

Quantifying Political Leaning from Tweets and Retweets

Felix Ming Fai Wong*, Chee Wei Tan[†], Soumya Sen*, and Mung Chiang*

*Princeton University, [†]City University of Hong Kong
 {mwthree, soumyas, chiangm}@princeton.edu, cheewtan@cityu.edu.hk

Abstract

Media outlets and pundits have been quick to embrace online social networks to disseminate their own opinions. But pundits' opinions and news coverage are often marked by a clear political bias, as widely evidenced during the fiercely contested 2012 U.S. presidential elections. Given the wide availability of such data from sites like Twitter, a natural question is whether we can quantify the political leanings of media outlets using OSN data. In this work, by drawing a correspondence between tweeting and retweeting behavior, we formulate political leaning estimation as an ill-posed linear inverse problem. The result is a simple and scalable approach that does not require explicit knowledge of the network topology. We evaluate our method with a dataset of 119 million election-related tweets collected from April to November, and use it to study the political leaning of prominent tweeters and media sources.

1 Introduction

One of the most challenging problems in the intersection of politics and online social media is to use Twitter to predict election outcomes. Although some success has been claimed (Tumasjan et al. 2010; Livne et al. 2011), it has also been argued that the election prediction problem is difficult because of sampling bias among the voter population (Metaxas and Mustafaraj 2012; Mustafaraj et al. 2011; Lumezanu, Feamster, and Klein 2012). In order to correct for bias, it would be helpful to have some prior understanding of the population of study. For example, the opinion of a politically biased person should be discounted, but a swing in opinions among unaligned voters is alarming. This motivates the usefulness of estimating the political leaning of the Twitter population.

Estimating political leaning is no easy task. In particular, there are two key challenges:

1. **Quantification:** Is it possible to assign meaningful numerical scores to tweeters about their position in the political spectrum?
2. **Scalability:** Given Twitter's large scale and server limitations, how can we devise a method that is efficient and scalable?

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Most of the existing approaches focus on using tweet text and/or the Twitter follower graph for the task and cannot meet at least one of the challenges. We take a new approach by incorporating retweet information. Analogous to using link analysis techniques for ranking webpages, we propose a consistency condition between tweeting and retweeting behavior, and use it to devise an inference technique that is:

1. **Simple:** it does not require explicit knowledge of the network topology, and works within rate limits imposed by the Twitter API;
2. **Efficient:** computationally efficient because it is formulated as a convex optimization problem, and data efficient because the time required to collect sufficient data to obtain good results is short; and
3. **Intuitive:** the computed scores have a simple interpretation of "averaging."

To evaluate our inference technique, we collected a set of 119 million tweets on the U.S. presidential election of 2012 over a timespan of seven months. Using the data, we quantify the political leaning of: (a) major media outlets that have a Twitter account, (b) the most prominent tweeters in terms of the number of retweets received, and (c) media outlets studied in the existing works that quantify media bias. The efficacy of our inference technique is demonstrated in our results agreeing with both conventional wisdom and results from similar but smaller scale studies.

Our study has a number of implications. (a) From a modeling perspective, we see evidence that tweeting and retweeting are indeed consistent, and this observation can be applied to develop new models and algorithms. (b) From an application perspective, besides election prediction, our method can be applied for other purposes, such as building an automated tweet aggregator that samples tweets from opposite sides of the political spectrum to provide users with a balanced view of controversial issues in the Twittersphere. Our methodology can also be applied to other fields marked by partisan viewpoints, such as market segmentation (e.g., iPhone vs Galaxy). (c) Regarding politics, our collected dataset and analysis shed light to the political landscape of the Twittersphere.

The organization of the rest of this paper is as follows. Section 2 reviews related work in studies of Twitter and

quantifying political orientation in traditional and online social media. Section 3 motivates and summarizes our proposed approach. Section 4 details our inference technique in terms of solving an optimization problem. Section 5 describes our dataset collected during the U.S. presidential election of 2012, which we analyze with our inference technique in Section 6. Then in Section 7 we further discuss our approach and compare it with existing approaches of quantifying media bias. Section 8 concludes the paper with future work.

2 Related Work

Our work is related to three lines of work: ideal point estimation, media bias quantification, and politics in online social media.

In political science, the ideal point estimation problem (Poole and Rosenthal 1985; Clinton, Jackman, and Rivers 2004) and its extensions (Gerrish and Blei 2012; 2011) aim to estimate the political leaning of legislators from roll call data. This line of work assumes legislators to vote probabilistically according to their positions (“ideal points”) in a latent space, and the latent positions are statistically inferred from observed data, i.e., how they vote. The main difference between our work and this line of work is in the data: while legislators are characterized by their voting history, which can be considered as their explicit stances on various issues, we do not have access to comparably detailed data for most Twitter users.

A variety of methods have been proposed to quantify the extent of bias in traditional news media. Indirect methods involve linking media outlets to reference points with known political positions. For example, (Lott and Hassett 2004) linked the sentiment of newspaper headlines to economic indicators. (Groseclose and Milyo 2005) linked media outlets to Congress members by co-citation of think tanks, and then assigned political bias scores to media outlets based on the Americans for Democratic Action (ADA) scores of Congress members. (Gentzkow and Shapiro 2010) performed an automated analysis of text content in newspaper articles, and quantified media slant as the tendency of a newspaper to use phrases more commonly used by Republican or Democrat members of the Congress. In contrast, direct methods quantify media bias by analyzing news content for explicit (dis)approval of political parties and issues. (Ho and Quinn 2008) analyzed newspaper editorials on Supreme Court cases to infer the political positions of major newspapers. (Ansolabehere, Lessem, and Snyder 2006) used 60 years of editorial election endorsements to identify a gradual shift in newspapers’ political preferences with time.

