Predicting the Topical Stance of Media and Popular Twitter Users

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Abstract. Controversial social and political issues of the day spur people to express their opinion on social networks, often sharing links to online media articles and reposting statements from prominent members of the platforms. Discovering the stances of people and entire media on current, debatable topics is important for social statisticians and policy makers. Many supervised solutions exist for determining viewpoints, but manually annotating training data is costly. In this paper, we propose a method that uses unsupervised learning and is able to characterize both the general political leaning of online media and popular Twitter users, as well as their stances with respect to controversial topics, by leveraging on the retweet behaviour of users. We evaluate the model by comparing its bias predictions to gold labels from the Media Bias/Fact Check website, and we further perform manual analysis.

Keywords: Stance Detection · Political Polarization.

1 Introduction

Online media and popular Twitter users, which we will collectively refer to as “influencers”, often have overt political leanings, which can be gleaned from their positions on a variety of political and cultural issues. Determining their leaning can be done through the analysis of their writing, which includes the identification of terms and arguments that are indicative of stance [17,16]. Performing such analysis automatically may be done using supervised classification, which in turn would require manually labeled data [17,10,23]. Alternatively, leanings can be inferred based on who shares the content (blogs, tweets, posts, etc.) on social media, as social media users typically share content that agrees with their positions [12,23,28,31]. In this paper, we make use of this to characterize influencers, based on the stances of the Twitter users that share their content. We apply unsupervised stance detection to tag automatically a large number of Twitter users with their positions on specific topics. The tagging identifies small cliques of vocal users based on the accounts that they retweet. Then, we use the users in these cliques to train a supervised classifier to tag a large number of users [13]. Once we have expanded our sets of tagged users, we determine which sources are most associated with each group based sharing by each group.
We apply this methodology to determine the positions of influencers on eight polarizing topics along with their overall leaning (right vs. left). In doing so, we can also observe the sharing behavior of right- and left-leaning users, and we can correlate their behavior with the credibility of sources. The contributions of this paper are as follows:

− We use unsupervised stance detection to automatically determine the positions of influencers and to ascertain their overall political leanings.
− We demonstrate the effectiveness of our approach by comparing our automatic labeling against manually labeled newspapers (labels from mediaBiasFactCheck.com) and popular users (manually labeled).
− We report on the overall sharing behavior of right and left-leaning users.

2 Related work

Recent work that attempted to characterize the stances and the ideological leanings of newspapers and Twitter users relied on the observation that users tend to retweet content that is consistent with their world view. This stems from selective exposure, which is a cognitive bias that leads people to avoid the cognitive overload associated with exposure to opposing views and to avoid cognitive dissonance in which people are forced to reconcile between their views and opposing views [24]. Concerning media, Ribeiro et al. [28] exploited the Facebook advertising services to infer the ideological leaning of online media based on the political leanings of Facebook users who consumed them. An et al. [1] used follow relationships to online media on Twitter to ascertain ideological leaning of media and users based on similarity between them. Wong et al. [31] used retweet behavior to infer the ideological leanings of online media sources and popular Twitter accounts. Barberá and Sood [4] used a statistical model based on the follower relationships to media sources and Twitter personalities to estimate their ideological leaning. As for individual users, much recent work focused on stance detection to determine a person’s position on a topic including the deduction of political preferences [2,5,6,15,20,21,22,29,30]. User classification is aided by the tendency of users to form so-called “echo chambers”, where they engage with like-minded users [15,20], and the tendency of users’ beliefs to be persistent over time [5,20,26]. Studies have examined the effectiveness of different features for stance detection, including textual features, such as hashtags, network interactions, such as retweeted accounts and mentions, and profile information, such as user location [5,20,21,30]. Network interaction features, particularly retweeted accounts, were shown to yield better results compared to using textual features [20,31,22]. Trabelsi and Zaïane [29] describe another unsupervised stance detection method that determines the viewpoints of individual comments as well as their authors. It analyzes online forum discussion threads, and therefore assumes a certain structure of the posts. It also assumes that users tend to reply to each others’ comments when they are in disagreement, whereas we assume the opposite in this paper. Their model leverages the posts’ contents, whereas we take advantage only of the retweet behaviour of users.
Multiple methods involving supervised learning were employed for stance detection. Such methods require the availability of an initial set of labeled users, and they use some of the aforementioned features for classification \cite{11,21,25}. Such classification can label users with precision typically ranging between 70% and 90\% \cite{27,25}. Label propagation is a semi-supervised method that starts with a seed list of labeled users and propagates the labels to other users who are similar based on the accounts they follow or retweet \cite{4,5,30}. Though label propagation may label users with high precision (often above 95\%), it tends to label users who have more extreme views, careful manipulation of thresholds if often required, and post checks are needed to ensure the efficacy of propagation. More recent work employs unsupervised stance detection, which involves mapping users into a lower dimensional space based on user-similarity, and then using clustering to find core sets of users representing different stances \cite{13}. This technique was shown to be highly effective with nearly perfect clustering accuracy for polarizing topics, and it requires no manual labeling of users. For these reasons, here we use this technique, and we couple it with supervised classification based on retweets in order to increase the number of labeled users \cite{10}. Other methods for user stance detection include collective classification \cite{14}, where users in a network are jointly labeled, and classification in a low-dimensional user-space \cite{12}.

