If Likes Were Votes: An Empirical Study on the 2011 Italian Administrative Elections

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Abstract

Is it possible to forecast electoral results by analyzing social media conversations? This paper aims to contribute to the debate raised by authors claiming to have successfully predicted the outcomes of an election from Twitter or Facebook data. Our work tested the purported predictive power of social media metrics against the 2011 Italian administrative elections. During the months before the election day, we collected the amount of Likes received on the Facebook pages of 229 candidates running for the mayor offices of the 29 provincial capitals. We built two forecast models with the goal of predicting the outcomes of the elections: the aim of the first one was to predict the candidates' vote shares, while the second was to forecast the name of the winning candidate. We found a non significant correlation between the share of candidate popularity on Facebook and the respective share of votes. However, in 39% of the cases, the most popular candidate on Facebook actually won the contest, and in another 43%, that candidate came in second. The contribution to the ongoing debate is therefore two sided: on the one hand, we provide a new case study from a cultural context and political system never analyzed before by this kind of study; on the other side, we propose two forecasting models that, although proven to be partially unsuccessful, can provide a foundation for improved forecasting models.

Introduction

On 15 and 16 May, 2011, the citizens of over one thousand Italian municipalities voted to elect a new mayor. The number of involved municipalities, including major cities such as Milan, Naples, Turin, and Bologna, as well as the national political debate, raised the importance of this election beyond the local and regional level.

This high level of expectation instigated an intense level of conversations in the media and among the people. Although the effect of these conversations in shaping political opinions is widely recognized (Bennett & Wells, 2009), the weight and degree of this effect are still not clear (Campus, Pasquino, & Vaccari, 2008).

Moreover, in the 2011 Italian elections, a significant part of this conversation happened, for the first time, online. Also groundbreaking, in 2011 in fact, more than half of Italian citizens used the Internet (ISTAT, 2011) with most of them also on Facebook. Even if a specific study, such as the one carried out by Pew in the United States after the 2008 presidential (Smith 2009) and 2010 midterm elections (Smith 2011), is still lacking, we can assume, following studies that point out similarities in news consumption among online Italians and Americans (Ceccarini & Di Pierdomenico, 2010), that part of the political conversations about the 2011 Italian elections also happened online.

As opposed to traditional face-to-face political conversations that always happened among family members or in cafés and town squares, online conversations leave traces (boyd, 2008). The properties of these traces make it possible, for the first time in history, to formally analyze this one-time ephemeral phenomenon (Giglietto, 2009). In this emerging field (Manovich, 2011), most of the studies use the data to describe and better comprehend events which happened in the past. On the contrary, more recent literature is pointing out the forecasting potentials of the data spontaneously produced and shared by millions of people online.

Literature Review

Forecasting Elections with Social Media

During the 2006 midterm elections, Facebook created a space named *US Politics* to host congressional candidates' profiles. 32% of candidates running for Senate and 13% of those running for the House actually updated the basic profile provided by Facebook with their contents.

According to Williams and Gulati (2009), the candidates' Facebook support had a significant effect on their final vote shares. The same authors also studied the 2008 presidential primaries, confirming the importance of Facebook support as a predictor of candidate viability in the majority of the contests (Gulati and Williams 2008).

During the 2008 presidential elections, Facebook improved this strategy by offering pages to candidates instead of personal profiles. Only a weak correlation was found between the House candidates' 2008 vote share and the number of their supporters on Facebook (Williams and Gulati 2009).

The relevance of social media consolidated in 2010 (Smith 2011). A few days after the elections, the Facebook political team released a note, claiming that over a sample of 98 races for the Senate and 34 for the House, in 74% and in 82% of the contests, respectively, the most popular candidate on Facebook actually won the race. A report from Trilogy Interactive tested these results by looking for a linear correlation between the margin between the winner and the second candidate and the margin of popularity on Facebook. The conclusion of this study could not confirm the existence of a correlation but pointed out the need for more studies in different national and political contexts (Olson & Bunnett, 2010).