There has been much interest in characterizing political polarization of online social media. Outside of Twitter, (Adamic and Glance 2005) analyzed link structure to uncover polarization of the political blogosphere. (Zhou, Resnick, and Mei 2011) incorporated user voting data into random walk-based algorithms to classify users and news articles in a social news aggregator. (Park et al. 2011) inferred the political orientation of news stories by the sentiment of user comments in an online news portal. (Weber, Garimella,

and Borra 2012) assigned political leanings to search engine queries by linking them with political blogs. Regarding Twitter, political polarization was studied in (Conover et al. 2011b). Machine learning techniques have been proposed to classify Twitter users using e.g., linguistic content, mention/retweet behavior and social network structure (Boutet, Kim, and Yoneki 2012; Al Zamal, Liu, and Ruths 2012; Pennacchiotti and Popescu 2011). (Conover et al. 2011a) applied label propagation to a retweet graph for user classification, and found the approach to outperform tweet content-based machine learning methods.

Our problem of assigning meaningful political leaning scores to Twitter users is arguably more challenging than the above classification problem. There have already been several works on quantifying political leaning using the Twitter follower network. (An et al. 2012) and (King, Orlando, and Sparks 2011) applied multidimensional scaling on media sources. The media sources’ pairwise distances were computed from their mutual follower sets. (Barberá 2012) proposed a probabilistic generative model of following behavior, and framed “party identification” (equivalent to political leaning estimation) as a statistical inference problem. (Golbeck and Hansen 2012) proposed a graph-based method to propagate ADA scores of Congress members on Twitter to media sources through their followers. A comparison between our approach and the above approaches will be presented in Section 7.

3 Proposed Approach

3.1 A Motivating Example

To motivate our approach based on retweets, we consider a small example based on some data extracted from our dataset on the presidential election.

Consider a pro-Republican media source A and a pro-Democrat media source B. We observe the number of retweets they received during two consecutive events. During the “Romney 47 percent comment” event¹ (event 6 in Table 1), source A received 791 retweets, while source B received a significantly higher number of 2,311 retweets. It is not difficult to imagine what happened: source B published tweets bashing the Republican candidate, and Democrat supporters enthusiastically retweeted them.

Then consider the first presidential debate. It is generally viewed as an event where Romney outperformed Obama. This time source A received 3,393 retweets, while source B received only 660 retweets. The situation reversed with Republicans enthusiastically retweeting.

This example provides two hints: (a) The number of retweets received by a tweeter (the two media sources) during an event can be a signal of its political leaning. In particular, one would expect a politically inclined tweeter to receive more retweets during an event favorable to the candidate it supports. (b) The action of retweeting carries implicit sentiment of the tweeter. This is true even if the original tweet does not carry any sentiment itself. The intuition is that tweeters tend to follow and retweet those who share similar

¹An “event” is a time interval with a peak in tweeting activity.

political views, e.g., a tweeter is more likely to retweet a newspaper to which it subscribes than any random newspaper, a manifestation of the homophily principle.

3.2 Summary of Our Approach

Our inference technique is built upon the assumption that the two forms of expressing political opinions, tweeting and retweeting, are *consistent*.

Given a large set of tweets, we group them into sets of relevance: in this paper, we group tweets by events because of simplicity (it can be done just by looking at a time series in our case study), but other forms of grouping is also possible, such as by issues (economic, diplomatic, religious). This grouping of tweets allows for a more fine-grained analysis, e.g., tracking change of political leaning over time, and provides more datapoints for our estimation problem.

The next step is to estimate, for every event, a numerical score that quantifies the approval of the candidates by the aggregate Twitter population. This can be done using off-the-shelf sentiment analysis tools. It may seem that the performance of our technique will crucially rely on the performance of sentiment analysis, but we will show in our case study that just getting the right trend in sentiment is sufficient. It has also been shown that Twitter sentiment trends computed with standard techniques correlate with poll results and socio-economic phenomena (O’Connor et al. 2010; Bollen, Pepe, and Mao 2011).

Recall that the action of retweeting carries information on the political opinions of the retweeter. We can thus define the political leaning of a retweeted tweeter as the *average approval score* a person wishes to express when retweeting any of its messages. This political leaning score is on the same scale as the average score (per tweet) from the previous step. Then for every event, we can average over the political leaning scores of all retweets in that event.

Now we have obtained one average score by analyzing tweets, and another by analyzing retweets. We apply the tweet-retweet consistency assumption to say that they are roughly the same, and this gives an equation per event. Finally, the estimated political leanings will be the best fit solution to the set of equations. A formal development of the above ideas will be presented below.

4 Formulation

4.1 Definitions

Consider two political parties or candidates running for an election. During the election campaign there have been E events which attracted considerable attention. We are interested in quantifying the political leaning of N prominent tweeters, e.g., media outlets and celebrities, using Twitter data collected during the E events.

For event i , let U_i be the set of users who tweeted about the event, and T_{iu} be the set of tweets sent by user $u \in U_i$ about the event. Also define each tweet t to carry a score $s_t \in [-1, 1]$, such that it is 1 if the tweet shows full support on one candidate, or -1 if full support is shown on the other

candidate. Then for user u its approval score is

$$\sum_{t \in T_{iu}} \frac{s_t}{|T_{iu}|}.$$

Averaging over all users in U_i , the *average tweet leaning* y_i of event i is²

$$y_i = \frac{1}{|U_i|} \sum_{u \in U_i} \sum_{t \in T_{iu}} \frac{s_t}{|T_{iu}|}. \quad (1)$$

For source j , we quantify its political leaning as³ $x_j \in \mathbb{R}$, interpreted as the *average approval* shown when someone retweets a tweet originating from j .