3 Data Collection

We collected data on eight topics that are considered polarizing in the USA, shown in Table 1. They include a mix of long-standing issues such as racism and gun control, temporal issues such as the nomination of Judge Brett Kavanaugh to the US Supreme Court and Representative Ilhan Omar’s controversial remarks, and non-political issues such as the benefits/dangers of vaccines. Further, though long-standing issues typically show right–left polarization, stances towards Omar’s remarks are not as clear with pronounced divisions on the left. Since we were interested in US users, we filtered tweets to retain the tweets of users who have stated that their location was in USA. We used a gazetteer that included words that indicate USA as a country (e.g., America, US) and state names along with their abbreviations (e.g., Maryland, MD).

4 Method for stance detection

In order to analyze the stance of influencers on a given topic, we first find the stances of Twitter users, and then we project them to the influencers that the users cite. A central (initial) assumption here is that if a user includes a link to some article in their tweet, they most likely agree or endorse the article’s message. Similarly, when a user retweets a tweet, they most likely agree with that tweet. We label a large number of users with their stance for each topic using a two-step approach, namely projection and clustering and supervised classification. For the projection and clustering step, we identify cliques of core vocal users using the unsupervised method described in \cite{13}.
Table 1. Controversial topics used in study.

| Topic                                | Keywords                                                                 | Date Range          | No. of Tweets |
|--------------------------------------|--------------------------------------------------------------------------|---------------------|---------------|
| Climate change                       | #greendeal, #environment, #climate, #climatechange, #carbonfootprint,    | Feb 25–Mar 4, 2019 | 1,284,902     |
|                                      | #climatehoax, #climategate, #globalwarming, #agw, #renewables            |                     |               |
| Gun control/rights                   | #gun, #guns, #weapon, #2a, #gunviolence, #secondamendment, #shooting,    | Feb 25–Mar 3, 2019 | 1,782,384     |
|                                      | #massshooting, #gunrights, #GunReformNow, #GunControl, #NRA              |                     |               |
| Ilhan Omar remarks on Israel lobby   | IlhanOmarIsATrojanHorse, #IStandWithIlhan, #ilhan, #Antisemitism,       | Mar 1–9, 2019       | 2,556,871     |
|                                      | #IlhanOmar, #IlhanMN, #RemoveIlhanOmar, #Byellhan, #RashidaTlaib, #AIPAC, |                     |               |
|                                      | #EverydayIslamophobia, #Islamophobia, #ilhan                            |                     |               |
| Illegal immigration                  | #border, #immigration, #immigrant, #borderswall, #migrant, #migrants,    | Feb 25–Mar 4, 2019 | 2,341,316     |
|                                      | #illegal, #aliens                                                        |                     |               |
| Midterm                              | midterm, election, elections                                            | Oct 25–27, 2018     | 520,614       |
| Racism & police brutality            | #blacklivesmatter, #bluelivesmatter, #KKK, #racism, #racist, #policebru- | Feb 25–Mar 3, 2019 | 2,564,784     |
|                                      | tality, #excessiveforce, #StandYourGround, #ThinBlueLine               |                     |               |
| Kavanaugh Nomination                 | Kavanaugh, Ford, Supreme, judiciary, Blacey, Grassley, Hatch, Graham,  |                     | 2,322,141     |
|                                      | Cornyn, Lee, Cruz, Sasse, Flake, Crapo, Tillis, Kennedy, Feinstein, Leahy, Durbin, Whitehouse, Klobuchar, Coons, Blumenthal, Hirono, Booker, Harris |                     |               |
| Vaccination benefits & dangers       | #antivax, #vaxxing, #BigPharma, #antivaxxers, #measlesoutbreak, #Antivaccine, | Mar 1–9, 2019       | 301,209       |
|                                      | #VaccinesWork, #vaccine, #vaccines, #Antivaccine, #vaccinesstudy, #antivaxx, #provaxx, #VaccinesSaveLives, #ProVaccine, #VaxxWoke, #mykidmychoice |                     |               |