During the 2011 general Canadian elections, Dare Labs and Optimum PR gathered the amount of Likes received by the pages of all candidates. According to results published on the project website, in the urban zones of Canada there was a remarkable correlation between the popularity of a candidate on Facebook and the number of vote actually received (Dare & Optimus PR, 2011).

Even if Facebook is the most diffuse social network and therefore the most suitable to be used for predictions representative of the population, several studies focused instead on Twitter.

During the 2009 federal German elections, a research group analyzed over 100,000 Tweets mentioning at least one party; they reached the surprising result that the mere number of mentions accurately reflected the electoral outcomes (Tumasjan, Sprenger, Sandner, & Welpe, 2010). A similar study tried to correlate the frequency of Tweets which mentioned one of the candidates and a specific opinion together with electoral polls; they discovered a significant level of correlation (O'Conor, Balasubramanyan, Routledge, & Smith, 2010).

The very same method proposed by Tumasjan was put to the test several times. A replica of the study was tried, unsuccessfully, by another research team on a sample of over eight million Tweets mentioning at least one of the candidates in the 2010 Brazilian presidential elections. The authors point out two improvements to Tumasjan's original methodology and demonstrate how this impacts the mean absolute error margin between the result and the prediction (Trumper, Meira, & Almeida, 2011).

Another replica of the German study was attempted, with minimal modifications, during the 2010 midterm elections in the U.S. Even in this case the research team was not able to replicate the original results and no significant correlation was reported (Gayo-Avello, Metaxas, & Mustafaraj, 2011).

The original study by Tumasjan and his team was also criticized in a paper published in a subsequent issue of the same journal where the original paper had been published. In an article eloquently titled "Why the Pirate Party Won the German Election of 2009" (Jungherr, Jurgens, & Schoen, 2011), doubts are raised about the results presented by their colleagues. According to the authors of this paper, the reported results were due to contingent conditions and the arbitrary choices of the researchers. In particular, extending the list of parties included in the study to all the parties taking part in the elections, shows that the pirate party was the most mentioned one. In a response to this paper, Tumasjan and his colleagues reacted to the critiques by better justifying the list of parties included in the study and the selected time frame (Tumasjan, Sprenger, Sandner, & Welpe, 2011).

Research Questions

The idea to test the purported predictive power of social media metrics against the 2011 Italian administrative elections comes from this contradictory and fascinating collection of results. To do so, we have formulated the following two research questions.

RQ1: Can a candidate's Facebook popularity be considered as an effective indicator of the electoral performance of the candidate?

RQ2: How do secondary variables -- such as the candidate's political party, the percentage of candidates with Facebook pages in a municipality, the number of potential voters, and the effective voters turn out -- affect the relationship between electoral performance and Facebook popularity?

Methodology

The sample of this study consisted of 229 candidates to the major offices of the 29 provincial capitals. By querying the Facebook internal search engine, we identified 104 pages. In line with studies concerning previous elections (Mascheroni & Minucci, 2010), 44.5% of the candidates were, therefore, present on Facebook with a page. From 25 April to 15 May, we gathered the number of Likes received by all the Facebook pages by periodically querying the Graph API.

At 11:05 on 14 May 2011, the day before the elections, monitored pages received a total amount of 179,003 Likes.

For each candidate, we calculated, by slightly modifying the methodology used by Olson e Bunnett (2010), a *Candidate Prediction Gap* (CPG) as the difference between a candidate's votes share and the respective Likes share. The Like share was calculated by dividing the amount of a candidate's Likes by the total amount of Likes received by all the candidates in the municipality.

For each municipality, we also calculated a *Municipality Prediction Gap* (ABS[MPG]) as the absolute average of candidates' CPG. To better comprehend the effect of secondary variables, we created homogeneous categories of municipalities based on the percentage of candidates on Facebook and the number of electors and voters.

For each municipality, we calculated an index of prediction precision. This index is based on the attribution of a specific score in one of the following cases:

	Score
Most popular candidate on Facebook arrived 2nd	3
2nd most popular candidate on Facebook won	3
2nd most popular candidate on Facebook arrived 2nd	4
Most popular candidate on Facebook won	6

Table 1. Scores for the index of prediction precision

Since some of the cases are mutually exclusive, the index score ranges from 0 to 10 in case both the first and the second candidate were correctly predicted.