Now let V_i be the set of users who retweeted any one of the N sources during event i , and $R_{uj}^{(i)}$ be the number of retweets sent by user u with the tweet originating from source j . Then the retweet approval score of user $u \in V_i$ is the average over all sources it has retweeted:

$$\sum_{j=1}^N \frac{R_{uj}^{(i)}}{\sum_{k=1}^N R_{uk}^{(i)}} x_j \quad (2)$$

and the *average retweet leaning* is the average over all u :

$$\frac{1}{|V_i|} \sum_{u \in V_i} \sum_{j=1}^N \frac{R_{uj}^{(i)}}{\sum_{k=1}^N R_{uk}^{(i)}} x_j \quad (3)$$

$$= \sum_{j=1}^N \left(\frac{1}{|V_i|} \sum_{u \in V_i} \frac{R_{uj}^{(i)}}{\sum_{k=1}^N R_{uk}^{(i)}} \right) x_j \quad (4)$$

$$= \sum_{j=1}^N A_{ij} x_j, \quad (5)$$

where A_{ij} is used to denote the inner summation term. The matrix \mathbf{A} with elements A_{ij} can be interpreted as a Retweet matrix that captures the tweet-and-retweet response feature in Twitter.

4.2 An Ill-posed Linear Inverse Problem

The main premise of this paper is the behavior of tweeting and retweeting is consistent. Mathematically, we require the average tweet and retweet leanings per event to be similar:

$$y_i \approx \sum_{j=1}^N A_{ij} x_j, \quad i = 1, \dots, E. \quad (6)$$

Our goal is to choose x_j ’s that minimize the error from the consistency equations Eq. (6), where the error measure is

²The specific forms of Eqs. (1) and (2) imply a user’s contribution is limited in $[-1, 1]$ regardless of the number of tweets/retweets it sends. It is possible to remove this restriction, i.e., treat all tweets/retweets the same, and it actually results in a simpler implementation (the Twitter streaming API keeps track of how many times a tweet has been retweeted), but in our initial study we found the resultant performance to be worse, probably due to the highly skewed activity of propagandists.

³We do not constrain x_j to be bounded in $[-1, 1]$, although x_j and y_i should be on the same scale, and a properly designed algorithm should be able to recover it.

conveniently chosen to be the sum of squared differences $\sum_i (\sum_j A_{ij} x_j - y_i)^2$. Writing in matrix form, we are solving the standard least squares problem

$$\text{minimize}_{\mathbf{x}} \quad \|\mathbf{Ax} - \mathbf{y}\|_2^2. \quad (7)$$

We often have many more tweeters (millions, but in our case study N ranges from 16 to 1000) than events ($E = 12$ in our case study), then $N > E$ and the system of linear equations $\mathbf{Ax} = \mathbf{y}$ is underdetermined, which means there are infinitely many solutions \mathbf{x} that can achieve the minimum possible error of 0 in Problem (7). Then the problem becomes an *ill-posed linear inverse problem* (Boyd and Vandenberghe 2004). The challenge of solving ill-posed problems is in selecting a reasonable solution out of the infinite set of feasible solutions. For example, in our initial studies the least-norm solution yielded unsatisfactory results.

4.3 Regularization

In statistical inference, solving ill-posed problems requires us to incorporate prior knowledge of the problem to rule out undesirable solutions. One such common approach is regularization, and we can change the objective function in Problem (7), $\|\mathbf{Ax} - \mathbf{y}\|_2^2$, to $\|\mathbf{Ax} - \mathbf{y}\|_2^2 + \lambda f(\mathbf{x})$, where $\lambda > 0$ is a regularization parameter, and $f(\mathbf{x})$ quantifies the “fitness” of a solution such that undesirable solutions have higher $f(\mathbf{x})$ values. For example, Tikhonov regularization for least-squares uses $f(\mathbf{x}) = \|\mathbf{x}\|_2^2$ (Boyd and Vandenberghe 2004). In this paper, we propose a regularization term that favors political leaning assignments \mathbf{x} with x_j being close to x_k if tweeters j and k have similar retweet responses.

Let S_{jk} be a similarity measure between tweeters j and k such that $S_{jk} \geq 0$ and $S_{jk} = S_{kj}$. Further, let \mathbf{S} be the symmetric matrix whose elements are S_{jk} . Then we set

$$f(\mathbf{x}) = \sum_{j=1}^N \sum_{k=1}^N S_{jk} (x_j - x_k)^2, \quad (8)$$

so that if S_{jk} is large (tweeters j and k are similar), then x_j should be close to x_k to minimize $(x_j - x_k)^2$.

Note that $f(\mathbf{x})$ can be rewritten in terms of a graph Laplacian. Let \mathbf{D} be defined as

$$D_{jk} = \begin{cases} \sum_{m=1}^N S_{jm} & j = k, \\ 0 & \text{otherwise,} \end{cases}$$

and \mathbf{L} be the graph Laplacian defined as $\mathbf{L} = \mathbf{D} - \mathbf{S}$. Then it can be shown that

$$\sum_{j=1}^N \sum_{k=1}^N S_{jk} (x_j - x_k)^2 = 2\mathbf{x}^T \mathbf{L} \mathbf{x}. \quad (9)$$

Finally, we impose the extra constraint $\mathbf{x}^T \mathbf{1} = 0$, which prevents solving for the trivial solution $\mathbf{x} = \mathbf{1}$ (such that the term $\mathbf{x}^T \mathbf{L} \mathbf{x}$ is minimized at 0) and has the interpretation that \mathbf{x} has at least one positive element and one negative element, i.e., each candidate or party has at least one tweeter supporting it. Then our optimization problem becomes

$$\begin{aligned} \text{minimize}_{\mathbf{x}} \quad & \|\mathbf{Ax} - \mathbf{y}\|_2^2 + \lambda \mathbf{x}^T \mathbf{L} \mathbf{x} \\ \text{subject to} \quad & \mathbf{x}^T \mathbf{1} = 0. \end{aligned} \quad (10)$$

It is a convex optimization problem and can be solved efficiently with standard numerical packages such as CVX (CVX Research, Inc. 2012).

