

What pushes their buttons? Predicting comment polarity from the content of political blog posts

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Abstract

Political blogs as a form of social media allow for a uniquely interactive form of political discourse. This is especially evident in focused blogs with a strong ideological identity. We investigate techniques to identify topics within the context of the community, which when discussed in a blog post evoke a discernible positive or negative collective opinion from readers who respond to posts in comments. This is done by using computational methods to assign sentiment polarity to blog comments and learning community specific models that summarize issues tackled by blogs and predict the polarity based on the topics discussed in a blog post.

1 Introduction

Recent work in political psychology has made it clear that political decision-making is strongly influenced by emotion. For instance, (Lodge and Taber, 2000) propose a theory of "motivated reasoning", in which political information is processed in a way that is determined, in part, by a quickly-computed emotional react to that information. Strong experimental evidence for motivated reasoning (sometimes called "hot cognition") exists (Huang and Price, 2001); (Redlawsk, 2002); (Redlawsk, 2006); (Isbell et al., 2006). However, despite some recent proposals (Kim et al., 2008) it is unclear how to computationally model a person's emotional reaction to news, and how to collect the data necessary

to fit such a model. One problem is that emotional reactions are different for different people - a fact exploited in the use of political "code words" intended to invoke a reaction in only a particular subset of the electorate (a technique sometimes called "dog whistle politics").

In this paper, we evaluate the use of machine learning methods to predict how *members of a specific political community will emotionally reaction to different types of news*. More specifically, we use a dataset of widely read ("A-list") political blogs, and attempt to predict the aggregate sentiment in the comment section of blogs, as a function of the textual content of the blog posting. In this paper, we consider only predicting polarity (positive and negative feeling). In contrast to work done traditionally in sentiment analysis which focuses on determining the sentiment expressed in text, in this work, we focus on the task of predicting the sentiment that a block of text will evoke in readers, expressed in the comment section, as a response to the blog post.

This task is related to, but distinct from, several other studies that have been made using comments and discussions in political communities, or analysis of sentiment in comments - (Yano et al., 2009), (O'Connor et al., 2010), (Tumasjan et al., 2010). Below we discuss the methods used to address the various parts of this task. First, we evaluate two methods to automatically determine the comment polarity: SentiWordNet (Baccianella and Sebastiani, 2010) a general purpose resource that assigns sentiment scores to entries in WordNet, and an auto-

mated corpus-specific technique based on pointwise mutual information. The quality of the polarity assessments by these techniques are made by comparing them to hand annotated assessments on a small number of blog posts. Second, we consider two methods for predicting comment polarity from post content: support vector machine classification, and sLDA, a topic-modeling-based approach. Finally, we demonstrate that emotional reactions are indeed community-specific, compare the accuracy of this approach to the more traditional approach of predicting sentiment of a text from the text itself, and present our conclusions.

2 Data

In this study, we use a collection of blog posts from five blogs: Carpetbagger(CB)¹, Daily Kos(DK)², Matthew Yglesias(MY)³, Red State(RS)⁴, and Right Wing News(RWN)⁵, that focus on American politics made available by (Yano et al., 2009). The posts were collected during November 2007 to October 2008, which preceded the US presidential elections held in November 2008. The blogs included in the dataset vary in political ideology with blogs like Daily Kos that are Democrat-leaning and blogs like Red State tending to be much more conservative. Since we are interested in studying the responses to blog posts, the corpus only contains posts where there have been at least one comment in the six days after the post was published. It is important to note that only the text in the blog posts and comments are used in this study. All non-textual information like pictures, hyperlinks, videos etc. are discarded. In terms of text processing, for each blog, a vocabulary is created consisting of all terms that occur at least 5 times in the blog. Stopwords are eliminated using a standard stopword list. Each blog post is then represented as a bag of words from the post. Table 2 shows statistics of the datasets. Each dataset is studied separately for the most part in the rest of the paper.

¹<http://www.thecarpetbaggerreport.com>

²<http://www.dailykos.com/>

³<http://yglesias.thinkprogress.org/>

⁴<http://www.redstate.com/>

⁵<http://rightwingnews.com/>

3 Labelling comments with sentiment polarity

The first step in understanding the nature of posts that evoke emotional responses is to get a measure of the polarity in the sentiment expressed in the comments section of a blog post. The measure indicates the ability of the issues in the blog post and its treatment, to evoke strong emotions in readers.