Finally, we categorized the candidates in seven political areas (from extreme right to extreme left). For each area, we calculated a *Party Prediction Gap* (PPG) as the average CPG of the candidates and an ABS[PPG] as the absolute average of the candidates.

Results

The margin of errors revealed by the average CPG is high. Considering the average of absolute values, the margin goes from 0 to 84.18% with an average CPG of 15.77%. Considering instead positive and negative values, the average CPG is -6.21%.

In both cases, the margin is well above what is normally considered acceptable for opinion and exit polls.

The 26 municipalities had a minimum of 3 to a maximum of 13 running candidates. Little more than half of these candidates were on Facebook (51.1%). The average ABS[MPG] was 18.99% with a minimum margin of error of 5.09% and a maximum of 51.99%. The average ABS[MPG] decreased as the number of candidates present on Facebook increased.

% of candidates on Facebook	Average ABS[MPG]	N
0 33	29,4294	6
34 66	19,1245	11
over 67	11,8778	9

Table 2. Average ABS[MPG] for number of candidates on Facebook

Is also interesting to note that the average ABS[MPG] in large cities is significant lower than in smaller cities.

Number of electors	Average ABS[MPG]	N
Less than 80,000	21,3799	15
80,0000 to 200,000	20,9231	6
Over 200,000	95,218	5

Table 3. Average ABS[MPG] for number of electors

The analysis of error margins for the political area is not particularly interesting if the absolute averages are taken into consideration. As shown in Table 4, the value of ABS[PPG] increases as the number of candidates in the category increases.

Political Area	ABS[PPG]	PPG	ABS[PPG] PPG	N
Right	10.01	**-8.66**	1.35	6
Center right	27.75	1.30	**26.45**	22
Center	6.07	1.47	4.60	8
Center left	18.71	4.42	14.29	22
5 Stars Movement	11.27	**-11.27**	0	10
Civic lists	8.91	5.82	3.09	8
Other	12.65	**-11.63**	1.02	28

Table 4. Average margins for political area

However, the average PPG values are interesting. All the CPG values are negative. This means that the predicted share was often higher than the actual vote share. This result affects the whole political area but not in the same way. Extreme forces score higher margins. This result could be explained by the higher level of the supporters' participation of these political areas. As pointed out in the literature, the consensus on the Internet is often strongly polarized (Mascheroni & Minucci, 2010).

Moreover, subtracting the PPG from the ABS[PPG], we can estimate the effect of overestimated Facebook consensus on the margin of error. Here, the behavior of the center-right (+26.45) appears to be significantly different from other political areas. Compared to other political areas, the center-right prediction was significantly more underestimated by Facebook. This result may depend on a lower investment in social media marketing by center-right candidates and from the profile of the Italian net-citizen (Ceccarini & Di Pierdomenico, 2010).

The index of prediction precision, contrary to what we have seen until now, is not based on the margin of error. This index aims to evaluate how much the degree of Facebook consensus correctly predicted the winner and the second place candidate.

The average index score is 4.71 over 10. If we, however, observe the frequency of occurrence of the four conditions used to calculate the index, we noticed in 39% of the cases, the most popular candidate on Facebook actually won the contest and in another 43% came in second. The combination of these results make it pretty likely that the most popular candidate on Facebook either won or came in second in the real electoral competition.

Conclusions

The contradictory scenario described in the literature is confirmed by this study. If, on one hand, the average margin of error between the share of Likes and the share of votes highlights the limits of this kind of prediction, on the other hand the second model show traces of a relationship between Facebook consensus of a candidate and his viability.

Moreover, the smaller margin of error, registered in the races where more candidates were on Facebook, suggests that the model could become more precise in a future where Facebook campaign marketing will become more widespread. The effect of the number of electors on the margin of error may suggest that the model works better when the number of citizens involved in the process is higher. In both cases, following the experience of diffusion of this innovation in the United States (Gulati and Williams 2011; Smith 2011), it is easy to predict that both the number of candidates adopting a Facebook marketing strategy and the number of citizens involved in online participation will grow in the future even in our country.