Definition of Source Similarity The choice of S_{jk} is largely independent of the optimization problem itself, and so we defer it to here. In our case study, we compute S_{jk} as follows: (1) Let \mathbf{a}_j be the j -th column vector of \mathbf{A} . Then for each \mathbf{a}_j , compute the detrended version $\tilde{\mathbf{a}}_j$ by subtracting the line of least squares fit from \mathbf{a}_j . (2) Set $S_{jk} = \tilde{\mathbf{a}}_j^T \tilde{\mathbf{a}}_k / (\|\tilde{\mathbf{a}}_j\|_2 \|\tilde{\mathbf{a}}_k\|_2)$, i.e., the cosine similarity between the two vectors. (3) Set $\mathbf{S} \leftarrow \mathbf{S} - \min(\mathbf{S})$.

Intuitively, if two sources are similar, the retweet response to their tweets should also be similar and the retweet response is captured by their vectors \mathbf{a}_j and \mathbf{a}_k . Detrending in step 1 is necessary because Twitter activity increases as time to the presidential election decreases, and we need to avoid emphasizing too much on later events when computing similarity. Taking cosine similarity as the similarity measure in step 2 accounts for the variation in popularity of different sources through normalization by vector magnitudes. Finally, step 3 is needed to make \mathbf{S} nonnegative, which is needed for the optimization problem to be convex.

Incorporating Prior Knowledge Prior knowledge can readily be incorporated into our method through introducing constraints to the optimization problem. Here we consider two examples:

Anchors. Suppose we know a certain tweeter j is strongly liberal. We can then set its political leaning x_j to be a fixed value, say +1. In the literature this idea has been used frequently (Ho and Quinn 2008; An et al. 2012; Golbeck and Hansen 2012).

Minimum pairwise distances. This is our preferred approach. Suppose we know two tweeters j and k have opposite political leanings. We can impose the constraint on the distance of their political leanings as $x_j - x_k \geq c$, where c is a nonnegative constant. We recommend setting c to be moderately small, and let the data decide whether the distance has to be large. In Section 6.3, for each optimization problem we set $c = 0.5$ and impose one such constraint on the most liberal and the most conservative sources.

5 Dataset

In this section we describe the collection and processing of our Twitter dataset of the U.S. presidential election of 2012. Our dataset was collected over a timespan of seven months, covering from the initial phases to the climax of the campaign.

Data Collection From April 8 to November 10 2012, we used the Twitter streaming API to collect 119 million tweets which contain any one of the following keyword phrases: “obama”, “romney”, “barack”, “mitt”, “paul ryan”, “joe biden”, “presidential”, “gop”, “dems”, “republican” and “democrat” (string matching is case-insensitive).

⁴A time interval starts at 00:00:00 of start date, and ends at 23:59:59 of end date. Timezone used is UTC.

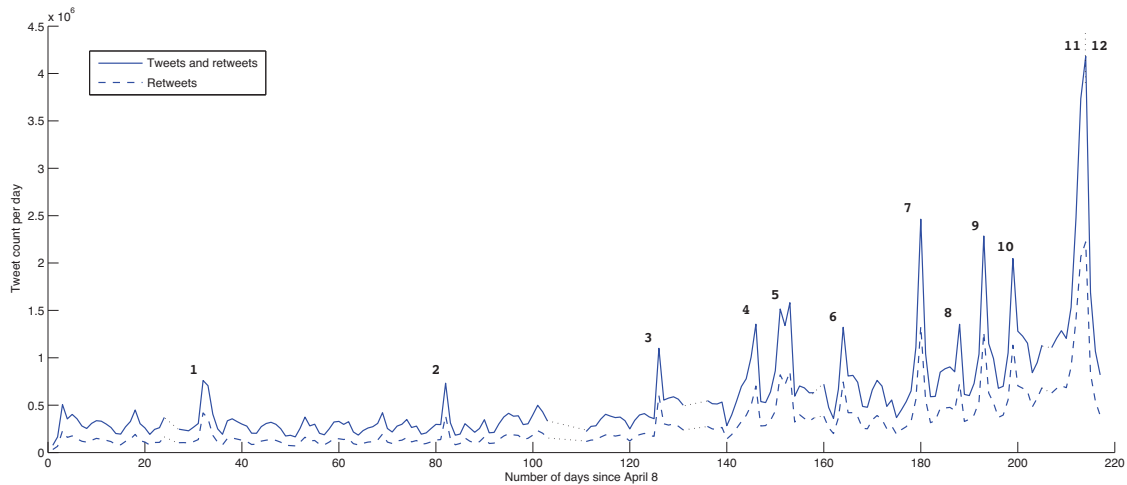


Figure 1: Number of tweets per day. Numbers on plot indicate events (see Table 1), and dotted lines indicate time periods when significant data were lost due to network outage (five instances).

