Modeling of Political Discourse Framing on Twitter

Kristen Johnson, Di Jin, and **Dan Goldwasser**
Department of Computer Science
Purdue University, West Lafayette, IN 47907
{john1187, jind, dgoldwas}@purdue.edu

Abstract

Framing is a political strategy in which politicians carefully word their statements in order to control public perception and discussion of current issues. Previous works exploring political framing have focused on analysis of frames in longer texts, such as newspaper articles, or tweets relevant to specific events. We present the first in-depth analysis of issue-independent framing for political discourse in social media, specifically the microblogging platform Twitter. Building upon the fifteen frames designed by Boydstun, we propose three additional frames relevant to Twitter and provide insights into the dynamic usage of frames by party and over time. Finally we present a global probabilistic model for combining linguistic, issue, and party bias features of the tweets of politicians for the task of tweet frame prediction.

1 Introduction

Today's social media venues, specifically microblogging platforms such as Twitter, are widely used by politicians to communicate with the public and share their stances. These platforms allow politicians to react quickly to events as they unfold and control the resulting discussion according to their views. Framing is one strategy which politicians can use to bias these discussions towards their stance. By emphasizing specific aspects of the issue, politicians create an association between the issue and a specific frame of reference, allowing them to influence public perception of an issue. For example, the debate around increasing the minimum wage can be framed as a *quality of life* issue or as an *economic* issue.

Different from previous works which concentrate on specific issues or focus on political discourse analysis in congressional speeches or newspaper articles, Twitter requires users to compress their ideas and reactions to only 140 characters. In this paper, we take a first step towards dealing with the unique challenges of modeling political discourse framing on Twitter and suggest weakly supervised models for automatically identifying the frames used in tweets. Given the highly dynamic nature of political discourse on Twitter, such models can easily adapt to new policy issues and variability in the language used to discuss them on Twitter. Our global model builds on several indicators capturing frame similarity (using a small seed set of keywords inspired by Boydstun et al.), tweet policy issues, user party affiliation, and frequent phrases used by politicians on Twitter. These indicators are extracted via weakly supervised models and then declaratively combined into a global model using Probabilistic Soft Logic (PSL), a recently introduced probabilistic modeling framework (Bach et al. 2013). PSL specifies high level rules over a relational representation of these features, which are compiled into a graphical model called a hinge-loss Markov random field that is used to make the frame prediction.

In summary, this paper makes the following contributions: (1) This work is among the first to look into general framing analysis of U.S. politicians on Twitter. Extending the annotation guidelines of Boydstun et al., we annotated 2,050 tweets, a subset of our total evaluation set of 92,457 tweets, for 17 different frames. (2) We suggest computational models, which easily adapt to new policy issues, for predicting frames on Twitter. Our results show the importance of global modeling, which increases the weighted average F_1 score from 52.21 when using linguistic information alone to 75.95 when using the joint model (party affiliation, issue, and linguistic information). (3) We evaluate the model empirically on real world events to show how it can help shed light on general framing trends in political discourse on Twitter.

2 Related Work

To the best of our knowledge this work is among the first to computationally model the general frames used by U.S. politicians on Twitter for a variety of political issues. Several previous NLP works have explored framing in public statements, congressional speeches, and news articles (Tsur, Calacci, and Lazer 2015; Card et al. 2015; Baumer et al. 2015). Our approach builds upon the previous work on frame analysis of Boydstun et al. by adapting and applying their annotation guidelines for Twitter. Other works focus on identifying and measuring political ideologies (Iyyer et al. 2014; Bamman and Smith 2015; Sim et al. 2013; Djemili et al. 2014), policies (Nguyen et al. 2015), and voting patterns (Gerrish and Blei 2012). Predicting political affiliation and other characteristics of Twitter users has also been explored (Volkova et al. 2015; Volkova, Coppersmith, and Van Durme 2014; Yano, Yogatama, and Smith ; Conover et al. 2011). Works focusing on inferring signed social networks (West et al. 2014), stance classification (Sridhar et al. 2015), social group modeling (Huang et al. 2012),

(1) Six years later health care costs have skyrocketed [1] and millions have lost access to their doctors. [8] #RepealObamacare

(2) Too many families feel the devastation of gun violence [9]. The American people deserve action from Congress [12] #WearOrange

(3) We must bolster the security of our borders [7] and craft an #immigration policy that grows our economy. [1]