At the same time it seems clear that candidates from different political areas and their supporters behave differently when it comes to online participation. The polarized forms of consensus highlighted in previous studies (Conover et al. 2011; Yardi and boyd 2010) tend to favorite extreme parties in these kinds of predictive models.

However, once these different behaviors become more clear and quantifiable, it is possible to imagine the development of correctives to the model to compensate for these factors in the same way it has happened in opinion and exit polls. It is therefore necessary to foster the development of new studies based on models previously presented in the literature and to accumulate more series of data. Since elections are pretty rare events in a country, it will become invaluable to collect comparable experiences from different countries.

References

Bennett, W. L., & Wells, C. 2009. Civic Engagement: Bridging Differences to Build a Field of Civic Learning. *International Journal of Learning and Media 1*(3): 1 10.

Campus, D., Pasquino, G., & Vaccari, C. 2008. Social Networks, Political Discussion, and Voting in Italy: A Study of the 2006 Election. *Political Communication 25*(4): 243 444.

Ceccarini, L., & Di Pierdomenico, M. 2010. Info nauti. Cittadini in rete. *Comunicazione politica* (3).

Conover, M. D., Ratkiewicz, J., & Francisco, M. 2011. Political polarization on twitter. In Proceedings of the 5th International Conference of the Association for the Advancement of Artificial Intelligence.

Dare, & Optimus PR. 2011. The social election experiment. Retrieved December 5, 2001, from goo.gl/a0ZHn.

Gayo Avello, D., Metaxas, P. T., & Mustafaraj, E. 2011. Limits of electoral predictions using Twitter. Proceedings of the 5th International AAAI Conference on Weblogs and Social Media.

Giglietto, F. 2009. Social semantics in a networked space. New perspectives for social science. In J. M. Aguado, B. Scott, & E. Buchinger (Eds.), *Technology and Social Complexity*. Murcia: University of Murcia Press.

ISTAT. 2011. *Cittadini e nuove tecnologie*. Roma.

Jungherr, a., Jurgens, P., & Schoen, H. 2011. Why the Pirate Party Won the German Election of 2009 or The Trouble With Predictions: A Response to Tumasjan, A., Sprenger, T. O., Sander, P. G., & Welpe, I. M. "Predicting Elections With Twitter: What 140 Characters Reveal About Political Sentiment." *Social Science Computer Review*.

Manovich, L. 2011. Trending: The Promises and the Challenges of Big Social Data.

Mascheroni, G., & Minucci, S. 2010. Le elezioni europee sul web: campaigning 2.0? *Comunicazione politica* (1).

Olson, S., & Bunnett, W. (2010). Facebook predicts electoral victory, or not? Retrived December 10, 2001 from goo.gl/yTC5s.

O'Conor, B., Balasubramanyan, Routledge, B. . R., & Smith, N. A. 2010. From tweets to polls: Linking text sentiment to public opinion time series. *Proceedings of the International AAAI Conference on Weblogs and Social Media* (pp. 122 129).

Trumper, D. S., Meira, W., & Almeida, V. 2011. From Total Hits to Unique Visitors Model for Election's Forecasting. *Proceedings of the ACM WebSci'11*. Koblenz.

Tumasjan, A., Sprenger, T. O., Sandner, P. G., & Welpe, I. M. 2010. Election Forecasts With Twitter: How 140 Characters Reflect the Political Landscape. *Social Science Computer Review I*(17).

Tumasjan, A., Sprenger, T. O., Sandner, P. G., & Welpe, I. M. 2011. Where There is a Sea There are Pirates: Response to Jungherr, Jurgens, and Schoen. *Social Science Computer Review*.

Yardi, S., & boyd, d. 2010. Dynamic Debates: An Analysis of Group Polarization Over Time on Twitter. *Bulletin of Science, Technology & Society*, *30*(5), 316 327.

boyd, danah. 2008. *Taken Ouf of Context: American Teen Sociality in Networked Publics*. University of California, Berkeley.