

# Quantising Opinions for Political Tweets Analysis

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## Abstract

There have been increasing interests in recent years in analyzing tweet messages relevant to political events so as to understand public opinions towards certain political issues. We analyzed tweet messages crawled during the eight weeks leading to the UK General Election in May 2010 and found that activities at Twitter is not necessarily a good predictor of popularity of political parties. We then proceed to propose a statistical model for sentiment detection with side information such as emoticons and hash tags implying tweet polarities being incorporated. Our results show that sentiment analysis based on a simple keyword matching against a sentiment lexicon or a supervised classifier trained with distant supervision does not correlate well with the actual election results. However, using our proposed statistical model for sentiment analysis, we were able to map the public opinion in Twitter with the actual offline sentiment in real world.

**Keywords:** Political tweets analysis, sentiment analysis, joint sentiment-topic (JST) model

## 1. Introduction

The emergence of social media has dramatically changed people's life with more and more people sharing their thoughts, expressing opinions, and seeking for support on social media websites such as Twitter, Facebook, wikis, forums, blogs etc. Twitter, an online social networking and microblogging service, was created in March 2006. It enables users to send and read text-based posts, known as *tweets*, with 140-character limit for compatibility with SMS messaging. As of September 2011, Twitter has about 100 million active users generating 230 million tweets per day. Twitter allows users to subscribe (called following) to other users' tweets. A user can forward or retweet other users' tweets to her followers (e.g. "RT @username [msg]" or "via @username [msg]"). Additionally, a user can mention another user in a tweet by prefacing her username with an @ symbol (e.g. "@username [msg]"). This essentially creates threaded conversations between users.

Previous studies have shown a strong connection between online content and people's behavior. For example, aggregated tweet sentiments have been shown to be correlated to consumer confidence polls and political polls (Chen et al., 2010; O'Connor et al., 2010), and can be used to predict stock market behavior (Bollen et al., 2010a; Bollen et al., 2010b); depression expressed in online texts might be an early signal of potential patients (Goh and Huang, 2009), etc. Existing work on political tweets analysis mainly focus on two aspects, tweet content analysis (Tumasjan et al., 2010; Diakopoulos and Shamma, 2010) or social network analysis (Conover et al., 2011; Livne et al., 2011) where networks are constructed using the relations built from those typical Twitter activities, following, re-tweeting, or mentioning. In particular, current approaches to tweet content analysis largely depend on sentiment or emotion lexicons to detect the polarity of a tweet message. There have been some work proposed to train supervised sen-

timent classifiers based on emoticons contained in tweet messages (Go et al., 2009; Pak and Paroubek, 2010) or manually annotated tweets data (Vovsha and Passonneau, 2011). However, these approaches can't be generalized well since not all tweets contain emoticons and it is also difficult to obtain annotated tweets data in real-world applications.

We proposed using a statistical modeling approach for tweet sentiment analysis by modifying from the previously proposed joint sentiment-topic (JST) model (Lin and He, 2009). Our approach does not require annotated data for training. The only supervision comes from a sentiment lexicon containing a list of words with their prior polarities. We modified the JST model by also considering other side information contained in the tweets data. For example, emoticons such as ":" indicate a positive polarity; hash tags such as "#goodbyegordon" indicate a negative feeling about Gordon Brown, the leader of the Labour Party. The side information is incorporated as prior knowledge into model learning to achieve more accurate sentiment classification results.

The contribution of our work is threefold. First, we conducted social influence study and revealed that the most influential users ranked using either re-tweets or the number of mentions are more meaningful than using the number of followers. Second, we performed statistics analysis on the political tweets data and showed that activities on Twitter can not be used to predict the popularity of parties. This is in contrast with the previous finding (Tumasjan et al., 2010) where the number of tweets mentioning a particular party correlates well with the actual election results. Third, we proposed using unsupervised statistical method for sentiment analysis on tweets and showed that it generated more accurate results than a simple lexicon-based approach or a supervised classifier trained with distant supervision when compared to the actual offline political sentiment.

The rest of the paper is organized as follows. Existing

Table 1: Keywords and hashtags used to extract tweets in relevance to a specific party.