In this step, users are mapped to a lower dimensional space based on their similarity, and then they are clustered. After performing this unsupervised learning step, we train a supervised classifier using the two largest identified cliques in order to tag many more users. For that, we use fastText, a deep neural network text classifier [19]. Once we have expanded our sets of labeled users, we identify influencers that are most closely associated with each group using a modified version of the so-called “valence score”, which varies in value between -1 and 1.
Table 2. Users per topic: total, clustered using unsupervised stance detection, and automatically labeled using supervised classification

| Topic                  | No. of Users | Clustered Users | Total Classified Users |
|------------------------|--------------|-----------------|------------------------|
| climate change         | 724,470      | 860             | 5,851                  |
| gun control            | 973,206      | 813             | 11,281                 |
| Ilhan Omar             | 563,706      | 723             | 25,484                 |
| immigration            | 940,840      | 901             | 22,456                 |
| midterm elections      | 312,954      | 860             | 12,765                 |
| police brutality & racism | 1,175,081  | 891             | 18,978                 |
| SCOTUS                 | 809,835      | 891             | 10,100                 |
| vaccine                | 194,245      | 545             | 556                    |

If an influencer is being cited evenly between groups, then it would be assigned a valence score close to zero. Conversely, if one group disproportionately cites an influencer compared to another group, then it would be assigned a score closer to -1 and 1. We perform these steps for each of the given topics, and finally we summarize the stances across all topics.

In the following subsections, we explain each of the steps in more detail.

Fig. 1. Top active users on the “midterm” topic: UMAP + Mean Shift.

Projection and Clustering Given the tweets for every topic, we computed the similarity between the top 1,000 most active users. To compute similarity, we constructed a vector for each user containing the number of all the accounts that a user has retweeted, and then we computed the pairwise cosine similarity between them. For example, if user A has only retweeted user B 3 times, user C 5 times and user E 8 times, then user A’s vector would be (0, 3, 5, 0, 8, 0, 0, ... 0). Solely using the retweeted accounts as features has been shown to be effective for stance classification [13,20].
Finally, we perform dimensionality reduction and we form clusters of users using Uniform Manifold Approximation and Projection (UMAP). When performing dimensionality reduction, UMAP places users on a two-dimensional plane such that similar users are placed closer together and dissimilar users are pushed further apart. Figure 1 shows the top users for the “midterm” topic projected with UMAP onto the 2D plane. After the projection, we use Mean Shift to cluster the users as shown in Figure 1. This is the best setup described by Darwish et al. [13]. Clustering high-dimensional data likely produces sub-optimal results, and projection into a lower dimensional space prior to clustering leads to much improved clusters [13].