ID	Dates ⁴	Description	# tweets (m)	# non-RT tweets (m)
1	May 9 - 12	Obama supports same-sex marriage	2.10	1.35
2	Jun 28 - 30	Supreme court upholds health care law	1.21	0.78
3	Aug 11 - 12	Paul Ryan selected as Republican VP candidate	1.62	0.96
4	Aug 28 - Sep 1	Republican National Convention	4.32	2.80
5	Sep 4 - 8	Democratic National Convention	5.81	3.61
6	Sep 18 - 12	Romney's 47 percent comment	4.10	2.55
7	Oct 4 - 5	First presidential debate	3.49	2.19
8	Oct 12 - 13	Vice presidential debate	1.92	1.19
9	Oct 17 - 19	Second presidential debate	4.38	2.67
10	Oct 23 - 26	Third presidential debate	5.62	3.35
11	Nov 4 - 6	Elections (before Obama projected to win)	7.50	4.40
12	Nov 7 - 9	Elections (after Obama projected to win)	6.86	4.43
Total			48.90	30.28

Table 1: Summary of events identified in the dataset.

Event Identification By inspecting the time series of tweet counts in Figure 1, we manually identified 12 events as listed in Table 1. We defined the dates of an event as follows: the start date was identified based on our knowledge of the event, e.g., the start time of a presidential debate, and the end date was defined as the day when the number of tweets reached a local minimum or dropped below that of the start date. After the events were identified, we extracted all tweets in the specified time interval⁵ without additional filtering, assuming all tweets are relevant to the event and those outside are irrelevant.

Extracting Tweet Sentiment We applied SentiStrength (Thelwall et al. 2010), a lexicon-based sentiment analysis package, to extract the sentiment of tweets. We adjusted the provided lexicon by compiling a high-frequency tweet-word list per event, and then removing words (four in total) that we consider to not carry sentiment in the context of elec-

⁵For retweets, we only include those with the original tweet being created within the time interval.

tions. Sentiment analysis was done as a ternary (positive, negative, neutral) classification.

For each tweet t in one of the 12 events, we set its score $s_t = 1$ if either (a) it mentions solely the Democrat camp (has “obama”, “biden” etc. in text) and is classified to have positive sentiment, or (b) it mentions solely the Republican camp (“romney”, “ryan” etc.) and has negative sentiment. We set $s_t = -1$ if the opposite criterion is satisfied. If both criteria are not satisfied, then set $s_t = 0$.

Figure 2 shows the values of y due to the above scoring mechanism. The values of all elements, i.e., the average tweet leaning of all events, are all close to 0 even though the possible range is $[-1, 1]$. This indicates the dataset is balanced in terms of praising/bashing both candidates, although it is slightly in favor of Obama. A closer look at the exact values indicates that the sentiment analysis results are reasonable: y_j is smaller for pro-Romney events, e.g., first presidential debate, and larger for pro-Obama events, e.g., Romney’s 47 percent comment.

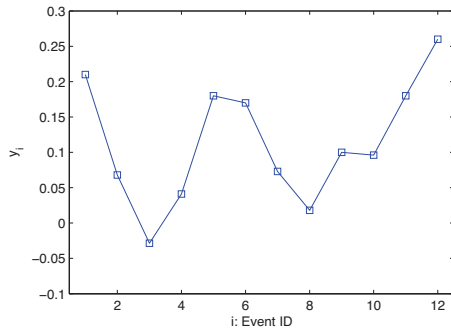


Figure 2: Average tweet leaning computed by sentiment analysis.

Noise Considerations There are three factors that can introduce noise to our computed \mathbf{y} and \mathbf{A} : (a) the dataset may contain irrelevant tweets, e.g., those about the Egyptian or French presidential election, (b) not all tweets created during an event time interval are necessarily talking about the event, and (c) political tweets are difficult to classify (Maynard and Funk 2011; Mejova, Srinivasan, and Boynton 2013), and off-the-shelf sentiment analysis tools may not perform sufficiently well (Gayo-Avello, Metaxas, and Mustafaraj 2011). Although more careful data processing is possible, we opted for the current simple approach because we believe our inference technique is robust to noise given sufficient data.

To understand the intuition, we can consider our formulation of quantifying political leaning as a system taking in *noisy* input signals \mathbf{y} and \mathbf{A} to output estimates \mathbf{x} . As the system accumulates more events, the size of input (sizes of \mathbf{y} and \mathbf{A} , which scale with E) increases, but the size of output (size of \mathbf{x} , which is N) remains the same. Effectively we are increasing information to improve estimation accuracy.

6 Experimental Results

6.1 Quantifying Major Media Sources

From the American National News Media list of Mondo Times,⁶ we extract a list of major media sources to which we apply our quantification method. We consider only media sources that are marked as popular, excluding radio shows (low popularity compared to other media), news aggregators (not consistent in reporting style) and news agencies.

Table 2 shows our results in quantifying the political leaning of these media sources. We caution that the results should not be considered as definitive proof of media bias, but as we can see, the numbers quantify conventional wisdom on which are liberal or conservative media sources. We single out two outliers and explain the unexpected results using their tweet contents:

CBS News. Compared to other events, which normally results in hundreds to low thousands of retweets, we observe a spike of 12,000 in its number of times being retweeted during event 10 (third presidential debate), and the most

⁶<http://www.mondotimes.com>, a news media directory used in (Ho and Quinn 2008).

Media Source	Our Score	Monde Classification
US News & World Report	-0.164	C
CNBC	-0.159	C
Fox News	-0.128	C
Washington Times	-0.102	C
CBS News	-0.076	L
HLN	-0.069	C
Newsweek	-0.051	N
The Week	-0.049	C
Chicago Tribune	-0.016	C
Christian Science Monitor	-0.015	N
LA Times	-0.011	L
ABC News	-0.002	L
MSNBC	0.006	L
USA Today	0.009	N
Wall Street Journal	0.039	C
Washington Post	0.053	L
Time	0.062	N
CNN	0.104	N
NY Times	0.205	L
Huffington Post	0.364	L

Table 2: Twitter political leaning scores of major media sources. Classification from Mondo Times: C: conservative/leans right, N: no bias, L: liberal/leans left.

retweeted tweet was an instant poll result (“BREAKING: who won the debate? ...”). The debate had a rather mixed review, as seen from the correspondingly low average tweet leaning y_{10} , and as a result the estimated political leaning of CBS News is skewed towards the negative side.