Party	Keywords and Hashtags
Conservative	Conservative, Tory, Tories, conservatives, David, Cameron, #tory, #torys, #Tories, #ToryFail, #Conservative, #Conservatives, #PhilippaStroud, #cameron, #tcot, #ToryManifesto, #toryname, #torynames, #ToryCoup, #VoteTory, #ToryMPname, #ToryLibDemPolicies, #voteconservative, #torywin, #torytombstone, #toryscum, #ToryLibDemPolicies, #Imvotingconservative, #conlib, #libcon, #libservative
Labour	labour, Gordon, Brown, Unionist, #labour, #brown, #gordonbrown, #labourdoorstep, #ThankYouGordon, #votelabour, #gordonbrown, #LabourWIN, #labourout, #uklabour, #labourlost, #Gordon, #Lab, #labourmanifesto, #LGBTLabour, #labservative, #goodbyegordon, #labourlies, #BrownResign, #GetLabourOut, #cashgordon, #labo, #Blair, #TonyBlair, #imvotinglabour, #Ivotedlabour
Liberal Democrat	Liberal, Democrat, Nick, Clegg, Lib, Dems, #Liberal, #libdem, #LibDems, #LibDemWIN, #clegg, #Cleggy, #LibDemFlashMob, #NickCleggsFault, #NickClegg, #lib, #libcon, #libservative, #libelreform, #liblabpact, #liberaldemocrats, #ToryLibDemPolicies, #libdemflashmob, #conlib, #nickclegg, #libdems, #IAgreeWithNick, #gonick, #libdemmajority, #votelibdem, #imvotinglibdem, #IvotedLibDem, #doitnick, #dontoitnick, #nickcleggsfault, #libdemfail

work on political tweets analysis is presented in Section 2. Section 3 reveals some interesting phenomena from statistics analysis of political tweets relevant to the UK General Election 2010. Section 4 proposes a modification on the previously proposed JST model with side information indicating the polarities of documents incorporated. Section 5 presents the evaluation results of the modified JST model in comparison with the original JST on both the movie review data and the Twitter sentiment data. Section 6 discusses the aggregated sentiment results obtained from the political tweets data related to the UK General Election 2010. Finally, Section 7 concludes the paper.

## 2. Related Work

Early work that investigates the political sentiment in microblogs was done by Tumasjan et al. (2010) in which they analysed 104,003 tweets published in the weeks leading up to German federal election to predict election results. Tweets published over the relevant timeframe were concatenated into one text sample and are mapped into 12 emotional dimensions using the LIWC (Linguistic Inquiry and Word Count) software (Pennebaker et al., 2007). They found that the number of tweets mentioning a particular party is almost as accurate as traditional election polls which reflects the election results.

Diakopoulos and Shamma (2010) tracked real-time sentiment pulse from aggregated tweet messages during the first U.S. presidential TV debate in 2008 and revealed affective patterns in public opinion around such a media event. Tweet message sentiment ratings were acquired using Amazon Mechanical Turk.

Conover et al. (2011) examined the retweet network, where users are connected if one re-tweet tweets produced by another, and the mention network, where users are connected if one has mentioned another in a tweet, of 250,000 political tweets during the six weeks prior to the 2010 U.S. midterm elections. They found that the retweet network exhibits a highly modular structure, with users being separated into two communities corresponding to political left and right. But the mention network does not exhibit such political segregation.

Livne et al. (2011) studied the use of Twitter by almost 700 political party candidates during the midterm 2010 elections in the U.S. For each candidate, they performed structure analysis on the network constructed by the “following” relations; and content analysis on the user profile built using a language modeling (LM) approach. Logistic regression models were then built using a mixture of structure and content variables for election results prediction. They also found that applying LDA to the corpus failed to extract high-quality topics.

## 3. Political Tweets Data

The tweets data we used in the paper were collected using the Twitter Streaming API<sup>1</sup> for 8 weeks leading to the UK general election in 2010. Search criteria specified include the mention of political parties such as Labour, Conservative, Tory, etc.; the mention of candidates such as Brown, Cameron, Clegg, etc.; the use of the hash tags such as #election2010, #Labour etc.; and the use of certain words such as “election”. After removing duplicate tweets in the downloaded data, the final corpus contains 919,662 tweets.