(4) #500Days ago Boko Haram kidnapped 276 schoolgirls, 219 are still missing. #BringBackOurGirls [15]

(5) I look forward to talking w/Bill Edwards on @1290WTKS at 8:44AM. We'll talk budget, Syria, ISIL, and @GaPorts. Tune in: [16]

(6) Senseless violence has no place in the world and especially not at church. My prayers are with Emanuel AME and everyone in Charleston today.[17]

Figure 1: Tweets Which Highlight Frame Classification Difficulty. The superscript number after each tweet or color section indicates the frame. Colors highlight phrases that indicate different frames. No highlight indicates the entire tweet falls under one frame.

and collective classification using PSL (Bach et al. 2015) are similar to our modeling approach.

From communications and political and social science research, several works have studied the role of Twitter and framing in shaping public opinion in specific situations, e.g. the Vancouver riots (Burch, Frederick, and Pegoraro 2015) and the Egyptian protests (Harlow and Johnson 2011; Meraz and Papacharissi 2013). Others have focused on sentiment and framing analysis of opponents (Groshek and Al-Rawi 2013) and network agenda modeling (Vargo et al. 2014) in the 2012 U.S. presidential election. Lastly, Jang and Hart studied frames used by the general population specific to global warming. Different from these works, we model the general frames, which are *issue-independent*, used by U.S. politicians to describe six different political issues.

3 Data Collection and Annotation

We collected 184,914 tweets from all members of the U.S. House of Representatives and Senate. These tweets were filtered by keywords, with an average of 20 words per issue, to remove any tweets not related to the following six issues: (1) abortion access, (2) the Affordable Care Act, (3) gun rights versus gun control, (4) immigration policies, (5) acts of terrorism, and (6) LGBTQ rights. Forty politicians (10 from each party of each branch), were chosen randomly for annotation.

Two graduate students used the Policy Frames Codebook developed by Boydstun et al. to annotate each tweet with one of 15 frames which generalize across issues[1]. Figure 1 shows examples of tweets and their corresponding frames. Based on the possibility of multiple frames per tweet and difficulty of labeling (as discussed in Card et al.), annotators used the following procedure: (1) assign a primary frame to the tweet if possible, (2) if not possible, assign two or more frames to the tweet where the first frame is the most comprehensive of all the frames, (3) when assigning frames 12 through 17, ensure that the tweet cannot be assigned to any other frames. Annotators spent one month labeling the randomly chosen tweets and then met to decide the appropriate frame(s) for tweets with more than one frame.

We observed that the first 14 frames outlined in the Codebook are directly applicable to the tweets of U.S. politicians. We propose the addition of the 3 frames (Frames 15, 16, and 17) at the bottom of Figure 1 for Twitter analysis: Factual (tweet presents a fact with no detectable spin), Promotion (discusses appearances, statements, or refers to political friends), and Personal Sympathy and Support (offers condolences or stands in support of others). For many tweets, one frame is not enough because of the compound nature of tweets, i.e., some are two separate sentences, each with a different frame (e.g., tweet (2) in Figure 1), or begin with one frame and end with another (e.g., tweet (1)). Another trait which makes labeling difficult is the appearance of subframes within a larger frame and the lack of context, e.g., tweet (3) contains two separate frames, but the entire tweet may fall under the Policy Frame (number 13).

4 Weakly Supervised Feature Extraction for Global PSL Models

We are interested in designing PSL models which are capable of predicting the frame of a given tweet and also adapt easily to the dynamic nature of language used in Twitter. Our approach consists of 6 weakly supervised models (whose only supervision is initial keywords and party) which extract tweet features for each PSL model. These features are represented as PSL predicates which are combined into the probabilistic rules of each model, as shown in Table 1. Each PSL model builds upon the previous model by combining rules to improve the overall prediction, e.g. PSL Model 5 incorporates the following features: unigrams, author party, issue of tweet, maximum similarity, and party-based bigrams.