3.1 SentiWordNet

In the first stage of the study, we use SentiWordNet (Baccianella and Sebastiani, 2010) which associates a large number of words in WordNet with a positive, negative and objective score (summing up to 1). Firstly, all the comments for a blog post in the comment section are aggregated and for the words in the comments that are found in SentiWordNet, the net positive and negative scores are computed. Since SentiWordNet entries are associated with word senses and because we don't perform word sense disambiguation, the SentiWordNet polarity of the most dominant word sense is used for words in the comment section. The sentiment in the comment section is deemed to be positive if the net positive score exceeds the negative score and negative otherwise. Therefore, each blog post is now associated with a binary response variable indicating the polarity of the sentiment expressed in the comments.

3.2 Using pointwise mutual information

A second technique to determine the sentiment polarity of comments uses the principle of pointwise mutual information (PMI)(Turney, 2002). We first construct a seed list of positive and negative words by choosing the 100 topmost positive and negative words from SentiWordNet and manually eliminating words from this list that don't pertain to sentiment in our context. (Appendix A has the list of seed words used.) This seed list is used to construct a larger set of positive and negative words by computing the PMI of the words in the seed lists with every other word in the vocabulary. It's important to note that this list is constructed for the specific corpus that we work with. Because every blog is processed separately, we construct a different sentiment word list for each blog based on the statistics

Blog	Pol align- ment	#posts	Vocabulary size	Avg #words per post	Avg #com- ments per post	Avg #words per comment section
Carpetbagger (CB)	liberal	1201	4998	170	31	1306
Daily Kos (DK)	liberal	2597	6400	103	198	3883
Matthew Yglesias (MY)	liberal	1813	4010	69	35	1420
Red State (RS)	conservative	2357	8029	158	28	806
Right Wing Nation (RWN)	conservative	1184	6205	185	33	1015

Table 1: Dataset statistics

of word occurrences. Words in the vocabulary are ranked by the difference in the average of the PMI with positive and negative seed words. The top 1000 words in the resultant sorted list are treated as positive words and the bottom 1000 words as negative words. The comment section of every post is tagged with a positive or negative polarity as in the previous section by computing the total positive and negative word counts.

Using the same seed word list, the procedure is performed separately for each blog resulting in sentiment polarity lists that are particular to the community and ideology associated with each blog. It should be noted that while this method provides better estimates of comment sentiment polarity (as seen in Section 4), it involves more manual work in constructing a seed set than the SentiWordNet method which does not require any manual effort.

3.3 Human labels

As a third method that is accurate but expensive, we manually labeled comments from approximately 30 blog posts from each blog, with a positive or negative label. The guideline in labeling was to determine if the sentiment in the comment section was positive or negative to the subject of the post. The chief intention of this exercise is to determine the quality of the polarity assessments of the SentiWordNet and PMI methods. While it is possible to directly use the assessments and train a classifier, the performance of the classifier will be limited by the very small number of training examples (30 instead of thousands of examples). The accuracy of the two

Blog	SentiWordNet accuracy	PMI accuracy
CB	0.56	0.78
DK	0.54	0.72
MY	0.61	0.83
RS	0.54	0.74
RWN	0.64	0.84

Table 2: Measuring accuracy of automatic comment polarity detection

automatic methods to determine comment polarity is shown in Table 2

The better accuracy of the PMI method can be explained by the fact that SentiWordNet is a general purpose list that is not customized for the domain which tends to make it noisy for text in the political domain. The PMI technique corresponds more closely with the human labels but it requires a little human effort in building the initial seed list of positive and negative words.

4 Predicting sentiment from blog content

We now address the problem of using machine learning techniques to predict the polarity of the comments based on the blog post contents.

4.1 SVM

Firstly, we use *support vector machines* (SVM) to perform classification. We frame the classification task as follows: The input features to the classifier are the words in the blog post i.e each blog post is treated as a bag of words and the output variable is the binary comment polarity computed in the previ-

Blog	SentiWordNet		PMI	
	SVM	sLDA	SVM	sLDA
cb	0.56	0.58	0.79	0.79
dk	0.61	0.64	0.75	0.77
my	0.67	0.59	0.87	0.87
rs	0.53	0.55	0.74	0.76
rwn	0.57	0.59	0.90	0.90

Table 3: Accuracy: Using blog posts to predict comment sentiment polarity

ous section. For our experiments, we used the SVM-Light package⁶ with a simple linear kernel and evaluated the classifier using 10 fold cross validation.