There are three main parties in the UK General Election 2010, Conservative, Labour, and Liberal Democrat. We first categorized tweet messages as in relevance to different parties if they contain keywords or hashtags as listed in Table 1. Figure 1 shows tweets volume distributions for different parties. Over 32% of tweets mention more than two parties in a single tweet and only 9.1% of tweets do not refer to any of the three parties. It can also be observed that among the three main UK parties, Labour appears to be the most popular one with over 59% relevant tweets, followed by Conservative (43%), and Liberal (22%).

Table 2 lists the top 10 most influential users ranked by the number of followers, the number of re-tweets, and the number of mentions. The ranked list by the number of followers contains mostly news media organisations and it does not overlap much with the other two ranked lists. On the contrary, the ranked lists by the number of mentions and the number of re-tweets have 6 users in common. Among

<sup>1</sup><https://dev.twitter.com/docs/streaming-api>

Table 2: Social influence ranking results.

	<i>No. of Followers</i>		<i>No. of Mentions</i>		<i>No. of Re-tweets</i>
CNN Breaking News	3058788	<b>UK Labour Party</b>	7616	<b>UK Labour Party</b>	4920
The New York Times	2414927	<b>John Prescott</b>	4588	<b>Ben Goldacre</b>	2022
Perez Hilton	1959948	<b>Eddie Izzard</b>	3267	<b>Eddie Izzard</b>	1688
Good Morning America	1713700	<b>Ben Goldacre</b>	3141	<b>John Prescott</b>	1516
Breaking News	1687811	The Labour Party	2839	<b>Sky News</b>	1196
Women’s Wear Daily	1618457	<b>Conservatives</b>	2824	David Schneider	1128
Guardian Tech	1594486	Ellie Gellard	2747	<b>Conservatives</b>	1031
The Moment	1591086	Alastair Campbell	2408	Mark Curry	1030
Eddie Izzard	1525589	<b>Sky News</b>	2117	Stephen Fry	995
Ana Marie Cox	1490816	Nick Clegg	2083	Carl Maxim	946

Table 3: Information diffusion attributes of tweets from different parties.

Party	Avg. Follower No.	Tweets	Retweeted Tweets	Retweeted times	Retweet Rate	Average Retweet Times per Tweet	Lifespan (hours)
Conservative	<b>5479</b>	1045	505	3616	0.48	3.46	20.58
Labour	4963	<b>2039</b>	<b>1338</b>	<b>15834</b>	<b>0.66</b>	<b>7.92</b>	32.41
Lib Dems	4422	163	90	768	0.55	4.71	<b>32.50</b>

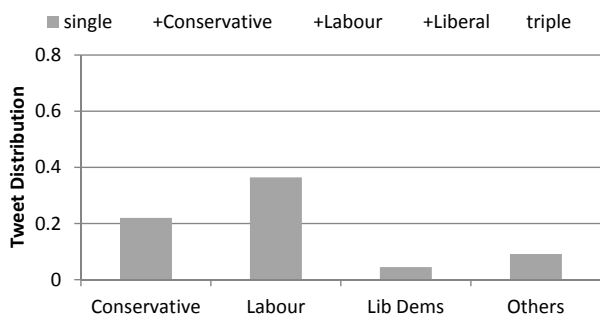


Figure 1: Tweets volume distributions of the political parties. “Single” denotes tweets mentioning only one party, legends proceeded with “+” denote tweets mentioning two parties, “triple” denotes tweets mentioning all the three parties.

the top 10 users ranked by the number of mentions or re-tweets, apart from the party-associated Twitter accounts (UK Labour Party and Conservatives) and politicians (John Prescott being the former Deputy Leader of the Labour Party and Nick Clegg being the leader of Liberal Democrat), the majority are famous actors or journalists, except Ellie Gellard who was a 21-year old student and a Labour supporter. We also notice that UK Labour Party has the most number of both re-tweets and mentions.

We then analyze the information diffusion attributes of tweets originated from the Twitter accounts of various parties and their most prominent supporters. We only extract Twitter users who have their tweets retweeted directly for more than 100 times. The results are summarized in Table 3. *Retweet rate* is the retweet to tweet ratio. It measures how well users from certain party engage with their audience. *Average Retweet times per tweet* calculates how many times a tweet has been retweeted on average. *Lifespan* is the average time lag in hours between the first appearance of a

seed tweet and the last appearance of its retweet.

