, especially those which follow or mention accounts that they had no previous connection with [39, p. 12].
• “Inhuman response times and coordinated activity across accounts” [39, p. 37].
• “Exceptionally high-volume tweeting with the same hashtag” or “measuring the same @handle without a reply from the account being addressed” [38, p. 7].

3. Features for identifying fake accounts

• Use of stock or stolen user photos or profile bios, and intentional misleading information and profile location.
Task 1: Cross-Section Train and Test on Month $t$

Figure S1: Predictive performance across campaigns and platforms for a 50/50 train/test split on the current month. Panels show monthly performance metrics and the number of troll posts in the train and test sets for (a) IRA Twitter dataset, (b) IRA Reddit dataset, (c) Venezuela Twitter dataset, and (d) China Twitter dataset. For Russian operation on Twitter, precision, recall, and F1 are all above 0.8 until mid-2017. They frequently drop below 0.6 afterwards due to the low level of IRA activity which results in small number of positive cases in train and test sets.
Task 2: Train on $t - 1$ and Test on All Users in $t$

This task effectively assesses how consistent troll content is over time by seeing whether troll activity in the previous month distinguishes such activity in the current month.

Figure S2: Predictive performance across campaigns and platforms for a test of train on $t - 1$ and test on all trolls tweets in month $t$. We removed any user-level feature for this test which includes account age and other related features. Each panel shows monthly performance metrics and number of trolls posts in the train and test sets for (a) IRA Twitter dataset, (b) IRA Reddit dataset, (c) Venezuela Twitter dataset, and (d) China Twitter dataset.
Task 3: Train on $t-1$ and Test on New Users in $t$

the hardest test for a supervised classifier in this space is identifying activity by previously-unseen accounts which are part of a previously-observed effort.

Figure S3: Predictive performance across campaigns and platforms for a test of training on last month and testing on tweets from new users in the current month. Each panel shows monthly performance metrics and number of troll posts in the train and test sets for the (a) IRA Twitter dataset, (b) IRA Reddit dataset, (c) Venezuela Twitter dataset, and (d) China Twitter dataset.
Task 4: Train on 1st Data Release and Test on 2nd Data Release

Assessing how well a classifier trained on the 1st release would perform in detecting tweets from users in the 2nd release provides evidence about whether content-based features provide information not found in the account-level features Twitter initially relied on.

(a) Russia in Twitter

(b) Venezuela in Twitter

Figure S4: Predictive performance for a test of training on month $t$ of the 1st data release and testing on month $t$ of the 2nd data release. Each panel shows monthly performance metrics and number of trolls posts in the train and test sets for (a) IRA Twitter dataset and (b) Venezuela Twitter dataset.
Task 5: Cross-Platform Train and Test in Month $t$

We remove platform-specific features and test whether classifiers trained on Twitter/Reddit data using mutual features in month $t$ could detect social media posts from troll on Reddit/Twitter in the same month. This experiment tests show similar influence operations are across platforms.

Figure S5: Predictive performance for cross-platform train and test in month $t$. Each panel shows monthly performance metrics and number of trolls posts in the train and test sets for (a) Training on Reddit posts in month $t$ and testing on tweets in month $t$, and (b) Training on tweets in month $t$ and testing on Reddit posts in month $t$. 
S4 Regression Analysis of Classifier Performance

This section presents regression results on the predictors of the classifiers’ prediction performance discussed in Section 2.2. We report regression tables for F1 scores in Table S1. In the regression tables, we report estimated coefficients for models in the following order:

Model 1 (baseline): Controlling for all Twitter and Reddit campaigns and prediction tasks.
Model 2: Time controls include quintic polynomial in time plus quarter fixed effects.
Model 3: Excluding Reddit data.
Model 4: Controlling for activity type including monthly shares of tweets with retweet, mention, and hashtag, tweets that are in reply to other tweets, and link to a local news website.
Model 5: Controlling for log(positives in test), log(positives in train), imbalance in test set.
Model 6: Controlling for count of major political events in US and average rating of independent raters.
Table S1: Comparing Estimated Coefficients and Standard Errors Between Various Regression Models Explaining F1 Score of Prediction.

| Column Number | Baselinea | (1)+ Temporal Controlsb | (2)+ Restrict to Twitterc | (3)+ Control for Activity | (4)+ Control for Imbalanced | (5)+ Control for Events e |
|---------------|-----------|--------------------------|---------------------------|---------------------------|-----------------------------|-----------------------------|
| Variables     | b/se      | b/se                     | b/se                      | b/se                      | b/se                        | b/se                        |
| Russia Twitter| 0.087***  | 0.095***                 |                           |                           |                             |                             |
|               | (0.02)    | (0.02)                   |                           |                           |                             |                             |
| China Twitter | 0.126***  | 0.143***                 | 0.045***                  | 0.062**                   | 0.009                       | 0.007                       |
|               | (0.02)    | (0.02)                   | (0.02)                    | (0.03)                    | (0.02)                      | (0.02)                      |
| Venezuela Twitter | 0.148***   | 0.171***                | 0.075***                 | -0.016                   | -0.075                      | -0.078*                     |
|               | (0.02)    | (0.03)                   | (0.02)                    | (0.05)                    | (0.05)                      | (0.05)                      |
| Prediction Task 2 | 0.002      | 0.008                   | -0.001                   | -0.007                   | -0.038***                   | -0.037***                   |
|               | (0.01)    | (0.01)                   | (0.01)                    | (0.01)                    | (0.01)                      | (0.01)                      |
| Prediction Task 3 | -0.081***  | -0.077***               | -0.075***              | -0.089***               | -0.094***                   | -0.094***                   |
|               | (0.02)    | (0.02)                   | (0.02)                    | (0.02)                    | (0.02)                      | (0.02)                      |
| Prediction Task 4 | -0.232***  | -0.226***               | -0.230***              | -0.245***               | -0.274***                   | -0.275***                   |
|               | (0.03)    | (0.03)                   | (0.03)                    | (0.03)                    | (0.03)                      | (0.03)                      |
| RT share      | 0.023     | -0.084                   | -0.082                   |                           |                             |                             |
|               | (0.07)    | (0.06)                   | (0.06)                    |                           |                             |                             |
| Reply share   | 0.061     | 0.278**                  | 0.277**                  |                           |                             |                             |
|               | (0.15)    | (0.12)                   | (0.12)                    |                           |                             |                             |
| Share w/hashtag | 0.010       | -0.001                  | -0.016                   |                           |                             |                             |
|               | (0.08)    | (0.07)                   | (0.07)                    |                           |                             |                             |
| Share w/mention | -0.524***  | -0.446***               | -0.444***               |                           |                             |                             |
|               | (0.11)    | (0.08)                   | (0.08)                    |                           |                             |                             |
| Share w/local news URL | -0.050       | -0.174                  | -0.171                   |                           |                             |                             |
|               | (0.17)    | (0.16)                   | (0.16)                    |                           |                             |                             |
| Log(positives in test) | 0.045***    | 0.046***                |                           |                           |                             |                             |
|               | (0.01)    | (0.01)                   |                           |                           |                             |                             |
| Log(positives in train) | 0.040***    | 0.040***                |                           |                           |                             |                             |
|               | (0.01)    | (0.01)                   |                           |                           |                             |                             |
| Class imbalance in test | 0.267***    | 0.272***                |                           |                           |                             |                             |
|               | (0.03)    | (0.03)                   |                           |                           |                             |                             |
| Count of major events | 0.000        |                        |                           |                           |                             |                             |
| Average rating of events |                   |                        |                           |                           |                             | -0.039*                     |
|               |           |                         |                           |                           |                             | (0.02)                      |

Mean of dependent variable 0.82 0.82 0.84 0.84 0.84 0.84
# Observations 415 415 364 364 364 364
R-Squared 0.36 0.41 0.41 0.49 0.60 0.60

Baseline campaign for columns 1 and 2 is Russian activity on Reddit. Baseline campaign for columns 3-6 is Russian activity on Twitter. Baseline task is cross-sectional prediction. Robust standard errors in parentheses: * .1, ** .05, *** .01.”)
## List of Major Political Events in U.S.