Table 3 shows the accuracy of the classifier for the different blogs and polarity measuring schemes. The errors in classification can be attributed in part to the inherent difficulty of the task due to the noise of the polarity labeling schemes and in part due to the difficulty in obtaining a signal to *predict comment polarity* from the body of the post.

4.2 Supervised LDA

Next, we use Supervised LDA (sLDA) (Blei and McAuliffe, 2008) to do the classification. sLDA is a model that is an extension of Latent Dirichlet Allocation (LDA) (Blei et al., 2003) that models each document as having an output variable in addition to the document contents. The output variable in the classification case is modeled as an output of a logistic regression model that uses the posterior topic distribution of the LDA model as features. In this task, the output variable is +1 or -1 depending on the polarity of the comment section. In the experiments with sLDA, we set the number of topics as 15 after experimenting with a range of topics and use 10-fold cross validation. The number of topics is set lower than it usually is with topic modeling, due to the relatively short length and small number of documents.

The advantage of sLDA in this task is that we induce topics from the bodies of the blog posts that serve to characterize the different issues that each blog addresses. In addition, the logistic regression parameters indicate how each topic influences the output variable. Table 4 shows the top 1 or 2

topics with the highest negative and positive logistic regression coefficients for each blog. Inspecting the top words of the topics confirms our notions of the kinds of issues that appeal to the readers of each of the blogs. For instance, in the topics induced from Daily Kos, a very liberal leaning blog, we see that the most negative topic (i.e. the topic that contributes the most to potential negative comments) talks about the Bush administration and Vice President Cheney, which was and remains quite unpopular with people from the left. The other negative topic concerns the war in Iraq which was also very unpopular within people whose beliefs are liberal-leaning. The most positive topic seemingly focuses on campaign funding. Our conjecture for the high comment polarity is the great success in the then Democratic candidate Obama’s fund raising attempts during the presidential campaign. In the second blog, Right Wing News, which is a conservative blog, we see a different picture. The most negative topic deals with Islam and Muslim people which are issues that have tended to evoke negative reactions from certain sections of people with conservative political beliefs. Global warming also evoked negative comments which is consistent with the conservative viewpoint that there isn’t evidence to suggest that greenhouse gases cause global warming. The most positive topic seems to be about anti-abortion issues which is an issue that frequently pops up in conservative political discourse. Topics from the other blogs also seem to be in line with the standard positions taken by liberal and conservatives on leading issues in US politics like taxation, immigration, public health and the presidential campaign which was in full flow at the time the data was collected.

Table 3 shows the accuracy of sLDA in predicting the comment polarity based on the blog posts. It can be seen from the table that sLDA performs marginally better than SVM when trained on blog posts, even though documents are now represented in the lower dimensional topic space in contrast to the high dimensional word space that was used with SVM. sLDA provides the additional advantage of providing an overall summary of the corpus via the topic tables it induces.

⁶<http://svmlight.joachims.org/>

Blog	Topic words	Topic co-efficient
CB	* bush president news administration house white officials report fox government office military department public cheney john journal week pentagon national	-0.79
	* huckabee giuliani romney mccain republican presidential religious campaign gop john party candidate mitt rudy mike conservative thompson support paul candidates	0.48
DK	* bush administration congress law government court house intelligence white executive committee time cheney federal course national act president congressional information	-1.54
	* iraq war bush troops news military american president iraqi starts maine cheers days jeers mccain moreville rightnow day americans people	-0.60
	* money health campaign foster energy district million people nrcc dccc care election time bill change funds don global federal economy	0.62
MY	* iraq war american military iraqi government people troops bush security united forces world country surge presence political force maliki afghanistan	-0.50
	* people care health don public immigration college political education school issue insurance social system policy real lot isn actually sense	1.05
RS	* economy market people financial economic markets money world rate rates federal mortgage government credit prices price term inflation reserve oil	-0.30
	* tax government taxes money economic care people spending million jobs american energy health increase pay economy private free federal business	0.61
RWN	* people muslim world country war american law muslims time police america rights free peace death city islamic government freedom united	-0.68
	* democrats warming global vote election obama energy democratic change votes climate people john gore political gas don voters party bill	-0.39
	* people life women woman time own little love person children world live read believe god isn school feel mean	0.47

