**140 Characters to Victory?: Using Twitter to Predict the UK 2015 General Election**

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**Research Highlights**

* We present a genuine forecast of a national election using Twitter data
* We demonstrate that Twitter is a useful tool for electoral forecasting
* Our forecast accurately predicts the top three parties in terms of vote share.
* Our findings suggest that Labour supporters were more active on Twitter.
* Geocoding of tweets is needed to accurately forecast outcomes for regional parties.

**Abstract**

This paper uses Twitter data to forecast the outcome of the 2015 UK General Election. While a number of empirical studies to date have demonstrated striking levels of accuracy in estimating election results using this new data source, there have been no genuine i.e. pre-election forecasts issued to date. Furthermore there have been widely varying methods and models employed with seemingly little agreement on the core criteria required for an accurate estimate. We attempt to address this deficit with our ‘baseline’ model of prediction that incorporates sentiment analysis and prior party support to generate a true forecast of parliament seat allocation. Our results indicate a hung parliament with Labour holding the majority of seats.

Keywords: Election, Forecasting, Twitter, Sentiment Analysis

**Introduction**

The election forecasting ‘industry’ is a growing one, both in the volume of scholars producing forecasts and methodological diversity. In recent years a new approach has emerged that relies on social media and particularly Twitter data to estimate election outcomes. While some studies have produced some highly accurate results there has been criticism over the lack of consistency and clarity in the methods used, along with inevitable problems of population bias. In this paper we set out a ‘baseline’ model for using Twitter as an election forecasting tool that we then apply to the UK 2015 General Election. The paper builds on existing literature by extending the use of Twitter as a forecasting tool to the UK context and identifying its limitations, particularly with regard to its application in a multi-party environment with geographic concentration of power for minor parties.

**Using Twitter to Predict Elections: The Story So Far**

The increasing use of social media globally has dramatically increased the amount of data available to track and predict trends in the economy, public opinion and population health (Pries et al., 2013; Ortiz et al., 2011; Mellon, 2014). The use of Twitter data to forecast elections has become increasingly prominent since the start of the current decade, however, there is no consensus over how to forecast with Twitter and the findings to date have been mixed. Tumasjan et al’s (2010) study of the 2009 German Federal election constitutes the first published attempt to use Twitter to estimate a national election result. As with the studies that have followed, it was not a genuine forecast in that it was conducted post-election. The results were encouraging, however, in that the authors claimed a high degree of accuracy for their analysis which compared the share of mentions of the six most prominent parties and associated politicians in tweets over a five week period prior to election day, to their final vote share. Criticism of the study and its somewhat crude ‘more tweets, equals more votes’ premise soon followed. In particular Jungherr et al. (2012) noted the lack of methodological justification for the time period used and how the tweets were captured. Re-running the analysis over a longer time span that ran closer to the election day resulted in a higher mean adjusted error (MAE) of 2.13 compared to the 1.65 of the original study and a much higher MAE than traditional polls.

Complementing this specific rebuttal, Gayo-Avello (2011, 2012) identified more general problems in the use of Twitter to predict election outcomes. Topmost among his concerns was the need to produce a true forecast, i.e. one that was issued prior to the election. In addition he stressed the need to take into account the biases within the Twitter using population and existing power distribution among the candidates and parties being studied. Finally he called on analysts to incorporate Tweet sentiment into the computation rather than rely simply on volume. Other published and unpublished empirical studies produced around the same time raised some major questions about the accuracy of twitter as a forecasting tool (Gayo-Avello et al. 2011; Bermingham and Smeaton 2011; O’Connor et al., 2010; Metaxas et al., 2011; Skoric et al. 2012; Sang and Bos, 2012)

Subsequent studies appear to have taken on board some of Gayo-Avello’s advice producing more encouraging results. DiGrazia et al. (2013) for example added a range of individual and district level controls to a regression model using Twitter mentions to predict vote share for candidates in the 2010 and 2012 U.S. Congressional elections. The authors concluded a positive and statistically significant relationship remained even after accounting for incumbency and parties’ existing levels of popularity. Franch (2013) took a more dynamic approach and examined sentiment expressed toward the three main party leaders across a number of social media platforms, including Twitter in the lead-up to the 2010 UK election. Using an auto regressive integrated moving average (ARIMA) model he regressed daily measures of party support from Yougov polls on their social media popularity scores and generated a set of final predictions that were within 1 percent of the three parties actual vote share. Ceron et al. (2014) used sentiment analysis to compute a Twitter popularity rating for Italian political leaders in the 2011 parliamentary elections and candidates in the French 2012 Presidential election. According to the authors the results were almost analogous to the predictions based on polls and in line with academic forecasts using offline data (Nadeau et al. 2012). Finally Caldarelli at al. (2014) introduced a ‘relative support’ parameter to their analysis that produced an ‘instant indicator’ of the comparative strength of two parties on Twitter (using mentions). This was used to predict the election results for the four main parties in the 2013 Italian parliamentary elections. While the results confirmed to the authors that Twitter is ‘an effective way to get indications of election outcomes’ they admitted that it over-predicted the vote of the two main parties. The error, they argued, followed from the inclusion of the party leaders’ names as search terms (Monti and Berlusconi), both of whom were former Prime Ministers and the latter was on trial at the time.