PSL Model 1 captures the belief that if a tweet and frame have a matching unigram, then that tweet may have that frame. Based on the Codebook descriptions of the 14 frames, we designed a list of 20 unigrams that are typically associated with each frame (e.g., possible unigrams of Frame 1 (Economic) include economy, taxes, etc.). If a tweet T has unigram U, it is represented in PSL notation via the binary predicate: HASUNIGRAM_F(T, U), where F represents 1 of the 17 possible frames. This feature is input to PSL Model 1 via the rule shown in line 1 of Table 1. Political party affiliation may indicate framing behavior and is represented by Model 2 (line 2). PSL Model 3 rules represent the idea that different parties will present issues differently, i.e., Republicans are known for discussing gun control in terms of an individual's rights (Frame 5), while Democrats frame the issue as a need for safety (Frame 7). A weakly supervised model extracts tweet issue information to be used as features for PSL Model 3. PSL Model 4 rules represent a Maximum Similarity metric that captures the idea that at least one word in a tweet should be *similar* to the unigrams used in Model 1. A weakly supervised model computes the `word2vec` similarity of each word in the tweet with every unigram associated with a frame, and uses this information as features (rules) in PSL Model 4.

PSL Models 5 and 6 capture the presence of bigrams and trigrams used by each party. Following the intuition that

[1]We refer the reader to Boydstun et al. for frame details.

Model	Rule Combinations	Example of PSL Rule Added by Each Successive Model
Model 1	Unigrams	HasUnigram_F(T, U) $\rightarrow$Frame(T, F)
Model 2	Model 1 + Party	HasUnigram_F(T, U) $\wedge$Party(T, P) $\rightarrow$Frame(T, F)
Model 3	Model 2 + Issue	HasUnigram_F(T, U) $\wedge$Party(T, P) $\wedge$Issue(T, I) $\rightarrow$Frame(T, F)
Model 4	Model 3 + Similarity	HasUnigram_F(T, U) $\wedge$MaxSim(T, F) $\rightarrow$Frame(T, F)
Model 5	Model 4 + Bigrams	HasUnigram_F(T, U) $\wedge$Party(T, P) $\wedge\text{PartyBigram}_P$(T, B) $\rightarrow$Frame(T, F)
Model 6	Model 5 + Trigrams	HasUnigram_F(T, U) $\wedge$Party(T, P) $\wedge\text{PartyTrigram}_P$(T, TG) $\rightarrow$Frame(T, F)

Table 1: Examples of PSL Model Rules. Each model builds successively on the rules of the previous model.

Frame No.	PSL Model Frame Predictions					
	M1	M2	M3	M4	M5	M6
1	72.13	73.68	79.63	81.32	81.63	**85.11**
2	14.29	14.29	44.44	66.67	66.67	**82.35**
3	39.58	39.17	45.25	57.78	66.67	**88.46**
4	63.56	67.83	65.19	69.91	79.53	**82.35**
5	57.96	58.91	63.32	63.27	60.24	**67.57**
6	60.0	60.0	60.87	60.87	61.54	**63.64**
7	60.0	60.49	65.16	72.9	75.86	**83.12**
8	63.41	66.94	67.42	70.13	72.47	**75.68**
9	30.19	31.82	45.1	55.17	55.17	**76.47**
10	20.0	31.58	47.06	66.67	66.67	**88.89**
11	12.25	15.25	24.62	24.24	26.24	**29.41**
12	57.23	58.25	60.76	65.22	69.57	**73.92**
13	31.25	32.7	39.23	40.94	44.34	**65.43**
14	50.0	56.15	64.71	72.73	72.73	**85.71**
15	64.0	68.97	71.43	81.82	81.82	**82.35**
16	68.52	69.51	75.91	76.81	77.1	**82.05**
17	70.34	72.58	69.15	71.53	76.92	**91.07**
W. Avg	52.21	54.3	59.0	63.54	66.37	**75.95**

Table 2: F_1 Scores of PSL Models. The highest prediction per frame is marked in bold. Frame numbers 1-14 are the frames of Boydstun et al.; 15-17 are our proposed Twitter-specific frames.

there will be differences in the way political parties frame issues, we use our *entire* tweet dataset, *including unlabeled tweets*, to extract the top 20 bigrams and trigrams per party, with no associations to any frames. Our idea is that bigrams and trigrams will represent common phrases used on Twitter, which we observe are different across parties. Corresponding rules are shown in the last two lines of Table 1.

5 Experimental Results

We evaluated our PSL models under supervised settings to learn how different attributes of the tweets and their authors interact with each other to contribute to the prediction. In these experiments we used five-fold cross validation with randomly chosen splits, while also ensuring that all frames were represented in these splits. Because we allow each tweet to have more than one frame, the prediction becomes a multilabel classification task. To evaluate our results we use the standard metrics for precision and recall, which are used to compute the F_1 scores shown in Table 2.