Table 4: Topics from sLDA and weights

4.3 Using comments to predict comment polarity

In the previous experiments we were using the bodies of the blog posts to predict comment polarity. There are multiple factors which make this a difficult task. One major factor is the difficulty of learning potentially noisy labels using automatic methods. More interestingly, we operate under the hypothesis that there is signal about comment polarity in the bodies of the blog posts. To test this hypothesis, we train classifiers on the comment sections themselves to predict comment polarity. This serves to eliminate the effect of our hypothesis and focus on the inherent difficulty in learning the noisy labels. Table 5 shows the results of these experiments. We see that once again, sLDA results are comparable to the accuracies reported by SVM and that PMI labels are less noisier than the labels obtained using

Blog	SentiWordNet		PMI	
	SVM	sLDA	SVM	sLDA
cb	0.66	0.56	0.79	0.79
dk	0.72	0.59	0.74	0.73
my	0.64	0.61	0.87	0.89
rs	0.65	0.57	0.75	0.80
rwn	0.65	0.60	0.90	0.90

Table 5: Accuracy: Using comments to predict comment sentiment polarity

Evaluating	Trained on DK	Trained on RWN
DK	0.75/0.77	0.61/0.62
RWN	0.74/0.71	0.90/0.90

Table 6: Cross blog results: Accuracy using SVM/sLDA

SentiWordNet. More importantly, we note that the accuracy in predicting the comment polarity while higher than the accuracy in predicting the polarity from blog posts, is not significantly higher which strongly suggests that blog posts have quite a bit of information regarding comment polarity.

4.4 Cross blog experiments

The effect of the nature of the blog on the classifier is examined by training models on the blog posts from a conservative blog (RWN) using PMI-determined polarities as targets and by testing the model by running liberal blog data (from DK) through it. Similarly, we test RWN blog entries by training it on a classifier trained on DK posts. The results of the experiments are in Table 6. For easy reference, the table also includes the accuracies when blogs are trained using posts from the same blog (obtained from Table 3). We see that the accuracy in predicting polarity degrades when blog posts are tested on a classifier trained on posts from a blog of opposite political affiliation. These results indicate that emotion is tied to the blog and community that one is involved in.

4.5 Conclusion

We addressed the task of predicting the emotional response that is induced in political discourses. To this end, we tackled the tasks of determining the sentiment polarity of comments in blogs and the task of predicting the polarity based on the content of the blog post. Our approach also characterized the issues talked about in specific blog communities. Our experiments show that the community specific PMI method provides a more accurate picture of the sentiment in comments than the generic SentiWordNet technique. We also see that the context of the community is key as seen in the poor performance of models trained on blogs from one end of the political spectrum in predicting the polarity of responses to blog posts in communities on the other end of the spectrum.