Overall, therefore, the extant literature appears to offer grounds for expecting that Twitter can serve as a useful tool in predicting electoral outcomes across a variety of national contexts, subject to certain corrective steps. Our approach begins with a ‘baseline’ model of Twitter forecasting that borrows from the KISS principle used in Agent Based Modelling whereby one starts with the most basic and transparent model which can then be built upon (Axelrod, 1997). In doing so we follow three of Gayo-Avello’s main recommendations. First we offer a genuine forecast based on Twitter data harvested no later than one month prior to election day. Second we adjust our forecast to take into account the sentiment of the tweet. Finally in calculating our predictions on seat rather than vote share we take into account the existing distribution of parliamentary representation and party power within each constituency.

**Methodology**

We began by collecting data from the Twitter streaming API (Burnap et al. 2014). Tweets were selected if they included party and/or leader names, as shown in Appendix Table 1. The search was not case sensitive so it effectively collected mentions with upper and lower case spelling. The collection was commenced on the 28th November 2014 and contained 13,899,073 tweets by the time the forecast was calculated on 9th March 2015. See Appendix Table 1 for search terms.

After harvesting the Twitter sample we then applied automated sentiment analysis using software developed by Thelwall et. al (2010), which allocates a string of text a positive and negative score ranging from -5 (extreme negative) to +5 (extreme positive), where each score is produced based on words in the string that are known to carry such emotive meaning (e.g. ‘love’=5, hate=’-4’). Where a tweet contained more than one of the search terms (e.g. “I’m voting *Labour* because I can’t stand *David Cameron*”), we removed the tweet from the sample to avoid misallocating the positivity in the tweet. Clearly, in the example, the positivity is directed towards Labour, but the automatic identification of sentiment direction was beyond the scope of this study.

We first calculated sentiment scores for each tweet and produced a list of all tweets with associated positive and negative sentiment scores. Applying a rationale that positive tweets containing party or leader names can be treated as vote intentions, we removed all tweets where sentiment scores were below -1, and kept those between -1 and +5. The value of the remaining sentiment scores were summed to produce a *party sentiment score* and *a leader sentiment score*. Scores for leaders representing the same party (e.g. Natalie Bennett and Caroline Lucas) were combined, as were party mentions (e.g. Tories, Conservatives etc). The reason for summing all tweet sentiment scores as opposed to counting the number of positive mentions was to record the overall magnitude of the sentiment. In a situation where Labour had the same number of positive tweets as the Conservatives, the summed sentiment score would differentiate the parties where the average sentiment was higher for one than the other. The summed sentiment scores for all parties and their leaders (e.g. Tories, Conservatives, David Cameron etc.) were then combined to produce a single *positive party sentiment sum* for each party. All positive party sentiment sums were combined to calculate the total sentiment, which was used to normalise the positive party sentiment sum for each party, with respect to all other parties, thus producing a party-specific Twitter positive sentiment proportion (see Table 2).

Visual inspection of the data identified an unusually high level of false-positives for the search terms “Labour” and “Greens”, due to the different contexts in which these terms can be used. Using 3-way human annotation, where three individuals manually annotated a random sample of 1,000 tweets including these terms according to whether each tweet was actually related to the UK Labour or Green Parties, we identified that 78.9% of tweets containing the word “Labour” were actually about the Labour Party and only 19.4% of the tweets containing the term “Greens” were actually about the Green Party. The reason for the high proportion of type one errors associated with the Green Party was due to the bulk of activity focusing on the Australian Green Party. This weighting was applied when calculating positive Twitter proportions and had the effect of reducing the overall representation of these party mentions in the relative proportions. Table 1 reports our estimates of vote shares.

In a final step we converted our vote shares into a seat forecast (see Table 2). To do so we applied our vote share to the UK 2010 results and calculated a measure of national swing which was then applied on a constituency by constituency basis to produce an estimate of which party would win a given seat. For example, in Halesowen and Rowley Regis, West Midlands, the vote share in 2010 was CON=41.2, LAB=36.6, LIB=14.8 (CON WIN). Using the Twitter vote share to calculate change from 2010, the projected split becomes CON=34.4, LAB=35.9, LIB-3.8 (LAB WIN), showing a swing from Conservative to Labour. This process was performed for all seats in the UK, and the final number of seats won was calculated for each party by selecting the maximum value for each seat (see Table 3).

**Discussion and Conclusions**

The results show the likely outcome is a hung parliament with the Labour party gaining most seats. While the predictions for the other parties look to be within an expected range, with the exception of the SNP which appears to be markedly lower than contemporary polls suggest. This result points to the limitations of using Twitter to forecast in multi-party systems where there is a ‘majority’ regionalist party. Without a means of geo-locating tweets there will always be an under-estimation of such support since the assumption of our calculations is that individuals are randomly distributed across the UK. Given the reduction in N after geocoding methods are applied (i.e. tweets including a precise location) – only around 1% of tweets are retained – we opted to retain our larger sample with an acceptance of the dilution in SNP support.