It can be observed that Conservative has the highest average follower number compared to the two other parties. However, the Labour Party appears to be the most active in using Twitter for the election campaign. It publishes the most number of tweets and also has the highest reweet rate and average retweet times per tweet. Tweets from both Labour and Liberal Democrat are more persistent compared to Conservative, evidenced by the longer average lifespan of their tweets. Nevertheless, activities on Twitter can not be used to predict the popularity of parties. Labour generates most activities in Twitter and yet it failed to win the General Election. This is in contrast with the previous finding (Tumasjan et al., 2010) where the number of tweets mentioning a particular party is almost as accurate as traditional election polls which reflects the election results.

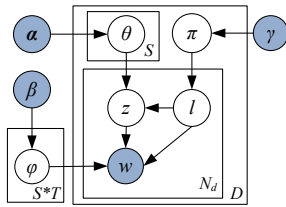
#### 4. Incorporating Side Information into JST

In Twitter sentiment analysis, emoticons such as “:-)”, “:D”, “:(” have been used as noisy message class labels (also called distant supervision) which indicate happy or sad emotion in supervised sentiment classifiers training (Go et al., 2009; Pak and Paroubek, 2010). However, this approach can not be used on our corpus since the tweets containing emoticons only account for 2% of the total tweets appeared in the corpus. Thus, we have to resort to unsupervised or weakly-supervised sentiment classification methods which do not rely on document labels. We have previously proposed the joint sentiment-topic (JST) model which is able to extract polarity-bearing topics from text and infer document-level polarity labels. The only supervision required is a set of words marked with their prior polarity information.

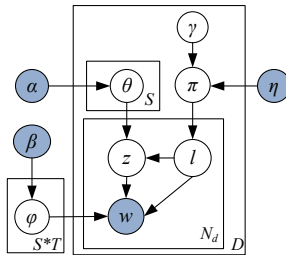
Assume that we have a corpus with a collection of  $D$  documents denoted by  $C = \{d_1, d_2, \dots, d_D\}$ ; each document in the corpus is a sequence of  $N_d$  words denoted by  $d = (w_1, w_2, \dots, w_{N_d})$ , and each word in the document is

an item from a vocabulary index with  $V$  distinct terms denoted by  $\{1, 2, \dots, V\}$ . Also, let  $S$  be the number of distinct sentiment labels, and  $T$  be the total number of topics. The generative process in JST which corresponds to the graphical model shown in Figure 2(a) is as follows:

- For each document  $d$ , choose a distribution  $\pi_d \sim \text{Dir}(\gamma)$ .
- For each sentiment label  $l$  under document  $d$ , choose a distribution  $\theta_{d,l} \sim \text{Dir}(\alpha)$ .
- For each word  $w_i$  in document  $d$ 
  - choose a sentiment label  $l_i \sim \text{Mult}(\pi_d)$ ,
  - choose a topic  $z_i \sim \text{Mult}(\theta_{d,l_i})$ ,
  - choose a word  $w_i$  from  $\varphi_{z_i}^{l_i}$ , a Multinomial distribution over words conditioned on topic  $z_i$  and sentiment label  $l_i$ .



(a) JST.



(b) JST with side information incorporated.

Figure 2: The Joint Sentiment-Topic (JST) model and the modified JST with side information incorporated.

Although the appearance of emoticons is not significant in our political tweets corpus, adding such side information has potential to further improve the sentiment detection accuracy. In the political tweets corpus, we also noticed that apart from emoticons, the used of hashtags could indicate polarity or emotion of the tweets. For example, the hashtag “#torywin” might represent a positive feeling towards the Tory (Conservative) Party, while “#labourout” could imply a negative feeling about the Labour Party. Hence, it would be useful to gather such side information and incorporate it into JST learning.