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Appendix A

Positive	wonderfulness, admirableness, admirability, wonderful, admirable, top-flight, splendid, first-class, fantabulous, excellent, good, balmy, mild, ennoble, dignified, amuse, agree, do_good, benefit, vest, prefer, placate, pacify, mollify, lenify, gentle, conciliate, assuage, appease, filigree, dazzle, admiringly, character, preeminence, note, eminence, distinction, radiance, amiability, bonheur, worship, adoration, divination, music, euphony, judiciousness, essentialness, essentiality, gain, crispness, urbanity, courtesy, decency, modesty, dedication, integrity, honourableness, honorableness, honor, goodness, good, morality, urbanity, tastefulness, elegance, healthfulness, nutritiveness, nutritiousness, wholesomeness, fineness, choiceness, loveliness, fairness, comeliness, beauteousness, picturesqueness, bluntness, good_nature, character, props, joke, jocularity, jest, worthy, salubrious, healthy, virtuous, esthetic, artistic, aesthetic, spiffing, superlative, sterling, greatest, superb, brilliant, boss, banner, olympian, majestic, straightarrow, wide-eyed, round-eyed, dewy-eyed, childlike, righteous, answerable, nice, decent, diffident, respected, reputable, self-respecting, self-respectful, dignified, constructive, sweet, fabulous, fab, charming, admirable, idyllic, idealized, idealised, ennobling, dignifying, nice, incumbent, clean, lucky, intellectual, formidable, awing, awful, awesome, awe-inspiring, amazing, important, joking, jocular, jocose, jesting, amicable, kind, genial, therapeutic, sanative, remedial, healing, curative, gracious, gainly, goody-goody, good, superb, solid, good, inspired, elysian, divine, worthy, quaint, discerning, golden, fortunate, blest, blessed, courteous, thorough, exhaustive, better, benign, pretty, piquant, engaging, attractive, well, veracious, right, grace, goodwill, belong, accommodate, serve, merit, deserve, shine, radiate, glow, beam, disillusion, disenchant, proclaim, laud, glorify, extol, exalt, cheer, consider, purify, enervate, recuperate, amusingly, dearly, dear, affectionately, thoroughly, soundly, well, simply, time, posterboard, fettle, mildness, clemency, successfulness, prosperity, wellbeing, well-being, upbeat, wholeness, haleness, purity, pureness, innocence, antithesis, serendipity, superordinate, superior, possible, pleaser, idolizer, idoliser, amoralist
Negative	tawdry, shoddy, cheapjack, scrimy, unsound, unfit, bad, sorry, sad, pitiful, lamentable, distressing, deplorable, abject, unfortunate, inauspicious, humbug, trouble, inconvenience, disoblige, bother, smell, stink, reek, twinge, sting, prick, burn, sting, burn, bite, desensitize, desensitise, resent, begrudge, pity, compassionate, abreact, agonize, agonise, muddy, settle, moan, groan, impugn, repudiate, deny, reject, disapprove, snub, repel, rebuff, sting, stick, disapprove, refute, rebut, controvert, foul, curdle, smite, afflict, ease, comfort, ail, inflame, woefully, sadly, lamentably, deplorably, hard, unluckily, unfortunately, regrettably, alas, worst, throe, woe, suffering, inconvenience, incommodiousness, solacement, solace, dyspnoea, dyspnea, throe, shrew, ruffian, rowdy, roughneck, hooligan, bully, plonk, sullenness, moroseness, glumness, moodiness, malignity, malevolence, guilt, sorrow, ruefulness, rue, regret, dolour, dolor, dolefulness, gloating, gloat, weakness, self-torture, self-torment, suffering, hurt, distress, torment, curse, straits, pass, head, excoriation, canard, scurrility, billingsgate, scribble, scrawl, scratch, prejudice, preconception, bias, pill, onus, load, incumbrance, encumbrance, burden, poignancy, pathos, penalty, badness, bad, fault, demerit, hardness, moldiness, harshness, cruelty, cruelness, spitefulness, spite, nastiness, cattiness, bitchiness, malice, malevolency, malevolence, heinousness, barbarousness, barbarity, atrocity, atrociousness, illegitimacy, unnaturalness, disagreeableness, incongruousness, incongruity, ruggedness, hardness, unneighborliness, unfriendliness, disagreeableness, sadness, lugubriousness, gloominess, shlock, schlock, dreck, mongrel, bastard, shenanigan, roguishness, roguery, rascality, mischievousness, mischief-making, mischief, devilry, devilry, devilment, shitwork, overexertion, overacting, hamming, shlep, schlep, worst, upset, scrofulous, sick, ill, sheltered, occult, trashy, rubbishy, undivided, worried, upset, disturbed, distressed, disquieted, troubled, unmanageable, uncontrollable, mussy, messy, unsympathetic, invalidating, disconfirming, wretched, woeful, miserable, execrable, deplorable, bush-league, bush, tinny, sleazy, punk, crummy, chintzy, cheesy, cheap, bum, inferior, indifferent, lowly, humble, insufficient, deficient, insubordinate, cross-grained, contrarious, spastic, spasmodic, convulsive, unaccepted, unacceptable, nonstandard, unsound, asocial, antisocial, feigned, broken-down, vicious, reprehensible, deplorable, criminal, condemnable, notorious, infamous, ill-famed, untreated, modified, limited, unmixed, unmingled, sheer, plain, cretinous, negative, imponderable, vexing, maddening, infuriating, exasperating, ungrateful, sore, painful, afflictive, harsh, unpeaceable, unforbearing, unpainted, underivative, scurrilous, opprobrious, abusive, verminous, outrageous, horrific, horrid, hideous, creepy, pestilent, pernicious, deadly, baneful, paranormal, grotty, nasty, awful, transcendental, preternatural, otherworldly, nonnatural, simulated, imitation, faux, false, fake, substitute, ersatz, strong, smart, wicked, terrible, severe, un pitying, ruthless, remorseless, pitiless, unlikeable, unlikable, unmourned, unlamented, rough, harsh, woeful, woebegone, lugubrious, heartsick, heartbroken, brokenhearted, bitter

Table 7: Seed words used in the PMI technique