More generally we consider our analysis to advance the literature in that it satisfies at least three of the core criteria identified as necessary to any application of this method. First and perhaps most importantly it is a genuine forecast made in advance of election day. In addition, it is adjusted to take into account the sentiment of the tweet as well as the prior support levels of the parties. Future applications need to incorporate methods for geo-location and also to apply corrections for bias in sample demographics. Fortunately work is currently underway by the authors (Sloan et al. 2013, Sloan et al. 2015) to address these issues and is predicted to be available in time for the next UK General Election.

Post Script

Our prediction that Labour would win 21 more seats than the Conservative party (306 to 285) proved to be inaccurate, indicating that Twitter was not immune from the problems that beset the most of the other polls and forecasts issued in advance of election day. Despite our distance from the final result in seat shares, however, it is encouraging to note that our method correctly predicted the order of the top three parties in terms of vote share: Conservative, Labour and UKIP, and the actual proportion of Labour votes with a notable degree of accuracy. It was also predictive of the large rise in UKIP support, and sharp drop in support for Liberal Democrats. While it is likely that geo-location of tweets to constituencies would have improved the accuracy of our seat-by-seat forecast, particularly within Scotland, the massive reduction in the number of tweets available for analysis that this would have led to would have introduced additional and potentially significant bias to the results. In particular, we know that geo-location tends to lead to over-representation of tweeters in urban areas compared with rural constituencies. Given that the latter is where it has been argued Labour lost the election we consider it unlikely that geo-locating tweets would have improved the results. This is something for future post-hoc analyses of our dataset to investigate. Finally, we consider that our approach allows us to discount more persuasively the “shy Tory” thesis that has been set forward as an explanation for the mismatch between the prior forecasts and the election outcome. While there may have been some self-censorship operating on Twitter, the relative anonymity it affords to individuals in expressing their opinions, alongside the entirely voluntary and informal nature of the views expressed we contend would very likely reduce the social desirability bias that affects respondents in a formal survey interview setting. The fact that we still under-estimated levels of Conservative support in our analysis by some margin is thus more likely due to the fact that they were simply failed to ‘show up’ in the same numbers as Labour supporters. A contention supported by recent analysis of the partisan distribution of Twitter users responding to the British Election Study (Gibson, 2015). Further research into the partisan distribution of Twitter users and particularly the extent of any Labour or Conservative bias in the population of users is needed to more fully assess this contention.

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**Table 1 – Twitter sentiment and vote share (some minor parties removed where we did not collect the leader)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Party +ve Sentiment Share | Leader +ve Sentiment | Total +ve Sentiment | +ve Twitter Proportion |
| Conservative | 0.107393085 | 0.404418497 | 0.511811582 | 0.292351853 |
| Labour | 0.305422798 | 0.189374473 | 0.494797271 | 0.28263311 |
| Lib Dem | 0.014556207 | 0.063081068 | 0.077637275 | 0.044347182 |
| SNP | 0.10048713 | 0.059566354 | 0.160053484 | 0.091424138 |
| Green | 0.048597728 | 0.124554097 | 0.044856119 | 0.02562226 |
| UKIP | 0.276503519 | 0.138688431 | 0.41519195 | 0.237161761 |
| DUP | 0.02433284 | 0.004705975 | 0.029038815 | 0.016587259 |
| Plaid | 0.001658883 | 0.001890266 | 0.003549149 | 0.002027309 |
| Sinn Fein | 1.34E-05 | 0.013720838 | 0.013734232 | 0.007845129 |

**Table 2 – 2015 vote share change from 2010 based on Twitter and Projected Seat Wins**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **2010 Share** | **2015**  **Twitter Share** | **Change** | **Seats** |
| Conservative | 36.1 | 29.3 | -6.8 | 285 |
| Labour | 29.0 | 28.3 | -0.7 | 306 |
| Lib Dem | 23.0 | 4.4 | -18.6 | 21 |
| SNP | 1.7 | 9.2 | +7.5 | 9 |
| Green | 1 | 2.3 | +1.3 | 1 |
| UKIP | 3.1 | 23.8 | +20.7 | 5 |
| DUP | - | 1.7 |  |  |
| Plaid | 0.6 | 0.2 | -0.4 | 3 |
| Sinn Fein | - | 0.8 |  |  |

APPENDIX

Twitter search terms

|  |  |
| --- | --- |
| Leaders | Parties |
| David Cameron  Ed Miliband  Nick Clegg  Nigel Farage  Natalie Bennett  Caroline Lucas  leanne wood  nicola sturgeon  alex Salmond  peter Robinson  gerry adams | Conservative Party  Tory Party  Tories  Labour Party  UKIP  Green Party  Labour  SNP  Scottish National Party  lib dems  liberal democrats  greens  UK independence party  BNP  British National Party  DUP  Democratic Unionist Party  Sinn Fein  SDLP  UUP  Ulster Unionist Party  Plaid |