Overall, prediction improves as the model has access to more information. Unlike text-categorization problems which can often achieve near-optimal performance using bag-of-words features alone, frame prediction requires more nuanced information. Model 1, which uses features similar to bag-of-words, achieves a weighted average F_1 score of 52.21. Our experiments show that connecting lexical features with additional information improves the per-model F_1 score dramatically, up to 75.95 for Model 6. For some frames (2, 9, 10, 14, 15) the addition of party bigrams does not improve the prediction. Conversely, use of party trigram information (Model 6) is able to further improve the results, indicating that trigrams are more useful for frame prediction.

Date	No.	Party	Different Frame Usage
6/12	17	Both	Personally offers prayers, sympathy, and/or condolences
6/12	9	Dem	Effects on LGBT community
6/12	9	Rep	Effects on Orlando community
6/12	3	Dem	Expresses responsibility for preventing gun violence; Refers to shooting as hate crime
6/12	3	Rep	Refers to shooting as act of evil or terrorism
6/15	7	Dem	Need laws as preemptive measure to prevent gun violence
6/15	7	Rep	Need to prevent threats posed by ISIS or sales to known terrorists
6/22	7	Dem	Defend against gun violence
6/22	7	Rep	Defend against terrorist threats

Table 3: Differences in Frame Expression by Party. The last column describes the focus of the tweets with the stated frame number.

6 Observations from Real World Events

In this section, we explore the ability of our model to locate framing trends which can be used to analyze political discourse on Twitter around real world events. We first learned the weights of PSL Model 6 using the labeled data and performed MPE inference on the 90,407 remaining *unlabeled* tweets to obtain their predicted frames. Figure 2 shows the *unsupervised* frame predictions for gun issue related tweets surrounding the shooting at the Pulse nightclub in Orlando, Florida. There are three interesting peaks of activity: (1) June 12$^{\text{th}}$, the day of the shooting, has the following top three frames for Republicans and Democrats: 17 (Personal Sympathy & Support), 9 (Quality of Life), 3 (Morality & Ethics). (2) June 15$^{\text{th}}$, the day Democrats filibustered for gun reform, has Frame 7 (Security & Defense) as the top frame for both parties. (3) June 22$^{\text{nd}}$ was the day Senators proposed a bipartisan ban on gun sales to people on the "no fly" list. Both parties use Frame 7 as their top frame these days but in different ways, as further highlighted in Table 3.

We conducted this experiment for two additional gun violence events and found similarities in the top frames used (17, 9, 3, 7, 6) and patterns over time. The general trend is to

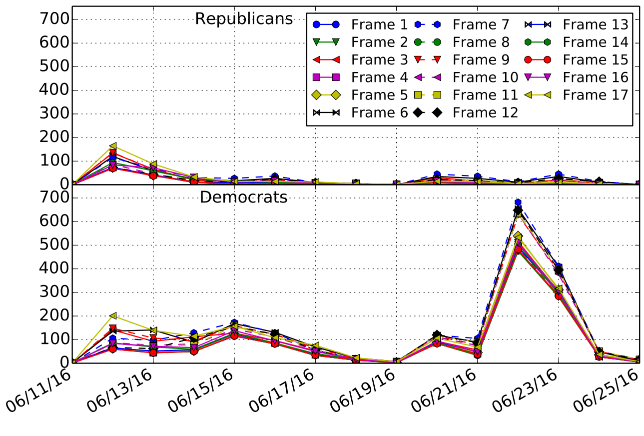

Figure 2: PSL Model 6 Prediction Around Orlando Shooting.

tweet frequently the day the event occurs and gradually become more silent until another event occurs. The frequencies of each frame vary across events and days, possibly indicating a change of focus as new information becomes available or a response to other politicians.

7 Conclusion

In this paper we present the problem of issue-independent framing analysis of U.S. politicians on Twitter, propose new Twitter-specific frames, and provide weakly supervised models which extract tweet information to be used as input for six global PSL models. Our global PSL models serve as an interesting exploratory tool to study the changing trends in framing patterns of political discourse on Twitter.

References

Bach, S. H.; Huang, B.; London, B.; and Getoor, L. 2013. Hinge-loss Markov random fields: Convex inference for structured prediction. In *Proc. of UAI*.