### Table S2: List of Major Political Events in U.S.

| Index | Date       | Event Description                                                                 | Source     | Country | State | City        | Category                                                                 | R1 | R2 | R3 | R4 | Overall |
|-------|------------|----------------------------------------------------------------------------------|------------|---------|-------|-------------|--------------------------------------------------------------------------|----|----|----|----|---------|
| 1     | 04/04/15   | Walter Scott was killed by a police officer (Michael Slager) in South Carolina.  | ABC News   | USA     | SC    | North Charleston | Police brutality - BLM                                                   | 0  | 0  | 1  | 1  | 0.25    |
| 2     | 04/08/15   | Dzhokhar Tsarnaev, allegedly responsible for the Boston marathon bombing in 2013, was found guilty. | ABC News   | USA     | MA    | Boston       | Terrorism                                                                | 0  | 0  | 1  | 0  | 0.25    |
| 3     | 04/12/15   | Freddie Gray was picked up by police and he suffered spinal injuries which caused his death. Six police officers were charged in connection with his death. | ABC News   | USA     | MD    | Baltimore    | Police brutality - BLM                                                   | 1  | 1  | 1  | 1  | 1       |
| 4     | 04/12/15   | Hillary Clinton announced her candidacy for the presidential run with a three-minute video. | ABC News   | USA     | -     | -            | Elections                                                                | 1  | 1  | 1  | 0  | 0.75    |
| 5     | 05/04/15   | Dean Skelos, a former Republican member of the New York State Senate, was arrested on corruption charges. Donald Trump launched his bid for the presidency at the Trump Tower in New York, saying “I am officially running for president of the United States, and we are going to make our country great again.” | ABC News   | USA     | NY    | -            | Political corruption                                                     | 0  | 0  | 0  | 0  | 0       |
| 6     | 06/16/15   | A 21-year old white man (Dylann Roof) with white supremacist beliefs opened fire in Charleston’s historic Emanuel AME Church, a predominantly African-American church. | ABC News   | USA     | SC    | Charleston   | Mass shooting - racism                                                   | 1  | 1  | 1  | 1  | 1       |
| 7     | 06/17/15   | Dzhokhar Tsarnaev, responsible for the Boston marathon bombing in 2013, was sentenced to death. | ABC News   | USA     | MA    | Boston       | Terrorism                                                                | 0  | 0  | 1  | 0  | 0.25    |
| 8     | 06/24/15   | The Supreme Court ruled in favor of same-sex marriage, allowing same-sex people to get married nationwide. | ABC News   | USA     | MD    | Baltimore    | Politics                                                                 | 1  | 1  | 1  | 1  | 1       |
| 9     | 06/26/15   | The Joint Comprehensive Plan of Action (JCPOA - Iran nuclear deal) was signed by the United States and other countries. | ABC News   | Austria | -     | Vienna       | Foreign relations                                                        | 1  | 1  | 1  | 1  | 1       |
| 10    | 07/14/15   | US and Cuba restored diplomatic relations after 4 decades. The first Republican Primary Debate took place. Ten participants gave their speeches, but Trump was the center of attention. | CNBC       | USA     | DC    | Washington DC | Foreign relations                                                        | 1  | 1  | 1  | 0  | 0.75    |
| 11    | 07/20/15   | John Kerry formally reopens the embassy in Cuba. Vester Lee Flanagan II killed two colleagues at a TV station in Virginia. He was inspired by the Charleston shooting. He then shot himself to death. | The Guardian | Cuba    | -     | La Habana     | Foreign relations                                                        | 0  | 0  | 0  | 0  | 0       |
| 12    | 08/06/15   | Hillary Clinton apologizes for the private email server she kept when she was Secretary of State. | ABC News   | USA     | VA    | Roanoke      | Mass shooting - racism                                                   | 1  | 1  | 0  | 0  | 0.5     |
| 13    | 08/14/15   | After the outbreak of the Refugee crisis in Syria, Obama announced a plan to allow 10,000 Syrian refugees to the US. | ABC News   | USA     | DC    | Washington DC | Immigration                                                              | 0  | 0  | 0  | 0  | 0       |
| 14    | 09/08/15   | Pope Francis officially began his visit to the United States. | ABC News   | USA     | DC    | Washington DC | Religion                                                                 | 0  | 0  | 0  | 0  | 0       |
Table S2: List of Major Political Events in U.S.