We show in the modified JST model in Figure 2(b) that the side information such as emoticons or hashtags indicating the overall polarity of tweets can be incorporated by updating the Dirichlet prior,  $\gamma$ , of the document-level sentiment distribution. In the original JST model,  $\gamma$  is a uniform prior and is set as  $\gamma = (0.05 \times L)/S$ , where  $L$  is the average

document length, and the value of 0.05 on average allocates 5% of probability mass for mixing. In our modified model here, a transformation matrix  $\eta$  of size  $D \times S$  is used to capture the side information as soft constraints. Initially, each element of  $\eta$  is set to 1. If the side information of a document  $d$  is available, then its corresponding elements in  $\eta$  is updated as:

$$\eta_{ds} = \begin{cases} 0.9 & \text{For the inferred sentiment label} \\ 0.1/(S-1) & \text{otherwise} \end{cases}, \quad (1)$$

where  $S$  is the total number of sentiment labels. For example, if a tweet contains “:-)”, then it is very likely that the sentiment label of the tweet is positive. Here, we set the probability of a tweet being positive to 0.9. The remaining 0.1 probability is equally distributed among the remaining sentiment labels. We then modify the Dirichlet prior  $\gamma$  by element-wise multiplication with the transformation matrix  $\eta$ .

## 5. Sentiment Analysis Evaluation

We evaluated our modified JST model on two datasets. One is the movie review data<sup>2</sup> consisting of 1000 positive and 1000 negative movie reviews drawn from the IMDB movie archive. The other is the Stanford Twitter Sentiment Dataset<sup>3</sup>. The original training set consists of 1.6 million tweets with equal number of positive and negative tweets labeled based on emoticons appeared in the tweets. The test set consists of 177 negative and 182 positive tweets and were manually annotated with sentiment. We selected a balanced subset of 60,000 tweets from the training set for training and the same test set for testing.

We implemented a lexicon-based approach which simply assigns a score +1 and -1 to any matched positive and negative word respectively based on a sentiment lexicon. A tweet is then classified as either positive, negative, or neutral according to the aggregated sentiment score. We used the MPQA sentiment lexicon<sup>4</sup> augmented with the additional polarity words provided by Twitrratr<sup>5</sup> for both the lexicon-based labeling and for providing prior word polarity knowledge into the JST model learning.

We also trained a supervised Maximum Entropy (MaxEnt) model on the two datasets. For the movie review data, we performed 5-fold cross validation and averaged results over 10 such runs. The evaluation results are shown in Table 4. It can be observed that the simple lexicon-based approach performed quite badly on both datasets. The supervised MaxEnt model gives accuracies of over 80%. Weakly-supervised JST model without using document label information performs worse than the supervised MaxEnt model. However, incorporating document labels as prior into the JST model improves upon the original JST without accounting for such side information. In particular, JST with side information incorporated outperforms MaxEnt on the movie review data and gives a similar result as MaxEnt on the Stanford Twitter sentiment data.

<sup>2</sup><http://www.cs.cornell.edu/people/pabo/movie-review-data>

<sup>3</sup><http://twittersentiment.appspot.com/>

<sup>4</sup><http://www.cs.pitt.edu/mpqa/>

<sup>5</sup><http://twitrratr.com/>

Method	Movie Review	Twitter Data
Lexicon	54.1	42.1
MaxEnt	82.5	81.0
JST	73.9	75.6
JST with side info	<b>85.3</b>	<b>81.2</b>

Table 4: Sentiment binary classification accuracy (%).

## 6. Political Tweets Sentiment Analysis Results

For employing the JST model for sentiment analysis on the political tweet data, we first manually identified a set of hash tags indicating positive and negative polarities towards a certain political party. Table 5 lists the indicative hashtags together with the total number of tweets containing these hashtags. The percentage of tweets with bias inferred from hashtags is 1.6, 1.8, and 5.2 respectively for Conservative, Labour, and Liberal Democrat. We also included tweets with emoticons and ended up with a total of nearly 50,000 tweets with bias inferred from either hashtags or emoticons. We trained the JST model from the UK political tweets data with or without the side information incorporated to detect sentiment of each tweet. For each party, we counted the total number of positive and negative mentions relating to this specific party across all the tweets. We define the bias measure towards a party  $i$  as:

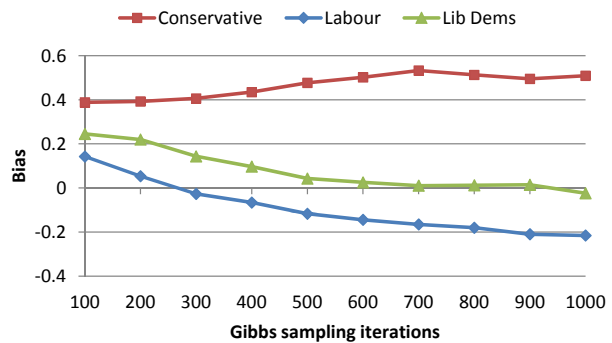
$$\text{Bias}_i = \frac{C_i^{\text{pos}}}{C_i^{\text{neg}}} - 1 \quad (2)$$

where  $C_i^{\text{pos}}$  and  $C_i^{\text{neg}}$  denotes the total number of positive and negative tweets towards a party  $i$ . The bias measure takes value 0 if there is no bias. And it is positive for positive bias and negative vice versa.