Supervised Classification Given the clusters of users that we obtained for each topic, we retained the two largest clusters for each topic, and we assigned cluster labels to the users contained therein. Next, we used all the automatically labeled users for each topic to train a supervised classifier using the accounts that each user retweeted as features (same as the features we used to compute user similarity earlier). For classification, we trained a fastText model using the default parameters. FastText is a deep neural network based classifier that has been shown to be effective for text classification [19]. We used the model to classify all other users in our dataset with five or more retweeted accounts, and we only accepted the classification if fastText was more than 80% confident. To obtain a rough estimate of the accuracy of the model, we trained fastText using a random 80% subset of the clustered users for each topic and tested on the remaining 20%. The accuracy was consistently above 95% for all topics. This does not mean that this model can determine stances for all users that accurately — the clustered users were selected to be the most active ones. Rather, it shows that the classifier can successfully capture what the previous, unsupervised step has already learned. Table 2 lists the total number of users who authored the tweets for each topic, the number of users who were automatically clustered using the aforementioned unsupervised clustering technique, and the number of users who were automatically labeled afterwards using supervised classification.

Calculating valence scores Given all the labeled users for each topic, we computed a valence score for each influencer. As mentioned earlier, the valence score ranges between $[-1, 1]$, where a value closer to 1 implies it is strongly associated with one group of users, -1 implies it is strongly associated with the other group of users, and 0 implies that it is being shared or cited by both groups. The original valence score described by Conover et al. [8] is calculated as follows:

$$V(u) = 2 \frac{tf(u, C_0)}{total(C_0)} - 1$$

where $tf(u, C_0)$ is the number of times (term frequency) item $u$ is cited by group $C_0$, and $total(C_0)$ is the sum of the term frequencies of all items cited by $C_0$. $tf(u, C_1)$ and $total(C_1)$ are defined in a similar fashion.
We used the above equation to compute valence scores for the retweeted accounts, but we employed a modified version for calculating the score for the media source \((M)\):

\[
V(M) = 2 \frac{tf(M, C_0)}{total(C_0)} - 1
\]

where

\[
tf(M, C_i) = \sum_{a \in M \cap C_i} \left[ \ln(Cnt(a, C_i)) + 1 \right]
\]

\[
total(C_i) = \sum_{M} tf(M, C_i)
\]

In the latter equation, \(Cnt(a, C_i)\) is the number of times article \(a\) was cited by users from cluster \(C_i\). In essence, we are replacing term frequencies with the natural log of the term frequencies. We opted to modify the equation in order to tackle the following issue: if users from one of the clusters, say \(C_1\), cite only one single article from some media source a large number of times (ex. 2,000 times), while users from the other cluster \((C_0)\) cite 10 other articles from the same media 50 times each, then using equation 1 would result in a valence score of \(-0.6\). We would then regard the given media as having an opposing stance to the stance of users in \(C_0\). Alternatively, using equation 2 would lead to a valence score close to 0. Thus, dampening term frequencies using the natural log has the desired effect of balancing between the number of articles being cited by each group and the total number of citations.

We split the valence scores between -1 and 1 into 5 equal size bands as follows:

\[
Cat(s) = \begin{cases} 
- -, & \text{if } s \in [-1, -0.6) \\
- , & \text{if } s \in [-0.6, -0.2) \\
0, & \text{if } s \in [-0.2, 0.2) \\
+, & \text{if } s \in [0.2, 0.6) \\
++, & \text{if } s \in [0.6, 1] 
\end{cases}
\] (3)

5 Characterizing the Influencers

We used valence to characterize the leaning of all cited influencers for each of the topics. Table 3 shows the valence categories for the top-cited media sources across all topics. It also shows each media’s factuality of reporting, i.e., trustworthiness, and bias (ranging from far-right to far-left) as determined by mediaBiasFactCheck.com. Since the choice of which cluster should be \(C_0\) and which would be \(C_1\) is arbitrary, we can multiply by \(-1\) the valence scores for any topic and the meaning of the results would stay the same. We resorted to doing so for some topics in order to align the extreme valence bands across all topics. Table 5 shows the most frequently cited media source for every topic and for every valence band.
Table 3. Media valences’ categories for each topic with included average column. Factuality: Very High (VH), High (H), Mixed (M), Low (L), Very Low (VL). Bias: Left (L), Left-Center (L-C), Center (C), Right-Center (R-C), Right (R), Far Right (Far R). Blank cells mean that we did not have information.