| Index | Date      | Event description                                                                 | Source                  | Country | State  | City            | Category                  | R1 | R2 | R3 | R4 | Overall |
|-------|-----------|------------------------------------------------------------------------------------|-------------------------|---------|--------|-----------------|---------------------------|----|----|----|----|---------|
| 18    | 10/04/15  | The US and other 11 countries found an agreement on the Trans-Pacific Partnership (TPP). | Council on Foreign Relations | -      | -      | -               | Foreign Relations         | 0  | 0  | 0  | 1  | 0.25    |
| 19    | 10/13/15  | The first Democratic Primary debate took place, and Clinton was joined by all the other candidates, including Bernie Sanders. | ABC News                | USA     | NV     | Las Vegas       | Elections                 | 0  | 0  | 1  | 0  | 0.25    |
| 20    | 10/15/15  | Obama decided to keep troops in Afghanistan through the end of his presidency.       | Council on Foreign Relations | USA     | DC     | Washington DC   | Foreign Relations         | 0  | 0  | 1  | 1  | 0.5     |
| 21    | 10/22/15  | Hillary Clinton testified before a House Select Committee regarding the Sept. 11, 2012, terrorist attack at the U.S. compound in Benghazi, Libya in which four Americans were killed, including Ambassador Chris Stevens. | ABC News                | USA     | DC     | Washington DC   | Politics                  | 1  | 1  | 0  | 0  | 0.5     |
| 22    | 11/30/15  | Sheldon Silver, a former Democratic New York Assemblyman, was found guilty of corruption. | New York Times          | USA     | NY     | NYC             | Political corruption      | 0  | 0  | 0  | 0  | 0       |
| 23    | 12/02/15  | 14 persons were killed and 21 wounded in a mass shooting in San Bernardino, California. The attacker claimed to have close connections with the Islamic State. | Washington Post         | USA     | CA     | San Bernardino  | Mass shooting - terrorism | 1  | 1  | 1  | 1  | 1       |
| 24    | 12/07/15  | Trump proposed a complete ban for Muslims to enter in the US.                        | ABC News                | USA     | SC     | Myrtle Beach    | Immigration               | 1  | 1  | 1  | 1  | 1       |
| 25    | 12/12/15  | 195 countries, US included, signed an agreement at the Paris summit on Climate Change, known as Paris Climate Agreement. | France                  | France  | -      | Paris           | Foreign relations         | 1  | 1  | 1  | 1  | 1       |
| 26    | 01/16/16  | Obama declared a state of emergency in response to the Flint water disaster. Two years before, the local government decided to switch the water source to Flint river, triggering an unprecedented public health crisis. | CBS News                | USA     | MI     | Flint           | Natural disaster          | 1  | 0  | 1  | 0  | 0.5     |
| 27    | 02/01/16  | Clinton won narrowly in the first contest of the primaries in the Iowa caucuses against Bernie Sanders. | ABC News                | USA     | IW     | -              | Elections                 | 0  | 0  | 1  | 0  | 0.25    |
| 28    | 02/09/16  | Both Trump and Sanders won with a large victory in the New Hampshire primaries.     | ABC News                | USA     | NH     | -              | Elections                 | 0  | 0  | 1  | 1  | 0.5     |
| 29    | 03/20/16  | Obama visited Cuba. It was the first time since the 1920s the US President paid a visit to Cuba. A former Stanford swimmer, Brock Turner, was found guilty of sexually assaulting a woman while in college. This case triggered debate over sexual abuses in the country. | New York Times          | USA     | Cuba   | -              | Foreign Relations         | 1  | 0  | 0  | 0  | 0.25    |
| 30    | 03/30/16  | Ted Cruz, the main Republican opponent of Trump, drops out from the run to the presidency. | CBS News                | USA     | CA     | Santa Clara County | Sexual crimes         | 1  | 1  | 1  | 0  | 0.75    |
| 31    | 05/03/16  | Trump won the Republican primaries, assuring his nomination for the presidential run. | ABC News                | USA     | IN     | Indianapolis    | Elections                 | 0  | 0  | 1  | 0  | 0.25    |
| 32    | 05/26/16  | Clinton obtained enough delegates to clinch her nomination for the presidential run. The deadliest mass shooting in the US history took place in Orlando at Pulse, a gay nightclub. 49 people were killed and at least 53 wounded by an American-born man (Omar Mateen) who claimed to have connections with ISIS. | ABC News                | USA     | -      | -              | Mass shooting             | 1  | 1  | 1  | 1  | 1       |
| 33    | 06/06/16  | -                                                                                  | ABC News                | USA     | -      | -              | Elections                 | 1  | 1  | 1  | 1  | 0.75    |
| 34    | 06/12/16  | -                                                                                  | New York Times          | USA     | FL     | Orlando         | Mass shooting             | 1  | 1  | 1  | 1  | 1       |
| Index | Date       | Event Description                                                                 | Source      | Country | State | City       | Category               | R1 | R2 | R3 | R4 | Overall |
|-------|------------|-----------------------------------------------------------------------------------|-------------|---------|-------|------------|------------------------|----|----|----|----|---------|
| 35    | 06/12/16   | Sanders said he would join Clinton in her effort to defeat Trump. FBI announced   | ABC News    | USA     | -     | -          | Elections              | 0  | 0  | 0  | 0  | 0.00    |
|       |            | it won’t recommend criminal charges against Clinton for using a private email      |             |         |       |            |                        |    |    |    |    |         |
|       |            | server when she was Secretary of State. This ended a year long investigation.    |             |         |       |            |                        |    |    |    |    |         |
| 36    | 07/05/16   | Alton Sterling (a black man) was assassinated in Baton Rouge after an argument    | ABC News    | USA     | -     | Baton Rouge| Political corruption   | 0  | 1  | 1  | 1  | 0.75    |
|       |            | with officers outside a liquor store. Philando Castile (a black man) was shot 7  |             |         |       |            |                        |    |    |    |    |         |
|       |            | times in his car in Minnesota after an officer pulled him over for a busted        |             |         |       |            |                        |    |    |    |    |         |
|       |            | taillight. The scene was broadcasted by his girlfriend on Facebook Live,        |             |         |       |            |                        |    |    |    |    |         |
|       |            | triggering a huge debate on social media nationwide. 12 police officers were    |             |         |       |            |                        |    |    |    |    |         |
|       |            | shot and 5 killed in Dallas by a sniper angry for the Sterling and Castile       |             |         |       |            |                        |    |    |    |    |         |
|       |            | killings. The attacker was then killed by the police. United States and South   |             |         |       |            |                        |    |    |    |    |         |
|       |            | Korea announce the THAAD plan, an advanced American missile defense system to    |             |         |       |            |                        |    |    |    |    |         |
|       |            | protect the South from North Korea’s increasing nuclear threat.                  |             |         |       |            |                        |    |    |    |    |         |
| 37    | 07/06/16   | FBI announced that it won’t recommend criminal charges against Clinton for using | ABC News    | USA     | LA    | Baton Rouge| Police corruption      | 0  | 0  | 0  | 0  | 0.00    |
| 38    | 07/06/16   | a private email server when she was Secretary of State. This ended a year long  | CBS News    | USA     | MN    | Falcon Heights| Political corruption | 1  | 1  | 1  | 1  | 1.00    |
|       |            | investigation. Alton Sterling (a black man) was assassinated in Baton Rouge       |             |         |       |            |                        |    |    |    |    |         |
|       |            | after an argument with officers outside a liquor store. Philando Castile (a      |             |         |       |            |                        |    |    |    |    |         |
|       |            | black man) was shot 7 times in his car in Minnesota after an officer pulled him  |             |         |       |            |                        |    |    |    |    |         |
|       |            | over for a busted taillight. The scene was broadcasted by his girlfriend on      |             |         |       |            |                        |    |    |    |    |         |
|       |            | Facebook Live, triggering a huge debate on social media nationwide. 12 police   |             |         |       |            |                        |    |    |    |    |         |
|       |            | officers were shot and 5 killed in Dallas by a sniper angry for the Sterling and |             |         |       |            |                        |    |    |    |    |         |
|       |            | Castile killings. The attacker was then killed by the police. United States and |             |         |       |            |                        |    |    |    |    |         |
|       |            | South Korea announce the THAAD plan, an advanced American missile defense system  |             |         |       |            |                        |    |    |    |    |         |
|       |            | to protect the South from North Korea’s increasing nuclear threat.                |             |         |       |            |                        |    |    |    |    |         |
| 39    | 07/07/16   | Sanders said he would join Clinton in her effort to defeat Trump. FBI announced  | ABC News    | USA     | TX    | Dallas     | Mass shooting           | 1  | 1  | 1  | 1  | 1.00    |
|       |            | it won’t recommend criminal charges against Clinton for using a private email     |             |         |       |            |                        |    |    |    |    |         |
|       |            | server when she was Secretary of State. This ended a year long investigation.    |             |         |       |            |                        |    |    |    |    |         |
| 40    | 07/07/16   | Sanders officially endorsed Clinton for president.                                | New York    | USA     | -     | -          | Foreign Relations      | 0  | 0  | 0  | 0  | 0.00    |
| 41    | 07/12/16   | Donald Trump officially endorsed Clinton for president.                           | ABC News    | USA     | NH    | Portsmouth| Elections              | 0  | 1  | 0  | 0  | 0.25    |
| 42    | 07/16/16   | US President Donald Trump announced Mike Pence as his running mate for the       | ABC News    | USA     | NY    | NYC        | Elections              | 0  | 0  | 1  | 0  | 0.25    |
| 43    | 07/17/16   | Ted Cruz did not endorse Trump at the Republican National Convention, and        | ABC News    | USA     | LA    | Baton Rouge| Mass shooting          | 0  | 0  | 0  | 0  | 0.00    |
| 44    | 07/20/16   | instead told people to "vote with your conscience".                              | ABC News    | USA     | OH    | Cleveland | Elections              | 0  | 0  | 0  | 0  | 0.00    |
| 45    | 07/21/16   | 3 police officers were killed by an attacker in Baton Rouge, who was later       | ABC News    | USA     | OH    | Cleveland | Elections              | 1  | 0  | 1  | 1  | 0.75    |
| 46    | 07/22/16   | The United States and South Korea announce the THAAD plan, an advanced American  | ABC News    | USA     | -     | -          | Elections              | 0  | 0  | 0  | 0  | 0.00    |
| 47    | 07/28/16   | San Francisco 49ers quarterback Colin Kaepernick opted not to stand for the     | The Atlantic| USA     | -     | -          | Foreign Relations      | 1  | 0  | 0  | 0  | 0.25    |
| 48    | 08/17/16   | San Francisco 49ers quarterback Colin Kaepernick opted not to stand for the     | The Atlantic| USA     | CA    | Santa Clara| Racism                | 1  | 1  | 1  | 1  | 1.00    |
| 49    | 08/26/16   | Colin Kaepernick opted not to stand for the national anthem to protest against   | The Atlantic| USA     | -     | -          | Elections              | 0  | 0  | 1  | 0  | 0.25    |
|       |            | the treatment of minorities. North Korea conducted its fifth nuclear missile test |             |         |       |            |                        |    |    |    |    |         |