Bach, S. H.; Broecheler, M.; Huang, B.; and Getoor, L. 2015. Hinge-loss markov random fields and probabilistic soft logic. *arXiv preprint arXiv:1505.04406*.

Bamman, D., and Smith, N. A. 2015. Open extraction of fine-grained political statements. In *Proc. of EMNLP*.

Baumer, E.; Elovic, E.; Qin, Y.; Polletta, F.; and Gay, G. 2015. Testing and comparing computational approaches for identifying the language of framing in political news. In *Proc. of NAACL*.

Boydstun, A.; Card, D.; Gross, J. H.; Resnik, P.; and Smith, N. A. 2014. Tracking the development of media frames within and across policy issues.

Burch, L. M.; Frederick, E. L.; and Pegoraro, A. 2015. Kissing in the carnage: An examination of framing on twitter during the vancouver riots. *Journal of Broadcasting & Electronic Media* 59(3):399–415.

Card, D.; Boydstun, A. E.; Gross, J. H.; Resnik, P.; and Smith, N. A. 2015. The media frames corpus: Annotations of frames across issues. In *Proc. of ACL*.

Conover, M. D.; Gonçalves, B.; Ratkiewicz, J.; Flammini, A.; and Menczer, F. 2011. Predicting the political alignment of twitter users. In *Proc. of PASSAT*.

Djemili, S.; Longhi, J.; Marinica, C.; Kotzinos, D.; and Sarfati, G.-E. 2014. What does twitter have to say about ideology? In *NLP 4 CMC*.

Gerrish, S., and Blei, D. M. 2012. How they vote: Issue-adjusted models of legislative behavior. In *Advances in Neural Information Processing Systems*, 2753–2761.

Groshek, J., and Al-Rawi, A. 2013. Public sentiment and critical framing in social media content during the 2012 u.s. presidential campaign. *Social Science Computer Review* 31(5):563–576.

Harlow, S., and Johnson, T. 2011. The arab spring— overthrowing the protest paradigm? how the new york times, global voices and twitter covered the egyptian revolution. *International Journal of Communication* 5(0).

Huang, B.; Bach, S. H.; Norris, E.; Pujara, J.; and Getoor, L. 2012. Social group modeling with probabilistic soft logic. In *NIPS Workshops*.

Iyyer; Enns; Boyd-Graber; and Resnik. 2014. Political ideology detection using recursive neural networks. In *Proc. of ACL*.

Jang, S., and Hart, P. 2015. Polarized frames on "climate change" and "global warming" across countries and states: Evidence from twitter big data. *Global Environmental Change* 32:11–17.

Meraz, S., and Papacharissi, Z. 2013. Networked gatekeeping and networked framing on #egypt. *The International Journal of Press/Politics* 18(2):138–166.

Nguyen, V.-A.; Boyd-Graber, J.; Resnik, P.; and Miler, K. 2015. Tea party in the house: A hierarchical ideal point topic model and its application to republican legislators in the 112th congress. In *Proc. of ACL*.

Sim; Acree; Gross; and Smith. 2013. Measuring ideological proportions in political speeches. In *Proc. of EMNLP*.

Sridhar, D.; Foulds, J.; Huang, B.; Getoor, L.; and Walker, M. 2015. Joint models of disagreement and stance in online debate. In *Proc. of ACL*.

Tsur, O.; Calacci, D.; and Lazer, D. 2015. A frame of mind: Using statistical models for detection of framing and agenda setting campaigns. In *Proc. of ACL*.

Vargo, C. J.; Guo, L.; McCombs, M.; and Shaw, D. L. 2014. Network issue agendas on twitter during the 2012 u.s. presidential election. *Journal of Communication* 64(2):296–316.

Volkova, S.; Bachrach, Y.; Armstrong, M.; and Sharma, V. 2015. Inferring latent user properties from texts published in social media. In *Proc. of AAAI*.

Volkova, S.; Coppersmith, G.; and Van Durme, B. 2014. Inferring user political preferences from streaming communications. In *Proc. of ACL*.

West, R.; Paskov, H. S.; Leskovec, J.; and Potts, C. 2014. Exploiting social network structure for person-to-person sentiment analysis. *TACL*.

Yano, T.; Yogatama, D.; and Smith, N. A. A penny for your tweets: Campaign contributions and capitol hill microblogs. In *Proc. of ICWSM*.