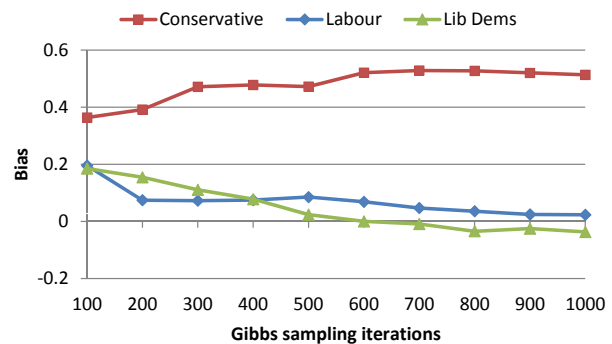
Figure 3 shows the bias measure values versus the JST Gibbs sampling training iterations. It can be observed that the bias values stabilise after 800 iterations. JST with or without side information incorporated gives similar results for both Conservative and Liberal Democrat. In general, the tweets reflect a positive bias towards Conservative and balanced positive and negative views on Liberal Democrat. The results differ for the Labour party that JST without considering side information detects a negative bias on Labour. However, with side information accounted, JST shows roughly balanced positive and negative views on Labour.

We further conducted experiments to compare the JST results with some of the baseline models including:

- *Lexicon Labeling*. We classify tweets as positive, negative, or neutral by a simply keyword matching against a sentiment lexicon obtained from MPQA and Twitrrat.
- *Naïve Bayes (NB)*. We have nearly 4% tweets containing either emoticons or the indicative hashtags as listed in Table 5. We used them as labeled training data to train a NB classifier which was then applied to assign a polarity label to the remaining tweets.



(a) JST.



(b) JST with side information incorporated.

Figure 3: Bias towards the three main UK parties.

Figure 4 compares the bias measure of the three main UK parties in tweets obtained by different approaches. It can be observed that the lexicon-labeling approach based on merely polarity word counts shows a positive bias on all the three parties with the most number of positive tweets on Liberal Democrat, followed by Labour and Conservative. NB shows that more people expressed negative opinions on Conservative, but favorable opinions on Labour and Liberal Democrat. In contrast, the results from the JST model shows that the Conservative Party receives more positive marks. The Labour Party gets more negative views. The Liberal Democrat has roughly the same positive and negative views. Finally, JST with side information incorporated displays the same trend except that the Labour party receives more balanced positive and negative views. Although we didn't perform rigorous evaluation on sentiment classification accuracy due to the difficulty in obtaining the ground truth labeling on such high volume tweets data, the results shows that using the JST model for the detection of political bias from tweets data gives the most correlated outcome with the actual political landscape.

We notice that JST with or without side information incorporated does not seem to differ much on the aggregated sentiment results generated. This is perhaps due to the low volume of tweets (4% of the total tweets) containing indicative polarity label information such as smileys or relevant hashtags. It is however worth to explore a self-training approach that tweet messages that are classified by JST with high confidence could be added into the labeled tweets pool to iteratively improve the model performance. We will leave

Table 5: Hashtags indicating bias towards a particular political party.