|       |            | since 2006, producing an explosive yield of 10 kilotonnes, the highest recorded  |             |         |       |            |                        |    |    |    |    |         |
|       |            | so far. This is relevant because Washington has struggled a lot to stop nuclear  |             |         |       |            |                        |    |    |    |    |         |
|       |            | tests in North Korea, which pose a serious threat to the US national security.   |             |         |       |            |                        |    |    |    |    |         |
| 50    | 09/09/16   | Clinton and Trump faced off in their first presidential debate at Hofstra        | ABC News    | USA     | NY    | NYC        | Elections              | 0  | 0  | 1  | 1  | 0.50    |
| 51    | 09/26/16   | Clinton and Trump faced off in their first presidential debate at Hofstra        | ABC News    | USA     | NY    | NYC        | Elections              | 0  | 0  | 1  | 1  | 0.50    |
| Index | Date     | Event description                                                                                                                                                                                                                                                                                                                                 | Source          | Country | State | City     | Category                | R1 | R2 | R3 | R4 | Overall  |
|-------|----------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------|---------|-------|----------|-------------------------|----|----|----|----|----------|
| 52    | 10/07/16 | The Department of Homeland Security announced that the Russian Government directed the recent compromises of e-mails from US persons and institutions, including from US political organizations. They hacked email systems belonging to the Democratic National Committee (DNC) and the chair of Hillary Clinton’s campaign, John Podesta. Wikileaks published its first trove of hacked emails from Clinton’s campaign chairman John Podesta on Friday Oct. 7 and since then, several batches of Podesta emails were released almost daily. | The Atlantic     | USA     | -     | -        | Russian interference   | 1  | 1  | 1  | 0  | 0.75     |
| 53    | 10/07/16 | The Washington Post released a video from 2005 in which Trump makes lewd comments about women. | ABC News         | USA     | -     | -        | Political corruption   | 1  | 1  | 1  | 1  |          |
| 54    | 10/08/16 | The second presidential debate took place. | ABC News         | USA     | DC     | Washington DC | Elections               | 0  | 0  | 1  | 0  | 0.25     |
| 55    | 10/09/16 | The final presidential debate took place. | ABC News         | USA     | DC     | Washington DC | Elections               | 0  | 0  | 1  | 0  | 0.25     |
| 56    | 10/19/16 | The FBI reviewed emails that appear to be pertinent to the investigation of Clinton’s private email server, which was closed in July. | ABC News         | USA     | -     | -        | Political corruption   | 1  | 0  | 0  | 1  | 0.5      |
| 57    | 10/28/16 | The FBI reviewed emails that appear to be pertinent to the investigation of Clinton’s private email server, which was closed in July. | Council on Foreign Relations | USA     | -     | -        | Elections               | 1  | 1  | 1  | 1  |          |
| 58    | 11/08/16 | Trump is elected as President of the United States. | | | | | | | | | |
| 59    | 12/15/16 | Facebook announces a plan to curb fake news after months of pressure from the public opinion. | CBS News         | USA     | -     | -        | Russian interference   | 1  | 0  | 0  | 0  | 0.25     |
| 60    | 01/20/17 | Trump officially begins his mandate as 45th president of the United States. | ABC News         | USA     | DC     | Washington DC | Elections               | 1  | 1  | 1  | 1  |          |
| 61    | 01/21/17 | Thousands of people descended in Washington D.C. for the Women’s March to challenge President Trump. Trump signed an executive order that promised to ban the access to the U.S to people coming from 7 Muslim-majority countries, Iraq, Iran, Libya, Somalia, Sudan, Syria and Yemen, for 90 days. | CBS News         | USA     | DC     | Washington DC | Politics                | 1  | 1  | 1  | 1  |          |
| 62    | 01/27/17 | The FBI reviewed emails that appear to be pertinent to the investigation of Clinton’s private email server, which was closed in July. | CBS News         | USA     | DC     | Washington DC | Immigration             | 1  | 1  | 1  | 1  |          |
| 63    | 02/13/17 | Michael Flynn, Trump’s national security adviser, resigns. | New York Times   | USA     | DC     | Washington DC | Politics                | 1  | 1  | 1  | 1  |          |
| 64    | 03/20/17 | James Comey confirms the Bureau is investigating on Russian interferences in 2016 US elections. | New York Times   | USA     | DC     | Washington DC | Russian interference   | 1  | 1  | 1  | 1  |          |
| 65    | 05/09/17 | Trump fires F.B.I Director James Comey. | New York Times   | USA     | DC     | Washington DC | Politics                | 1  | 1  | 1  | 1  |          |
| 66    | 05/17/17 | The Justice Department appointed former FBI director Robert Mueller as special counsel in the investigation over the Russian interference in 2016 elections. | New York Times   | USA     | DC     | Washington DC | Russian interference   | 1  | 0  | 1  | 0  | 0.75     |
| 67    | 06/01/17 | Trump announces that the US will withdraw from the Paris Agreement on climate change. | CNBC              | USA     | DC     | Washington DC | Foreign Relations       | 1  | 1  | 1  | 1  |          |
| 68    | 06/12/17 | The Senate blocked a Republican attempt to repeal the Obamacare. | CNBC              | USA     | DC     | Washington DC | Politics                | 0  | 1  | 1  | 1  | 0.75     |
| 69    | 07/12/17 | Trump declares the opioid crisis a national emergency. | CNBC              | USA     | DC     | Washington DC | Politics                | 0  | 0  | 0  | 0  |          |
| Index | Date     | Event description                                                                                                                                                                                                                                                                                                                                 | Source          | Country   | State | City          | Category                  | R1 | R2 | R3 | R4 | Overall |
|-------|----------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------|-----------|-------|---------------|----------------------------|----|----|----|----|---------|
| 70    | 07/27/17 | A violent protest organized by a group of Neo Nazi and white supremacists took place in Charlottesville, Virginia. During the clashes with anti fascist groups, a white supremacist drove a car into the crowd, killing a peaceful protester named Heather Heyer.                                                                 | CBS News        | USA       | VA    | Charlottesville | Racism                     | 1  | 1  | 1  | 1  | 1       |
| 71    | 08/12/17 | Trump’s chief strategy Steve Bannon was fired by the president. North Korea announced to have successfully tested a hydrogen bomb that could be loaded on to a long-range missile, threatening the US. Stephen Paddock, a 64-year old retiree with no known terrorist affiliation, killed at least 59 people at a musical festival in Las Vegas, in the deadliest mass shooting of the US history. The New York Times publishes an article reporting years of allegations of sexual harassment against Harvey Weinstein. Trump threatens to withdraw from the Iran Nuclear Deal if Congress and U.S. allies do not get to an agreement proposed by his administration. | CNN USA        | USA       | VA    | Washington DC | Politics                    | 1  | 0  | 1  | 0  | 0.5     |
| 72    | 08/18/17 | North Korea announced to have successfully tested a hydrogen bomb that could be loaded on to a long-range missile, threatening the US. Stephen Paddock, a 64-year old retiree with no known terrorist affiliation, killed at least 59 people at a musical festival in Las Vegas, in the deadliest mass shooting of the US history. The New York Times publishes an article reporting years of allegations of sexual harassment against Harvey Weinstein. Trump threatens to withdraw from the Iran Nuclear Deal if Congress and U.S. allies do not get to an agreement proposed by his administration. | BBC News       | North Korea | -     | -               | Foreign Relations               | 1  | 1  | 0  | 0  | 0.5     |
| 73    | 09/03/17 | Sayfullo Saipov, a terrorist, rented a pickup truck and mowed down pedestrians on a bike path in Lower Manhattan, killing eight and injuring about a dozen more.                                                                                                                                                                                                                      | Washington Post | USA       | NV    | Las Vegas     | Mass shooting                | 1  | 1  | 1  | 1  | 1       |
| 74    | 10/01/17 | An armor-clad shooter (Devin Patrick Kelley) entered a church in Sutherland Spring, Texas, and opened fire, killing 26 parishioners and injuring at least 19 others.                                                                                                                                                                                                                   | BBC News        | USA       | -     | -               | Sexual crimes                | 1  | 1  | 1  | 1  | 1       |
| 75    | 10/05/17 | Secretary of State Rex Tillerson defined the situation in Myanmar an ethnic cleansing. The Pentagon said a North Korean missile traveled about 1,000 kilometers before crashing into the Sea of Japan. Ex- Trump security adviser Michael Flynn pleaded guilty to lying to the FBI, and he started cooperating with FBI in investigating links between Trump campaign and Russia. The New York Times publishes an article reporting years of allegations of sexual harassment against Harvey Weinstein. Trump threatens to withdraw from the Iran Nuclear Deal if Congress and U.S. allies do not get to an agreement proposed by his administration. | CNBC USA       | USA       | DC    | Washington DC | Foreign Relations               | 0  | 0  | 1  | 0  | 0.25    |
| 76    | 10/13/17 | Ex-Trump campaign chair Paul Manafort was indicted of “conspiracy against the United States”. Sen. Al Franken resigns from Senate over sexual misconduct allegations. Trump announces that the US recognizes Jerusalem as Israel’s capital and he is ready to move the American embassy there, risking a huge backlash from the Muslim world. | CNBC USA       | USA       | -     | -               | Russian interference          | 1  | 0  | 1  | 1  | 0.75    |
| 77    | 10/26/17 | A terrorist, rented a pickup truck and mowed down pedestrians on a bike path in Lower Manhattan, killing eight and injuring about a dozen more.                                                                                                                                                                                                                   | CNBC USA       | USA       | NY    | NYC            | Terrorism                   | 1  | 0  | 0  | 1  | 0.5     |
| 78    | 10/30/17 | An armor-clad shooter (Devin Patrick Kelley) entered a church in Sutherland Spring, Texas, and opened fire, killing 26 parishioners and injuring at least 19 others.                                                                                                                                                                                                                   | CNBC USA       | USA       | TX    | San Antonio (Sutherland Springs) | Mass shooting                | 1  | 0  | 1  | 1  | 0.75    |
| 79    | 10/31/17 | The New York Times publishes an article reporting years of allegations of sexual harassment against Harvey Weinstein. Trump threatens to withdraw from the Iran Nuclear Deal if Congress and U.S. allies do not get to an agreement proposed by his administration. | The Guardian    | Myanmar   | -     | -               | Foreign Relations               | 0  | 0  | 0  | 0  | 0       |
| 80    | 11/05/17 | The Pentagon said a North Korean missile traveled about 1,000 kilometers before crashing into the Sea of Japan. Ex-Trump security adviser Michael Flynn pleaded guilty to lying to the FBI, and he started cooperating with FBI in investigating links between Trump campaign and Russia. The New York Times publishes an article reporting years of allegations of sexual harassment against Harvey Weinstein. Trump threatens to withdraw from the Iran Nuclear Deal if Congress and U.S. allies do not get to an agreement proposed by his administration. | CNBC USA       | North Korea | -     | -               | Russian interference          | 1  | 0  | 1  | 0  | 0.5     |