| media                  | factuality | bias     | Average | climate change | gun control | immigration | midterm | police & racism | SCOTUS | vaccine |
|------------------------|------------|----------|---------|----------------|-------------|-------------|---------|-----------------|--------|---------|
| thehill.com            | H          | L-C      | +       | 0              | ++          | +           | +       | +               | +      | ++      |
| theguardian.com        | H          | L-C      | ++      | +++            | +++         | +++         | +++     | +++             | +++    | ++      |
| washingtonpost.com     | H          | L-C      | +++     | +++            | +++         | +++         | +++     | +++             | +++    | ++      |
| breitbart.com          | VL         | Far R    | -       | -              | -           | -           | -       | -               | -      | -       |
| foxnews.com            | M          | R        | ++      | ++             | +           | ++          | ++      | ++              | ++     | ++      |
| nytimes.com            | H          | L-C      | +++     | ++             | +           | +           | +++     | +++             | ++     | ++      |
| cnn.com                | M          | L        | +       | +              | +           | +           | +       | +               | ++     | ++      |
| apple/news             |            |          | +       | 0              | 0           | 0           | 0       | +               | ++     | ++      |
| dailycaller.com        | M          | R        | --      | --             | --          | --          | --      | --              | --     | --      |
| rawstory.com           | M          | L        | +++     | +++            | +++         | +++         | +++     | +++             | +++    | ++      |
| huffingtonpost.com     | H          | L        | +++     | +++            | +++         | +++         | +++     | +++             | +++    | ++      |
| truepundit.com         | L          |          |         |                |             |             |         |                 |        |         |
| nbcnews.com            | H          | L-C      | +       | -              | +           | +           | +       | +               | +      | +       |
| westernjournal.com     | M          | R        | --      | --             | --          | --          | --      | --              | --     | --      |
| reuters.com            | VH         | C        | +       | +              | +           | +           | +       | +               | +      | +       |
| washingtonexaminer.com | H          | R        | --      | --             | --          | --          | --      | --              | --     | --      |
| thegatewaypundit.com   | VL         | Far R    | --      | --             | --          | --          | --      | --              | --     | --      |
| politico.com           | H          | L-C      | +       | +              | +           | +           | +++     | +++             | ++     | ++      |
| npr.org                | VH         | L-C      | +       | 0              | +++         | 0           | +++     | +++             | ++     | ++      |
| townhall.com           | M          | R        | --      | --             | --          | --          | --      | --              | --     | --      |
| msn.com                | H          | L-C      | +       | +              | +           | 0           | 0       | 0               | 0      | 0       |
| nypost.com             | M          | R-C      | --      | 0              | --          | --          | --      | --              | --     | --      |
| vox.com                | H          | L        | +++     | +++            | +++         | +++         | +++     | +++             | +++    | +++     |
| thedailybeast.com      | H          | L-C      | +++     | +              | +++         | ++          | +       | +               | +      | +       |
| bbc.com                | H          | L-C      | +       | +              | +++         | 0           | +       | +               | +      | +       |
| independent.co.uk      | H          | L-C      | +++     | +              | +++         | +           | +++     | +++             | +++    | +++     |
| ilovemyfreedom.org     | VL         | Far R    | --      | --             | --          | --          | --      | --              | --     | --      |
| thinkprogress.org      | M          | L        | +++     | +++            | +++         | +++         | +++     | +++             | +++    | +++     |
| dailywire.com          | M          | R        | --      | --             | --          | --          | --      | --              | --     | --      |
| pscp.tv                | --         |          | --      | --             | --          | --          | --      | --              | --     | --      |
| dailymail.co.uk        | VL         | R        | --      | --             | 0           | --          | --      | --              | --     | --      |
| msnbc.com              | M          | L        | +++     | +++            | +++         | +++         | +++     | +++             | +++    | +++     |
| dailykos.com           | M          | L        | +++     | +++            | +++         | +++         | +++     | +++             | +++    |
| bloomberg.com          | H          | L-C      | +       | +              | 0           | +++         | +       | +               | +      | +       |
| usatoday.com           | H          | L-C      | +       | +              | 0           | +++         | 0       | +               | 0      | +       |
Of the 5,406 unique media sources that have been cited in tweets across all topics, 806 have known political bias from mediaBiasFactCheck.com. Figure 2 shows the confusion matrix between our valence categories and the labels from mediaBiasFactCheck.com.