Wall Street Journal. Somewhat surprisingly, most of its retweeted tweets are actually quite neutral. This can be explained by the claimed separation between the Journal’s news section and editorial section (Groseclose and Milyo 2005), and from the tweet contents, we do find most of the tweets coming from news reports, rather than editorials. Our result agrees with the results in multiple works (Groseclose and Milyo 2005; Lott and Hassett 2004), which ranked Wall Street Journal as the most and the second-most liberal media outlet respectively.

6.2 Quantifying Prominent Tweeters

We rank Twitter users by their total number of times being retweeted during the 12 events, and identify the top 1,000 of them.⁷ Figure 3 shows the histogram of the computed scores for $\lambda = 10^{-5}$ together with a number of notable tweeters by where they lie in the score spectrum. The results are qualitatively the same for $10^{-4} \leq \lambda \leq 10^{-7}$. These results are discussed as follows:

Parody accounts. Among the top 1,000 tweeters we identify three parody Twitter accounts (FiredBigBird, BigBirdRomney, BIGBIRD) created in response to the Big Bird comment in event 7, and one account (InvisibleObama) created in response to the “invisible chair” skit during event

⁷Note the analysis here and that in Section 6.1 are obtained by solving (10) two times with different N (here: $N = 1000$, Section 6.1: $N = 20$). We do not combine the computation because most of the media sources are not in the top 1,000 list.

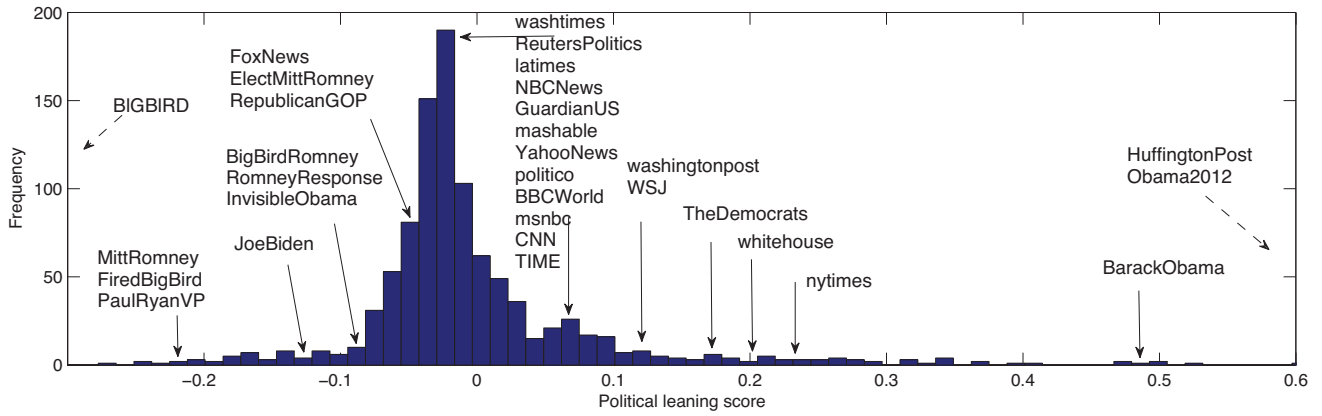


Figure 3: Histogram of political leaning scores of top 1,000 tweeters found by our inference technique.

4. These accounts, being sarcastic in nature, are against the Republican camp but were found to have pro-Republican scores. The reason is that they received most of the attention during the event of interest, and these events are pro-Republican. Accounting for this type of behavior will require further content or network analysis.

Candidates. The results for candidates’ accounts appear correct, including their election campaign accounts and the accounts of their political parties (TheDemocrats, RepublicanGOP). Biden’s account appears to be the only exception. Again, part of the reason is the skew in attention to the vice presidential debate, which is computed to have a low average tweet score y_8 (see Figure 2).

News media. Compared to politicians and celebrities, most media sources are concentrated at the center of the score spectrum, with moderate variation according to their political leaning scores. This suggests media sources tend to be objective relative to other prominent Twitter users.

6.3 Comparison with Existing Results

We apply our inference technique to the three sets of media sources used in the empirical studies of (An et al. 2012; Groseclose and Milyo 2005; Ho and Quinn 2008). We exclude sources that either (a) no longer exist due to a merge or a change in TV program host, or (b) have less than 25 retweets.⁸ For all three references we report the resultant Kendall’s τ statistic, and for (An et al. 2012; Groseclose and Milyo 2005) we also report their Spearman’s ρ and Pearson correlation coefficients because we have access to their actual ADA scores.

Table 3 summarizes the statistical test results. For all three references, the correlation between our rankings and previously reported results are statistically significant. It is not surprising that our results are in better agreement with those in (An et al. 2012; Groseclose and Milyo 2005), because they both study major media sources, as opposed to (Ho and Quinn 2008), which includes many traditional and regional newspapers with smaller Twitter presence.

⁸As a comparison, the least popular included sources have more than 150 retweets.

Reference	Kendall’s τ	p-value
(An et al. 2012)	0.46	0.0052
(Groseclose and Milyo 2005)	0.50	0.0064
(Ho and Quinn 2008)	0.39	0.026
	Spearman’s ρ	p-value
(An et al. 2012)	0.60	0.0075
(Groseclose and Milyo 2005)	0.62	0.010
	Pearson coeff.	p-value
(An et al. 2012)	0.59	0.0079
(Groseclose and Milyo 2005)	0.80	0.00019

Table 3: Correlation test results.