| 81    | 11/22/17 | Rep. John Conyers Jr. resigns over sexual harassment allegations. Trump announces that the US recognizes Jerusalem as Israel’s capital and he is ready to move the American embassy there, risking a huge backlash from the Muslim world. Sen. Al Franken resigns from Senate over sexual misconduct allegations. Trump signed an important tax reform which slashes taxes on corporations and alleviates the burden on most individuals. | WASHINGTON POST | USA       | DC    | Washington DC | Sexual crimes                | 0  | 0  | 1  | 0  | 0.25    |
| 82    | 11/28/17 | Trump announces that the US recognizes Jerusalem as Israel’s capital and he is ready to move the American embassy there, risking a huge backlash from the Muslim world. Sen. Al Franken resigns from Senate over sexual misconduct allegations. Trump signed an important tax reform which slashes taxes on corporations and alleviates the burden on most individuals. | WASHINGTON POST | USA       | DC    | Washington DC | Sexual crimes                | 0  | 0  | 1  | 0  | 0.25    |
| 83    | 12/01/17 | Rep. John Conyers Jr. resigns over sexual harassment allegations. Trump announces that the US recognizes Jerusalem as Israel’s capital and he is ready to move the American embassy there, risking a huge backlash from the Muslim world. Sen. Al Franken resigns from Senate over sexual misconduct allegations. Trump signed an important tax reform which slashes taxes on corporations and alleviates the burden on most individuals. | The Guardian    | USA       | DC    | Washington DC | Sexual crimes                | 0  | 0  | 1  | 0  | 0.25    |
| 84    | 12/05/17 | Nickolas Cruz, a 19-year old former student at Marjory Stoneman Douglas High School in Parkland, Florida, opened fire at the school, killing 17 people.                                                                                                                                                                                                                   | The Guardian    | USA       | DC    | Washington DC | Politics                  | 0  | 1  | 1  | 0  | 0.5     |
| 85    | 12/22/17 | Nickolas Cruz, a 19-year old former student at Marjory Stoneman Douglas High School in Parkland, Florida, opened fire at the school, killing 17 people.                                                                                                                                                                                                                   | CNBC USA       | USA       | DC    | Washington DC | Politics                  | 0  | 1  | 1  | 0  | 0.5     |
| 86    | 01/01/18 | Nickolas Cruz, a 19-year old former student at Marjory Stoneman Douglas High School in Parkland, Florida, opened fire at the school, killing 17 people.                                                                                                                                                                                                                   | CBS News        | USA       | CA    | -               | Politics                  | 0  | 0  | 0  | 0  | 0       |
| 87    | 02/10/18 | Nickolas Cruz, a 19-year old former student at Marjory Stoneman Douglas High School in Parkland, Florida, opened fire at the school, killing 17 people.                                                                                                                                                                                                                   | CBS News        | USA       | FL    | Parkland     | Mass shooting                | 1  | 1  | 1  | 1  | 1       |
| Index | Date   | Event description                                                                                                                                                                                                                                                                                                                                                                                                                                                                 | Source      | Country | State | City       | Category                  | R1 | R2 | R3 | R4 | Overall |
|-------|--------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------|---------|-------|------------|---------------------------|----|----|----|----|---------|
| 88    | 02/14/18 | Thousands of protesters gathered in Washington for the "March of Our Lives," to voice in favor of stricter gun control.                                                                                                                                                                                                                                                                                                                                 | CBS News    | USA     | DC    | Washington DC | Politics                  | 1  | 1  | 1  | 0  | 0.75    |
| 89    | 03/24/18 | Stormy Daniels, a famous porn star, released a 60 minute interview to CBS News talking about her affair with president Trump.                                                                                                                                                                                                                                                                                                                                 | CBS News    | USA     | -     | -          | Scandal                   | 1  | 1  | 1  | 1  | 1       |
| 90    | 03/25/18 | Attorney General Jeff Sessions announces a new 'zero tolerance' policy for criminal illegal entry along the Southwest border. Mark Zuckerberg appeared before Congress to apologize for the shortcomings of Facebook in protecting users' data in the wake of the Cambridge Analytica scandal and Russian interference in 2016 elections. | Washington Post | USA     | -     | -          | Immigration               | 0  | 0  | 0  | 0  | 0       |
| 91    | 06/04/18 | Trump announces the decision to pull out from the Iran Nuclear Deal (JCPOA).                                                                                                                                                                                                                                                                                                                                                                                                                                                                 | CBS News    | USA     | DC    | Washington DC | Russian interference     | 1  | 0  | 1  | 0  | 0.5     |
| 92    | 06/10/18 | Trump meets Kim Jong Un in a historical summit in Singapore, marking the first meeting in history between a sitting president of the US and a North Korean leader. Trump announces he is nominating Judge Brett Kavanaugh to the Supreme Court, replacing the retiring Judge Anthony Kennedy. | CBS News    | USA     | DC    | Washington DC | Foreign Relations         | 1  | 1  | 1  | 1  | 1       |
| 93    | 06/11/18 | Trump announces he is nominating Judge Brett Kavanaugh to the Supreme Court, replacing the retiring Judge Anthony Kennedy.                                                                                                                                                                                                                                                                                                                                 | CNN         | Singapore | -     | -          | Foreign Relations         | 1  | 1  | 0  | 0  | 0.75    |
| 94    | 06/12/18 | Protesters in Parliament Square, London, gathered during a demonstration against Trump's visit to the UK. Dr. Christine Blasey Ford concluded a testimony before the Senate Judiciary Committee about her allegation of sexual assault against Supreme Court Judge Brett Kavanaugh when they were in high school. | Financial Times | UK      | -     | London     | Politics                  | 0  | 0  | 0  | 0  | 0       |
| 95    | 08/05/18 | US Supreme Court nominee Brett Kavanaugh testifies before a Senate committee during his confirmation hearing. Washington Post journalist Jamal Khashoggi was murder in the Saudi Arabia's embassy in Istanbul. He was a convinced critic of the Saudi regime. | Financial Times | USA     | DC    | Washington DC | Sexual crimes             | 1  | 1  | 1  | 1  | 1       |
| 96    | 08/11/18 | Supreme Court Judge Brett Kavanaugh was confirmed to the court with a largely divided Senate vote (50-48).                                                                                                                                                                                                                                                                                                                                                       | Financial Times | USA     | DC    | Washington DC | Sexual crimes             | 1  | 1  | 1  | 1  | 1       |
| 97    | 09/11/18 | A gunman (Robert Bowers) opened fire in a synagogue in Pittsburgh, killing 11 people and injuring 6 others. In the midterm elections, Democrats took control of the House, while Republicans were able to maintain the control of the Senate. | Financial Times | USA     | PA    | Pittsburgh   | Mass shooting             | 1  | 1  | 1  | 1  | 1       |
| 98    | 09/27/18 | A gunman (Ian David Long) opened fire at a bar in Southern California, killing 12 people. Senators Mike Lee, Bernie Sanders, and Chris Murphy proposed to withdraw U.S. forces which are supporting the Saudi-led coalition in Yemen as a response to the murder of journalist Jamal Khashoggi. | Financial Times | USA     | -     | -          | Politics                  | 0  | 1  | 1  | 1  | 0.75    |
| 99    | 09/27/18 | A massive wildfire ("Camp Fire") broke out in California, destroying the town of Paradise and killing 88 people.                                                                                                                                                                                                                                                                                                                                                       | Financial Times | USA     | CA    | Paradise     | Natural disaster          | 0  | 1  | 1  | 0  | 0.5     |
| 100   | 10/04/18 | A gunman (Ian David Long) opened fire at a bar in Southern California, killing 12 people. Senators Mike Lee, Bernie Sanders, and Chris Murphy proposed to withdraw U.S. forces which are supporting the Saudi-led coalition in Yemen as a response to the murder of journalist Jamal Khashoggi. | Financial Times | USA     | CA    | Thousand Oaks | Mass shooting             | 0  | 1  | 0  | 1  | 0.5     |
| 101   | 10/07/18 | The government partially shut down after the House and the Senate fail to pass a spending bill.                                                                                                                                                                                                                                                                                                                                                                                                                   | Financial Times | USA     | DC    | Washington DC | Politics                  | 0  | 1  | 1  | 1  | 0.75    |
| 102   | 10/27/18 | The government partially shut down after the House and the Senate fail to pass a spending bill.                                                                                                                                                                                                                                                                                                                                                                                                                   | Financial Times | USA     | CA    | Paradise     | Natural disaster          | 0  | 1  | 1  | 0  | 0.5     |
| 103   | 12/06/18 | The government partially shut down after the House and the Senate fail to pass a spending bill.                                                                                                                                                                                                                                                                                                                                                                                                                   | Financial Times | USA     | CA    | Thousand Oaks | Mass shooting             | 0  | 1  | 0  | 1  | 0.5     |
| 104   | 12/07/18 | The government partially shut down after the House and the Senate fail to pass a spending bill.                                                                                                                                                                                                                                                                                                                                                                                                                   | Financial Times | USA     | DC    | Washington DC | Politics                  | 0  | 1  | 1  | 1  | 0.75    |
S6 Features Extracted from Twitter Data