Party	Polarity	Hashtags	No. of Tweets	Percentage
Conservative	Positive	#Imvotingconservative, #VoteTory, #voteconservative	541	1.6%
	Negative	#Toryfail, #imNOTvotingconservative, #keptoriesout	5721	
Labour	Positive	#votelabour, #labourWIN, #imvotinglabour, #Ivotedlabour, #ThankYouGordon	7572	1.8%
	Negative	#Labourfail, #labourout, #labourlost, #goodbyegordon, #BrownResign, #GetLabourOut	2361	
Lib Dems	Positive	#IAgreeWithNick, #gonick, #libdemmajority, #votelibdem, #imvotinglibdem, #LibDemWIN, #IvotedLibDem, #doitnick	3464	5.2%
	Negative	#dontdoitnick, #nickleggsfault, #libdemfail	7085	

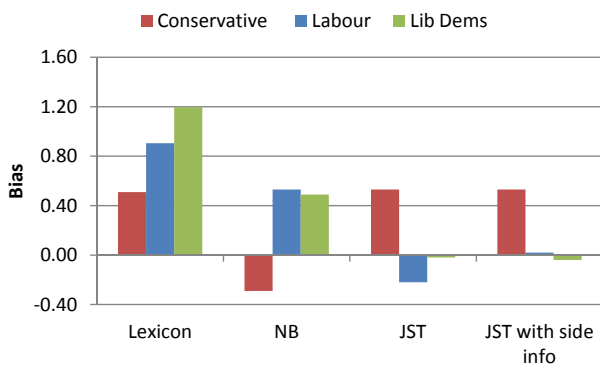


Figure 4: Bias measurement derived from different methods on the three main UK parties.

it as future work for further exploration.

## 7. Conclusions

In this paper, we have analyzed tweet messages leading to the UK General Election 2010 to see whether they reflect the actual political landscape. Our results show that activities on the Twitter cannot be used to predict the popularity of election parties. We have also extended from our previously proposed joint sentiment-topic model by incorporating side information from tweets which include emoticons and hashtags that are indicative of polarities. The aggregated sentiment results are more closely match the offline public sentiment as compared to the simple lexicon-based approach or the supervised learning method based on distant supervision.

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## 8. References

J. Bollen, A. Pepe, and H. Mao, 2010a. *Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena*. <http://arxiv.org/abs/0911.1583>.  
 Johan Bollen, Huina Mao, and Xiao-Jun Zeng. 2010b. Twitter mood predicts the stock market. *Journal of Computational Science*.

B. Chen, L. Zhu, D. Kifer, and D. Lee. 2010. What Is an Opinion About? Exploring Political Standpoints Using Opinion Scoring Model. In *AAAI*.  
 M.D. Conover, J. Ratkiewicz, M. Francisco, B. Gonçalves, A. Flammini, and F. Menczer. 2011. Political polarization on twitter. In *Proceedings of the 5th International Conference on Weblogs and Social Media*.  
 N.A. Diakopoulos and D.A. Shamma. 2010. Characterizing debate performance via aggregated twitter sentiment. In *Proceedings of the 28th international conference on Human factors in computing systems (CHI)*, pages 1195–1198.  
 A. Go, R. Bhayani, and L. Huang. 2009. Twitter sentiment classification using distant supervision. Technical report, Stanford University.  
 T.T. Goh and Y.P. Huang. 2009. Monitoring youth depression risk in Web 2.0. *VINE: The journal of information and knowledge management systems*, 39(3):192–202.  
 C. Lin and Y. He. 2009. Joint sentiment/topic model for sentiment analysis. In *Proceeding of the 18th ACM conference on Information and knowledge management (CIKM)*, pages 375–384.  
 A. Livne, M.P. Simmons, E. Adar, and L.A. Adamic. 2011. The party is over here: Structure and content in the 2010 election. In *Proceedings of the 5th International AAAI Conference on Weblogs and Social Media (ICWSM)*.  
 B. O’Connor, R. Balasubramanian, B.R. Routledge, and N.A. Smith. 2010. From tweets to polls: Linking text sentiment to public opinion time series. In *Proceedings of the International AAAI Conference on Weblogs and Social Media*, pages 122–129.  
 A. Pak and P. Paroubek. 2010. Twitter as a corpus for sentiment analysis and opinion mining.  
 J.W. Pennebaker, R.J. Booth, and M.E. Francis. 2007. Linguistic inquiry and word count (liwc2007). *Austin, TX: LIWC (www.liwc.net)*.  
 A. Tumasjan, T.O. Sprenger, P.G. Sandner, and I.M. Welpe. 2010. Predicting elections with twitter: What 140 characters reveal about political sentiment. In *International AAAI Conference on Weblogs and Social Media*.  
 A.A.B.X.I. Vovsha and O.R.R. Passonneau. 2011. Sentiment analysis of twitter data. pages 30–38.