We also evaluate the sensitivity of our inference technique to the regularization parameter λ . Figure 4 is a plot of test statistics w.r.t. (An et al. 2012) computed with varying λ , and the results are relatively stable over a wide range of λ ($0.01 \leq \lambda \leq 0.1$). A comparison with the other two references gives similar results. This suggests fine-tuning λ may not be necessary.

6.4 Time Dynamics

One advantage of using tweet-retweet response to infer political leaning is the ability to do fine-grained temporal analysis. We illustrate with a simple qualitative analysis.

We quantify the political leaning of the set of 1,000 tweeters in Section 6.2, but this time we vary the amount of information used for estimation. We start by running our inference technique using data from events 1 to 2, then we use events 1 to 3, and so on. Then each Twitter user has a sequence of 11 political leaning scores, and we plot the trajectories of a select set of users in Figure 5. Note the plots are on the same scale on y-axis.

Candidates and media sources. For candidates, we take the Twitter accounts of the four (vice-)presidential candidates and their respective political parties, which results in a total of 6 accounts. For media sources, we use the sources in Section 6.1 that also appear in the top 1,000 tweeter list. The result is a set of 12 accounts. From Figure 5, we can see the qualitative behavior is similar for the two types of accounts. The scores initially drift but eventually stabilize at around 6

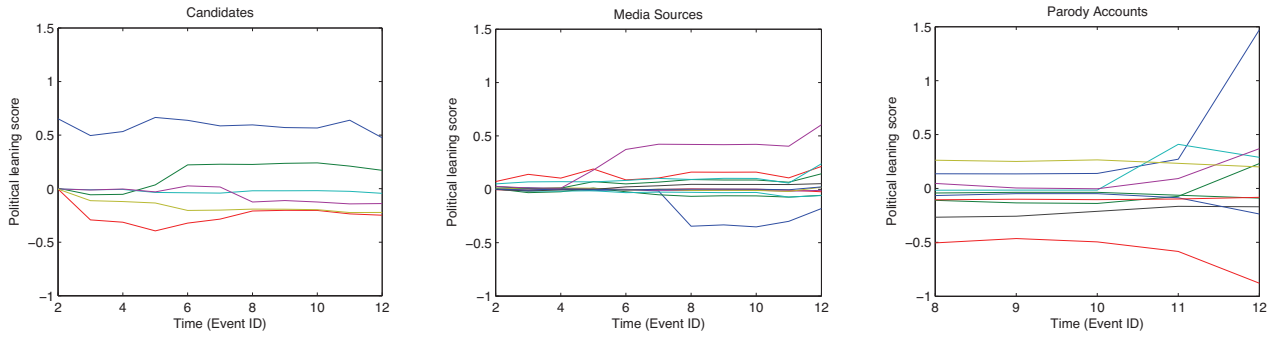


Figure 5: Trajectories of political leaning scores of different Twitter users. Each line is the score of one user varying with time.

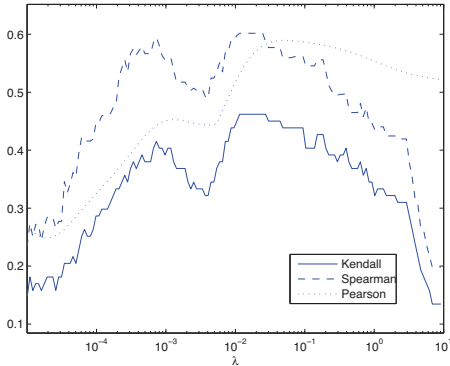


Figure 4: Test statistics w.r.t. (An et al. 2012).

to 8 events, suggesting that a sufficient number of events is needed to ramp up the accuracy of estimation. Afterwards any change to the scores is gradual. This observation is reasonable because all candidates and most media sources have predefined political stances.

Parody accounts. Besides the four accounts mentioned in Section 6.2, we manually inspected the top 100 tweeters of the top 1,000 list and added six more accounts.⁹ Figure 5 shows the political leaning scores of these accounts appear to be more chaotic.

7 Discussion

7.1 Regularization

The form of regularization that we adopt is not an arbitrary choice, but is motivated by the fact that the levels of attention received by different Twitter sources can vary by orders of magnitude. To illustrate, let us consider two sources j and k with j being much more popular. We can expect source j to receive many more retweets and using the notation in Section 4, $\mathbf{a}_j \gg \mathbf{a}_k$ (recall they are column vectors of \mathbf{A}). Then if we solve for \mathbf{x} directly as in Problem (7), the effect

⁹Twitter requires parody accounts that impersonate celebrities to add phrases such as “role-playing” and “parody account” to their bios. Other types of parody accounts, such as the ones related to Big Bird, are easy to identify by the username.

of x_j dominates over that of x_k , and we will not be able to estimate x_k accurately.

Regularization tackles the above issue by making less popular sources’ leaning scores track those of more popular sources, and our optimization problem (10) can now be interpreted as a hierarchical process: first we solve for x_j of popular sources j by minimizing $\|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2$, then we solve for the remaining x_j ’s by making them track those of popular and similar sources by minimizing $\lambda\mathbf{x}^T\mathbf{L}\mathbf{x}$.

7.2 Performance Dependencies

Dependence on \mathbf{y} . The reason we apply sentiment analysis on tweets to compute \mathbf{y} is purely for the ease of automation. In fact, the values of \mathbf{y} do not need to be derived from tweets. Our approach can readily accommodate exogenous information by a different choice of \mathbf{y} such as poll results (then the assumption of tweet-retweet consistency is changed to poll-retweet consistency).