We notice that many of the media that have a negative valence score (categories − and −−) are being classified on the right side of the political spectrum by mediaBiasFactCheck.com, while most media with positive scores (categories + and ++) are being classified as slightly left-leaning. Although there are almost no extreme-left cases, there is a correlation between bias and our valence score. mediaBiasFactCheck.com seems to rarely categorize media sources as “extreme-left”. This could be a reflection of reality or it might imply that mediaBiasFactCheck.com has an inherent bias.

We also computed the valence scores for the top 200 retweeted accounts, and we assigned each account a valence category based on the score. Independently, we asked a person who is well-versed with US politics to label all the accounts as either right, left or center. When labeling accounts, right-leaning included those expressing support for Trump, the Republican party, and gun rights, opposition to abortion, and disdain for Democrats. As for left-leaning, they include those attacking Trump and the Republicans, and expressing support for the Democratic party and for Liberal social positions. If the retweeted account in question happens to be a media source, mediaBiasFactCheck.com was used. Table 4 compares the per-topic valence for each retweeted account along with the average category and the independently assigned truth label.
It is noteworthy that all top-200 retweeted accounts have extreme valence categories on average across all topics. All their average valence scores, with one exception, appear between -0.6 and -1.00 for the right, and between 0.6 and 1 for the left (see Figure 3).

Of those manually and independently tagged accounts, all that were tagged as left-leaning have a strong positive valence score and all that were tagged as right-leaning have a strong negative valence score. Only two accounts were manually labeled as “center”, namely Reuters and CSPAN, which is a US channel that broadcasts Federal Government proceedings, and they had valence scores of 0.55 and 0.28, respectively. Though their absolute values are lower than those of all other sources, they are mapped to the + valence category.

Table 3 summarized the valence scores for the media across all topics. Table 5 lists the most cited media sources for each topic and for each of the five valence bands. The order of the bands from top to bottom is: ++, +, 0, –, and −−. The table also includes the credibility and the political leaning tags from mediaBiasFactCheck.com. The key observations from the table as follows:

1. Most right-leaning media appear overwhelmingly in the – and −− valence categories. Conversely, left-leaning media appear in all valence categories, except for the −− category. This implies that left-leaning users cite right-leaning media sparingly, while right-leaning users routinely cite left-leaning media. We looked at some instances where right-leaning users cite left-leaning media, and we found that in many cases the cited articles reinforced a right-leaning viewpoint. For example, right-leaning users shared a video from thehill.com, a left-center site, 2,398 times for the police_racism topic. The video contains a statement defending Trump against charges of racism by Lynne Patton, a long-time African American associate of Trump.3

2. Most right-leaning sources in the −− category have mixed, low, or very low credibility. Conversely, most left-leaning sites appearing in the – valence category have high or very high credibility. Similarly for the vaccine topic, where high credibility sources, such as [http://fda.gov](http://fda.gov) and [http://nih.gov](http://nih.gov), are frequently cited by anti-vaccine users, mostly to support their beliefs.

3. The placements of sources in different categories are relatively stable across topics. For example, [washingtonPost.com](http://washingtonPost.com) and [theguardian.com](http://theguardian.com) exclusively appear in the ++ category, while [breitbart.com](http://breitbart.com) and [foxnews.com](http://foxnews.com) consistently appear in the −− category.