This section presents list of features (i.e. predictors) extracted from each post-URL pair for Twitter influence operations.

Table S3: List of Features Extracted from Each Tweet-URL pair.

| Category     | Feature Description                                                                 | Count |
|--------------|--------------------------------------------------------------------------------------|-------|
| Content      | Word count/average word density of a tweet/URL                                       | 4     |
|              | Character count of a tweet/URL/domain                                                 | 3     |
|              | Topic of a tweet (training LDA on whole training data)                                | 100   |
|              | Upper case count of a tweet/URL                                                       | 2     |
|              | Number of hashtag/URL/sentence/syllable/punctuation                                   | 5     |
|              | Count and Proportion of Part of Speech (POS) count                                    | 10    |
|              | Readability Scores of a tweet                                                         | 7     |
|              | Number of sub-directories of a URL                                                    | 1     |
|              | Positive and Negative emotion scores of a tweet/URL                                   | 4     |
|              | Anxiety and Anger score of a tweet/URL                                                | 4     |
|              | Certainty/Differentiation/Subjectivity scores of a tweet/URL                          | 6     |
|              | Informal/swear/netspeak/nonfluent score of a tweet/URL                                | 8     |
|              | Personal pronouns/1st pers singular/1st pers plural scores of a tweet/URL              | 6     |
|              | Total number of emoticons in a tweet                                                  | 1     |
|              | Time orientations/past focus/present focus/future focus of a tweet/URL                | 8     |
|              | Polarity score of a tweet/URL                                                         | 8     |
|              | Risk/reward/power scores of a tweet/URL                                              | 6     |
| Meta-Content | Number and ratio of top 25/50 words written by trolls                                 | 4     |
|              | Top 100 words used by trolls                                                         | 100   |
|              | Number and ratio of top 3/5/10/25 hashtags written by trolls                         | 8     |
|              | Top 100 hashtags used by trolls                                                      | 100   |
|              | Number and ratio of top 3/5/10/25 bigrams written by trolls                          | 8     |
|              | Top 100 bigrams written by trolls                                                     | 100   |
|              | Number and ratio of top 3/5/10/25 far-left, left, left-center, center, right-center, right, far-right, local, national, political, and opensourse words written by trolls | 88    |
|              | Number and ratio of top 3/5/10/25 far-left, left, left-center, center, right-center, right, far-right, local, national, political, and opensourse hashtags written by trolls | 88    |
Number and ratio of top 3/5/10/25 far-left, left, left-center, center, right-center, right, far-right, local, national, political, and opensource bigrams written by trolls

Top 25 users mentioned by trolls

Is it a news, political, link-aggregator, contact-page, commercial, adult, sport, or non-US audience website? (For definition and methodology of creating these categories of website see: https://www.pewresearch.org/internet/2018/04/09/bots-in-the-twittersphere-methodology/)

Is it a local or national news website? (See Table 2-3 in [41] for a full list of national and local news websites respectively.)

Is it a left, right, far-left, far-right, or centrist website? (We obtained list of websites in each category by consulting https://mediabiasfactcheck.com/)

Is it an opensource.co (fake news) website? (See https://github.com/several27/FakeNewsCorpus)

Is it a social media or youtube link?

Is it an image-sharing or video-hosting website? (For a list of image sharing websites see: https://en.wikipedia.org/wiki/List_of_image-sharing_websites. For a list of video hosting services see: https://en.wikipedia.org/wiki/List_of_video_hosting_services)

Number of unique URLs/URL domains in a tweet

Is the URL shortened?

Is it a news website?

Is it among the top 25/50 domains shared by trolls?

Top 25 domains shared by trolls

Is it among the top 5/10/25/50 political/local/national websites shared by trolls?

Top 25 political/local/national news websites used by trolls

Is it among the top 5/10/25/50 opensource.co websites shared by trolls?

Is it among the top 3/5/10/25 left/far-left centerX/right/far-right websites shared by trolls?

Top 25 left/far-left-center/right/far-right websites shared by trolls

Is it among the top 3/5 URL-shortener websites shared by trolls?