Dependence on \mathbf{A} . While the performance of our method does not depend on the number of tweets, it does depend crucially on the number of retweets. In particular, if there are too few retweets, the resultant \mathbf{A} will be too noisy for reliable leaning score estimation. This is the reason we focus on estimating the political leaning of *prominent* tweeters. For normal tweeters who have not received sufficient retweets for our method to work, it is not difficult to envision a scheme to use prominent tweeters as reference points for estimation.

Dependence on choice of sources. Besides the number of retweets, the political balance of Twitter sources is crucial. For example, if the sources in question consist solely of liberals, certainly some sources will be erroneously classified as conservative so as to explain the observed \mathbf{y} . In our case study we are careful in achieving this balance even for small N (Sections 6.1 and 6.3). This also shows that the value of N is not a crucial factor of performance.

7.3 Comparison with Existing Approaches

Content-based analysis Here we compare with media bias studies in economics and political science (Lott and Hassett 2004; Groseclose and Milyo 2005; Gentzkow and Shapiro 2010; Ho and Quinn 2008; Ansolabehere, Lessem,

and Snyder 2006) which analyze news media content directly. Except for (Gentzkow and Shapiro 2010), all studies require some form of manual coding and analysis, which is expensive and time-consuming. A more fundamental problem is the scarcity of data. Because the amount of data available for analysis is limited by how fast the media sources publish, researchers may need to aggregate data created over long periods of time, often years, to perform reliable analysis.

Analyzing media sources through their outlets in online social networks, e.g., Twitter, offers many unprecedented opportunities. Communication in social media involves many more participants and happens at much shorter timescales as compared to print or broadcast media. Hence data are generated at much higher rates, and we can quickly collect sufficient data for analysis (seven months in our case study). Social media sources also provide a range of data not previously available, such as timestamps and citations, to support richer analysis.

Graph-based analysis Although incorporating graph information is often useful, the huge sizes of most online social networks mean it is difficult for an average researcher to obtain an up-to-date snapshot of a network. In the context of Twitter, the rate limiting mechanisms set by the Twitter API¹⁰ prevents crawling the network to any reasonable size. This problem is exemplified in (Barberá 2012), which had to analyze a random subsample of users because of rate limiting. In contrast, our method requires only one connection to the real-time Twitter stream.

We also argue that using retweets is more robust than using the Twitter graph to infer political leaning. Retweeting is an explicit act of approval, but following (a tweeter) is not. A Twitter user may follow two media sources with opposite political stances because he/she wants to get a balanced view. It is also possible that a user follows a prominent tweeter, becomes no longer interested but forgets to unfollow, and creates a stale edge in the Twitter network. Analyzing retweets avoids these issues.

Perhaps a more fundamental problem lies in interpreting results from any graph-based analysis. While political bias quantities derived from a content-based analysis have clear statistical interpretations, this is not the case for the analyses in (An et al. 2012; King, Orlando, and Sparks 2011; Golbeck and Hansen 2012). In contrast, the political leaning scores computed by our method have the intuitive interpretation of an average political approval score displayed by a retweet.

Unsupervised learning on retweet data Although we are not aware of any related work in the context of Twitter, it is not difficult to devise other statistical or machine learning-based methods that incorporate retweet behavior to estimate political leaning. For example, one can build a retweet graph as in (Conover et al. 2011a) and apply standard graph analysis techniques, but this suffers from the mentioned problem of result interpretation. Alternatively, one can devise a

generative model of retweet behavior and do statistical inference similar to ideal point estimation, but our approach is simpler, both in terms of the number of modeling assumptions (e.g., utility functions) and the resultant optimization problem (e.g., Gibbs sampling).

7.4 Bias or leaning?

We take the same stance as (Golbeck and Hansen 2012) in avoiding the terms “bias” or “slant” in this paper, because we cannot prove them solely by observing retweet behavior. In particular, if our method determines a tweeter to be politically leaning towards one candidate, there are two possible reasons: (a) the source is not biased but it tends to be followed by politically biased people who selectively retweet the source’s comments that support their personal political views, or (b) it tends to say things that politically biased people find more agreeable. In this paper we do not attempt to distinguish between the two factors. Future work using a text-based analysis of tweet contents is needed to detect actual bias.

8 Conclusions and Future Work

Motivated by the election prediction problem, we study in this paper the problem of quantifying the political leaning of prominent members in the Twittersphere. By taking a new point of view on the consistency relationship between tweeting and retweeting behavior, we formulate political leaning quantification as an ill-posed linear inverse problem solved with regularization techniques. The result is an automated method that is simple, efficient and has an intuitive interpretation of the computed scores. Compared to existing manual and Twitter network-based approaches, our approach is able to operate at much faster timescales, and does not require explicit knowledge of the Twitter network, which is difficult to obtain in practice.

To evaluate our inference technique, we collected a large dataset of 119 million U.S. election-related tweets over a span of seven months. We applied our inference technique to quantify the political leaning of media outlets and prominent Twitter users. We also showed our results are in good agreement with existing work quantifying media bias, and analyzed the time dynamics of the computed political leaning scores.

This work is a step toward systematic approaches in quantifying behavior on social and political issues. The Retweet matrix and retweet average scores can be used to develop new models and algorithms to analyze more complex tweet-and-retweet features. It is interesting to see that our simple model of tweet and retweet dynamics can be applied to achieve useful results, but our approach in using solely retweet information has its limitations. In particular, our approach does not quantify less popular sources who do not get retweeted often, and parody accounts which show less regularity in their tweeting behavior. Many other extensions are possible, especially by obtaining and incorporating more information, such as the sentiment of retweets, network structure and user history. Our methodology may also be applicable to other OSNs with retweet-like endorsement

¹⁰As of the time of writing, each authenticated client can make 350 requests/hour, i.e., crawl the neighbors of at most 350 Twitter users.

mechanisms, such as Facebook and YouTube with “like” functionality.

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