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3 [http://thehill.com/hilltv/rising/431899-lyrne-patton-defends-trump-from-cohen-racism-charge](http://thehill.com/hilltv/rising/431899-lyrne-patton-defends-trump-from-cohen-racism-charge)
Table 4. User valence categories for each topic, preceded by an average column, and a ground truth label. When a cell is blank, there is no data for that particular topic. Moreover, the value of “?” for the truth label means that it could not be determined.

| Account           | Truth | Average | climate-change | gun control | ilhan | immigration | midterm | police & racism | SCOTUS | vaccine |
|-------------------|-------|---------|----------------|-------------|-------|-------------|---------|----------------|--------|---------|
| realdonaldtrump   | R     | ++      | 0              | -           | -     | -           | -       | -              | -      | -       |
| charliekirk11     | R     | ++      | -              | -           | -     | -           | -       | -              | -      | -       |
| kylegriffin1      | L     | +++     | ++             | -           | -     | -           | -       | -              | -      | -       |
| dbongino          | R     | -       | -              | -           | -     | -           | -       | -              | -      | -       |
| kamalaharris      | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| mitchellvii       | R     | -       | -              | -           | -     | -           | -       | -              | -      | -       |
| realsavedra       | R     | -       | -              | -           | -     | -           | -       | -              | -      | -       |
| krassenstein      | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| realjack          | R     | -       | -              | -           | -     | -           | -       | -              | -      | -       |
| nbcnws            | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| education4libs    | R     | -       | -              | -           | -     | -           | -       | -              | -      | -       |
| nra               | R     | -       | -              | -           | -     | -           | -       | -              | -      | -       |
| donaldjtrumpjr    | R     | -       | -              | -           | -     | -           | -       | -              | -      | -       |
| shannonrwatts     | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| thehill           | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| realjameswoods    | R     | -       | -              | -           | -     | -           | -       | -              | -      | -       |
| gopchairwoman     | R     | -       | -              | -           | -     | -           | -       | -              | -      | -       |
| jackposobiec      | R     | -       | -              | -           | -     | -           | -       | -              | -      | -       |
| funder            | L     | +++     | ++             | +           | +     | +           | +       | +              | +      | +++     |
| cnn               | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| ajplus            | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| rashidatalib      | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| stevescalise      | R     | -       | -              | -           | -     | -           | -       | -              | -      | -       |
| jordan_sather_    | ?     | -       | -              | -           | -     | -           | -       | -              | -      | -       |
| aoc               | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| msnbc             | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| edkrassen         | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| ryanafournier     | R     | -       | -              | -           | -     | -           | -       | -              | -      | -       |
| thomas1774paine   | R     | -       | -              | -           | -     | -           | -       | -              | -      | -       |
| nowthisnews       | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| amy_siskind       | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| hillaryclinton    | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| proudresister     | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| abc               | L     | +++     | +               | +           | +     | +           | +       | +              | +      | +++     |
| 1romans58         | R     | -       | -              | -           | -     | -           | -       | -              | -      | -       |
### 6 Conclusion

We have presented a method for detecting the general political leaning of media sources and popular Twitter users, as well as their stances on specific controversial topics. Our method uses retweeted accounts, and a good combination of dimensionality reduction and clustering algorithms, namely UMAP and Mean Shift, in order to produce sets of users that have opposing opinions on specific topics. Next, our method expands the discovered sets using supervised learning that is trained on automatically tagged large sets of users according to their stance of preset topics. Users’ stances are then projected to the influencers that are being cited in the tweets for each of the topics using the so-called “valence score”. The projection allows us to tag a large number of influencers with their stances on specific topics and with their political leaning in general (i.e., “left” vs. “right”) with high accuracy and with minimal human effort. We conducted our experiments over datasets of tweets about eight trendy and controversial topics, and we evaluated...
the predictions of our method with respect to independent manual analysis. The main advantage of our method is that it does not require manual labeling of entity stances, which requires both topical expertise and time.

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