Is it among the top 3/5/10/20 local news websites in swing states shared by trolls?

Is it among the local news in swing states websites?

Is it among the top 3/5/10 contact-page/link-aggregator websites used by trolls?
| Top 10 contact-page/link-aggregator websites used by trolls | 20 |
|----------------------------------------------------------|----|
| **User** | **Timing** | **User** | **Timing** |
| Days since the creation of account | 1 |
| Days since the creation of account power by 2 | 1 |
| Whether days since creation of account is less than 7/30/90 days | 3 |
| Whether account creation date is in 2009-2018 | 10 |
| Whether account creation date is before 2013-2017 | 5 |
| Whether account creation date is in first/second half of 2013-2017 | 10 |
| **Content** | **Timing** | **Content** | **Timing** |
| Whether tweet time in within US/Russia working hour | 2 |
| Whether tweet published on Sunday through Saturday in US/Russia time | 14 |
| Whether tweet published on US/Russia weekend | 2 |
| Time of day during which a tweet is posted | 7 |
| **Network** | **Weighted degree of hashtags contained in a tweet in the co-occurring and co-shared hashtags networks of trolls (For each feature, we compute and use the following statistics: min, max, mean, median, std, kurtosis, skewness, entropy, pagerank, eigenvector, and betweenness.)** | 22 |
| **Weighted degree of URLs contained in a tweet in the co-occurring and co-shared URL networks of trolls (For each feature, we compute and use the following statistics: min, max, mean, median, std, kurtosis, skewness, entropy, pagerank, eigenvector, and betweenness.)** | 22 |
| **Weighted degree of mentioned users in a tweet in the co-occurring and co-shared mentions networks of trolls (For each feature, we compute and use the following statistics: min, max, mean, median, std, kurtosis, skewness, entropy, pagerank, eigenvector, and betweenness.)** | 22 |
| **Weights between hashtags contained in a tweet in the co-occurring and co-shared hashtag networks of trolls (For each feature, we compute and use the following statistics: min, max, mean, median, std, kurtosis, skewness, and entropy.)** | 16 |
| **Weights between URL contained in a tweet in the co-occurring and co-shared URL domain networks of trolls (For each feature, we compute and use the following statistics: min, max, mean, median, std, kurtosis, skewness, and entropy.)** | 16 |
| **Weights between mentioned users contained in a tweet in the co-occurring and co-shared mentions networks of trolls (For each feature, we compute and use the following statistics: min, max, mean, median, std, kurtosis, skewness, and entropy.)** | 16 |
| **Total** | **1,300** |
S7  Features Extracted from Reddit Data

This section presents list of features (i.e. predictors) extracted from each post-URL pair for Reddit influence operations.

Table S4: List of Features Extracted from Each Reddit Post-URL pair.

| Category       | Feature Description                                                                 | Count |
|---------------|-------------------------------------------------------------------------------------|-------|
| Content       | Word count of a title/URL                                                           | 2     |
|               | Character count of a title/URL/domain                                                | 3     |
|               | Average word density of a title/URL                                                 | 2     |
|               | Topic of a Reddit title (training LDA on whole training data)                       | 100   |
|               | Number of punctuation/sentences of a title                                          | 2     |
|               | Number of syllables and upper cases in a title/URL                                  | 4     |
|               | Number and proportion of Part of Speech (POS) in a title                            | 10    |
|               | Readability Scores of a title                                                       | 7     |
|               | Number of sub-directories of a URL                                                  | 1     |
|               | Positive and Negative emotion scores of a title/URL                                 | 4     |
|               | Anxiety and Anger score of a title/URL                                              | 4     |
|               | Certainty and Differentiation scores of a title/URL                                 | 4     |
|               | Subjectivity score of a title/URL                                                   | 2     |
|               | Informal/swear/netspeak/nonfluent score of a title/URL                              | 8     |
|               | Personal pronouns/1st pers singular/1st pers plural scores of a title/URL            | 6     |
|               | Total number of emoticons in a title                                                | 1     |
|               | Time orientations/past focus/present focus/future focus of a title/URL              | 8     |
|               | Polarity score of a title/URL                                                       | 8     |
|               | Risk/reward/power scores of a title/URL                                             | 6     |
| Meta-Content  | Number and ratio of top 25/50 words written by trolls                               | 4     |
|               | Top 100 words used by trolls                                                        | 100   |
|               | Number and ratio of top 3/5/10/25 bigrams written by trolls                         | 8     |
|               | Top 100 bigrams written by trolls                                                   | 100   |
|               | Number and ratio of top 3/5/10/25 far-left, left, left-center, center, right-center, right, far-right, local, national, political, and opensource words written by trolls | 88    |
|               | Number and ratio of top 3/5/10/25 far-left, left, left-center, center, right-center, right, far-right, local, national, political, and opensource bigrams written by trolls | 88    |
|               | Is it a news/political/link-aggregator website?                                     | 3     |
| Feature                                                                 | Frequency |
|------------------------------------------------------------------------|-----------|
| Is it a local/national news website?                                   | 2         |
| Is it a contact-page/commercial/adult/sport website?                   | 4         |
| Is it a non-US audience website?                                       | 1         |
| Is it a left/right/far-left/far-right/centrist website?                | 5         |
| Is it an opensource.co (fake news) website?                            | 1         |
| Is it a social media/youtube link?                                    | 2         |
| Is it an image-sharing/video-hosting website?                          | 2         |
| Number of unique URLs/URL domains in a post                           | 2         |
| Is the URL shortened?                                                  | 1         |
| Is it a news website?                                                  | 1         |
| Is it among the top 25/50 domains shared by trolls?                    | 2         |
| Top 25 domains shared by trolls                                        | 25        |
| Is it among the top 5/10/25/50 political/local/national websites shared by trolls? | 12     |
| Top 25 political/local/national news websites used by trolls           | 75        |
| Is it among the top 5/10/25/50 opensource.co websites shared by trolls? | 4         |
| Is it among the top 3/5/10/25 left/far-left:center/right/far-right websites shared by trolls? | 20       |
| Top 25 left/far-left:center/right/far-right websites shared by trolls | 125       |
| Is it among the top 3/5 URL-shortener websites shared by trolls?       | 2         |
| Is it among the top 3/5/10/20 local news websites in swing states shared by trolls? | 4         |
| Is it among the local news in swing states websites?                   | 1         |
| Is it among the top 3/5/10 contact-page/link-aggregator websites used by trolls? | 6         |
| Top 10 contact-page/link-aggregator websites used by trolls            | 20        |
| User Timing                                                            | 1         |
| Days since the creation of account                                     |           |
| Days since the creation of account power by 2                          | 1         |
| Whether days since creation of account is less than 7/30/90 days       | 1         |
| Whether account creation date is in 2009-2018                          | 10        |
| Whether account creation date is before 2013-2017                      | 5         |
| Whether account creation date is in first/second half of 2013-2017     | 5         |
| Content Timing                                                         | 1         |
| Whether posting time in within US working hour                         |           |
| Whether posting time in within Russia working hour                     | 1         |
| Whether posting time is on Sunday through Saturday in US/Russia calendar | 14        |
| Whether posting time is on US/Russia weekend                           | 2         |
| Time of day during which a Reddit post is published                    | 7         |
| Network | Weighted degree of URLs contained in a tweet in the co-occurring and co-shared URL networks of trolls (For each feature, we compute and use the following statistics: min, max, mean, median, std, kurtosis, skewness, entropy, pagerank, eigenvector, and betweenness.) | 22 |
| Weighted degree of URLs contained in a tweet in the co-occurring and co-shared URL domain networks of trolls (For each feature, we compute and use the following statistics: min, max, mean, median, std, kurtosis, skewness, and entropy.) | 16 |
| **Total** | 986 |
Table S5: Summary of important features across influence operations.

| Operation  | Top 10 Most Frequent Top Monthly Important Features (In Frequency Order) |
|------------|------------------------------------------------------------------------|
| China      | Top users mentioned by trolls, Days since creation, Top users mentioned by trolls in tweets with a political URL, Top users mentioned by trolls in tweets with a local news URL, Top words used by trolls, Whether account created before 2013, Ratio of stop words, Top bigrams used by trolls, Whether account created before 2016, Readability score. |
| Russia     | Days since creation, Top users mentioned by troll, Account creation date before 2013, Being retweet, Number of mentioned users in a tweet, Top hashtags used by trolls, Account creation date in first half of 2015, Top users mentioned by trolls in tweets with a political URL, Top users mentioned by trolls in tweets with a far-right URL, Top users mentioned by trolls in tweets with a fake news URL. |
| Russia     | Top bigrams used by trolls, Top words used by trolls, Account creation year, Days since creation, Top URL domains shared by trolls, Length of URL, Top alt-media subreddits targeted by trolls, Top subreddits targeted by trolls, Whether domain is `imgur.com`, Top conspiracy websites shared by troll. |
| Venezuela  | Top users mentioned by trolls in tweets with a political URL, Top users mentioned by trolls, Top URL domains shared by trolls, Days since creation, Account creation date before 2015, Top users mentioned by trolls in tweets with a far-right URL, Account creation date in second half of 2017, Length of URL, Whether domain is `trumpservativenews.club`. |
S9 Evaluating Detection Performance by Varying Predictor Sets

We compare predicting performance of models trained on various sets of predictors to measure the relative contribution of each. The baseline model is a classifier trained only on content-based predictors (Model 1). Then we include meta-content features in Model 2. Next we add content and user timing features in Model 3 and 4 respectively. Finally, in last column we add network features (Model 5).

Table S6: Prediction Performance with Varying Predictor Sets.

| Model Number | Experiments                        | Only Content | (1)+ Meta Content | (2)+ Content Timing | (3)+ User Timing | (4)+ Network |
|--------------|-----------------------------------|--------------|-------------------|--------------------|-----------------|--------------|
|              | China                             | (1)          | (2)               | (3)                | (4)             | (5)          |
| Within-Month Train/Test |                      | 0.69         | 0.88              | 0.88               | 0.89            | 0.88         |
| Train on $t - 1$ Test on $t^a$ |                        | 0.83         | 0.93              | 0.93               | NA$^b$          | 0.94         |
| Train on $t - 1$ Test on New Users in $t$ |                    | 0.67         | 0.88              | 0.88               | 0.89            | 0.89         |
| Reddit       |                                   |              |                   |                    |                 |              |
| Within-Month Train/Test |                      | 0.68         | 0.80              | 0.80               | 0.82            | 0.82         |
| Train on $t - 1$ Test on $t^a$ |                        | 0.63         | 0.82              | 0.82               | NA$^b$          | 0.81         |
| Train on $t - 1$ Test on New Users in $t$ |                    | 0.67         | 0.71              | 0.71               | 0.74            | 0.74         |
| Venezuela    |                                   |              |                   |                    |                 |              |
| Within-Month Train/Test |                      | 0.97         | 0.98              | 0.98               | 0.99            | 0.99         |
| Train on $t - 1$ Test on $t^a$ |                        | 0.93         | 0.99              | 0.99               | NA$^b$          | 0.96         |
| Train on $t - 1$ Test on New Users in $t$ |                    | 0.84         | 0.87              | 0.86               | 0.92            | 0.91         |
| Within-Month Cross-Release |                   | 0.59         | 0.53              | 0.53               | 0.49            | 0.49         |

$^a$ All user-level identifiers are removed for this test.

$^b$ Not Applicable.
S10 Supplementary Results for Russian IRA Influence Operation on Twitter

S10.1 Types of Users Mentioned by IRA Trolls

To better characterize how Russian IRA trolls were utilizing the mentioning tactic, we collected a list of congress members, cabinet members, US presidential candidates, political journalists, newspapers, and US extremist organizations on Twitter and plot the share of IRA tweets associated with each of these categories in Fig S6. The plots show consistent mentioning of these 6 groups of users in IRA tweets without any considerable changes until late 2017.

Figure S6: Timeline of IRA trolls mentioned users’ types. (a) Share of tweets mentioning members of the congress and cabinet and US 2016 presidential candidates. (b) Share of tweets mentioning US political journalists, US newspapers, and US extremists organizations and individuals.
Figure S7: Descriptive plots for Russian IRA’s influence operation on Twitter.
S10.3 Varying Train and Test Periods

Intuitively, we would expect that testing on a shorter period of data would lead to higher performance. To show this, we use the Russian Twitter data and train classifiers on month $t - 1$ and on test on new users in the next week. For months with 1,000 or greater number of troll posts, we achieve average weekly F1 score of 0.85. Originally we trained our classifiers on one month of trolling activity within a give influence operation. We do not claim that the one month training window is the optimal scenario. However, to show that training on a longer period does not necessarily leads to better prediction performance, we use the Russian Twitter data and train classifiers on $t - 3$ through $t - 1$ and predict on $t$.

![Graph showing prediction performance with varying train/test periods.](image)

(a)

(b)

Figure S8: Prediction performance when varying train/test periods. (a) While we obtained average monthly F1 score of 0.81, the average weekly scores is 0.85 for months with more 1000 positive data points in test set. (b) Comparing training on previous three months and previous one month and testing on current month. Results show that training on longer period does not necessarily yield better.
S11  Train and Test Against Various Control Users

We used a combination of random and politically-engaged American Twitter users as the control users (i.e. negative class). To measure how distinctive the activity of trolls is from each of the random and politically-engaged users, we compare performance of separate classifiers trained and tested against only random and politically-engaged users respectively.

Table S7: Prediction Performance with Various Control Users.

| Country       | Task 1       | Task 2       | Task 3       | Task 4       | Task 5       |
|---------------|--------------|--------------|--------------|--------------|--------------|
|               | Train/Test Against | Train/Test Against | Train/Test Against | Train/Test Against |
|               | Random Users  | Political Users | Both          | Twitter      | Reddit       |
| China         | 0.89 (0.07)   | 0.90 (0.08)   | 0.88 (0.08)   |              |              |
| Russia        | 0.90 (0.10)   | 0.85 (0.13)   | 0.85 (0.13)   |              |              |
| China         | 0.93 (0.04)   | 0.94 (0.03)   | 0.93 (0.04)   |              |              |
| Russia        | 0.88 (0.11)   | 0.81 (0.13)   | 0.81 (0.13)   |              |              |
| China         | 0.91 (0.09)   | 0.89 (0.12)   | 0.89 (0.12)   |              |              |
| Russia        | 0.88 (0.11)   | 0.82 (0.13)   | 0.81 (0.13)   |              |              |
| Russia        | 0.88 (0.06)   | 0.77 (0.12)   | 0.75 (0.11)   |              |              |
| Russia (Train on Twitter) | 0.70 (0.02)   | 0.63 (0.02)   | 0.68 (0.03)   |              |              |
| Russia (Train on Reddit) | 0.36 (0.05)   | 0.29 (0.04)   | 0.37 (0.03)   |              |              |
Figure S9: Russian Trolls Activity on Reddit (a) Monthly activity of IRA trolls. (b) Variations in selected subreddit categories targeted by IRA trolls overtime. Russian trolls activity had 3 phases: (1) *Karma farming*: between Jul-Nov 2015 trolls were increasingly posting in popular culture subreddits; (2) *Inactivity*: between Dec 2015 and Mar 2016, the troll activity decreased to few dozens of post in each month; and (3) *Political Engagement*: between Apr-Oct 2016, troll increased their activity again by posting mostly political content (See https://www.reddit.com/r/ListOfSubreddits/wiki/listofsubreddits for categories of subreddits.)
Figure S10: Descriptive plots for Venezuela’s operation on Twitter. Trolls barely used hashtags (a), retweeted other users (b), or mentioned other users (c). However, they almost always shared a link to a website (d). 95% of retweets were from the troll account named @TrumpNewsz (e). Most of the websites shared by trolls were either fake or a non-mainstream URL shortener.
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