

Determining the Presence of Political Parties in Social Circles

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Abstract

We derive the political climate of the social circles of Twitter users using a weakly-supervised approach. By applying random walks over a sub-sample of Twitter's social graph we infer a distribution indicating the presence of eight Flemish political parties in users' social circles in the months before the 2014 elections. The graph structure is induced through a combination of connection and retweet features and combines information of over a million tweets and 14 million follower connections. We solely exploit the social graph structure and do not rely on tweet content. For validation we compare the affiliation of politically active Twitter users with the most-influential party in their network. On a validation set of around 700 politically active individuals we achieve F_1 scores of 0.85 and greater. We asked the Twitter community to evaluate our classification performance. More than half of the 2258 users who responded reported a score higher than 60 out of 100.

Introduction

The landscape of political activism has shifted to so-called new media (Bennett 2003). Blogs and social networks play an important role in the diffusion of political ideas (Adamic and Glance 2005). We investigate the spread of influence of political parties in Twitter. We look at the contributions of eight Flemish political parties in the months before the 2014 elections in Belgium.

Electoral prediction from Twitter data has received a lot of criticism over past years (Gayo-Avello 2012), mainly due to the biased nature of the Twitter population towards youths. We postulate that political influences travel through social graphs similarly to how ideas spread *viva voce*. Many social networks exhibit homophilic properties (Conover et al. 2011a), implying that personal networks are grounded in sociodemographic, behavioral and intrapersonal characteristics (McPherson, Smith-Lovin, and Cook 2001). Based on these properties we extract link-based features from interaction data on Twitter and simulate a random walk over an induced graph structure. For validation we compare the affiliation of politically active Twitter users with the most-influential party in their network. We observe good performance with F_1 scores of 0.85 and higher in an experiment with inferred hyperparameters. One week before the Flemish elections we

asked the relevant Twitter community to evaluate our performance in the wild. As expected, we received diverse opinions given the controversial nature of the study. More than half of the 2258 users who responded reported feedback scores of 60 out of 100 or higher.

Methodology

We provide a classification of nodes in a social graph based on link structure. Specifically, we determine the presence of a collection of labeled nodes in the neighborhoods of nodes in the network. We then choose the label of the most prominent node in each individual node's neighborhood as its label. We postulate that the most prevalent political party in an individual's network can give an indication of that individual's political affiliation.

To begin, we identify k Twitter users whom we label manually. In our case these k users correspond to the official accounts of political parties. Due to rate limitations enforced by Twitter we are only able to retrieve information about a specific subset of users. We choose to select only those users that follow at least k_{min} of the k labeled users. Formally, we define the social graph as a directed, weighted graph $G(V, E, W)$ where the set of nodes V , the set of edges E and weight matrix W respectively designate the set of n users, the connections between those users and the intensity of the connections. A positive, non-zero weight w_{ij} implies a connection from user i to user j . Note that the elements of W are unbounded in magnitude.

The graph G is instantiated from real-world Twitter interaction data. For each of the target users (i.e., those who follow at least k_{min} of the k labeled users) we retrieve the users following them and their 200 most-recent tweets. Using this method we are able to materialize a sub-graph that we can use for the purpose of classification. Note, however, that this sub-graph also contains users who were observed but not necessarily targeted. For example, a user following any of the targeted users but who were themselves not targeted will also be contained in the data sample. We distinguish between disjoint sets $V_{observed}$ and $V_{targeted}$ as results for users in the former might be unreliable due to data sparsity. We compute the strength of connections between users as a weighted sum of interaction counts (e.g., a retweet or a tweet subscription). Consider a sample of size n and p distinct interactions I_k , for

Input: $G = (V, E, W), L^0$
1: $t \leftarrow -1$
2: **repeat**
3: $t \leftarrow t + 1$
4: **for** $v \in V - V_l$ **do**
5: $L_v^t \leftarrow \sum_u W_{uv}^\top L_u^{t-1}$
6: Normalize L_v^t (L_1 norm).
7: **end for**
8: **until** convergence
Output: Distributions $L_v^t | v \in V$

Algorithm 1: Iterative formulation of an absorbing random walk over a social graph. L^t denotes the $n \times k$ matrix of labels at time t in the iterative formulation. At time $t = 0$ users $i \in V_l$ are assigned the label distribution with $L_{ii} = 1$ and the remaining matrix consists of all zeros, where V_l denotes the set of k initially labeled users.

every user i in our sample

$$W_i^\top = f \left(\begin{bmatrix} I_{1i,1} & I_{2i,1} & \cdots & I_{pi,1} \\ I_{1i,2} & I_{2i,2} & \cdots & I_{pi,2} \\ \vdots & \vdots & \ddots & \vdots \\ I_{1i,n} & I_{2i,n} & \cdots & I_{pi,n} \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_p \end{bmatrix} \right)$$

where I_{kij} is the occurrence count of directed interactions I_k from user i to user j , α_k is the independent, global weight assigned to interaction I_k and f an element-wise activation function; $\{\alpha_1, \dots, \alpha_p\}$ and f are the model's parameters.

Our choice of function f depends on numerous factors related to the data sample. In large graphs every user is influenced by many others. However, the strength of an incoming edge is determined relatively to every other incoming edge at a single node. This has a damping effect when the number of edges increases. A single strong connection can be suppressed as an increasing data volume introduces a large amount of weak connections. Previous work (Zhu, Ghahramani, and Lafferty 2003; Azran 2007) makes use of the softmax function. We considered several alternatives used as activation functions of artificial neurons, such as the linear threshold and logistic activation functions.

Due to the unbounded nature of the weights, we encounter numerical instability if we apply an exponential weighting function. We developed a new method to counter the damping effect of weak connections. We apply a high-pass logistic filter followed by a quadratic inflation of the weights:

$$f(x) = \left(\frac{x}{1 + e^{\beta-x}} \right)^2$$

As a result, large numbers of low-magnitude weights become less dominant in the graph, while still retaining some magnitude. Stronger connections are not influenced by the logistic filter and are inflated by their exponentiation. The choice of β determines the range of the high-pass filter and acts as a bias term. We choose $\beta = 6.0$ such that the seemingly linear part of the sigmoid function lies at the right side of the y-axis.

Actual classification of nodes is performed through an iterative algorithm (Algorithm 1) (Baluja et al. 2008; Bha-

gat, Cormode, and Muthukrishnan 2011) equivalent to performing random walks over an absorbing Markov chain.¹ Their formulation is similar to the iterative formulation of the PageRank algorithm (Page et al. 1999), which is preferred over the closed formula solution for scalability reasons. We will now elaborate on the Markov chain formulation of the problem at hand as it gives insight in the inner workings of the method.

We present our social graph as a first-order Markov chain where the set of states $Q = \{q_1, \dots, q_n\}$ of the automata corresponds to the set of social network users V . The row-stochastic transition matrix $A = D^{-1}W$ is derived from weight matrix W by normalizing its rows, where D is a diagonal matrix of size n with elements $d_i = \sum_j w_{ij}$.

We write V_l for the set of k users in V who are initially assigned a label. We organize weight matrix W , and consequently transition matrix A , such that the first k rows of both matrices correspond to these k labeled users. We take these k users as absorbing states in the Markov chain such that for user i $A_{ii} = 1$ and $A_{ij} = 0$ for all $j \neq i$. Note that this absorbing Markov chain is not irreducible as a random walk over the chain currently at state q_i at time t_i might be unable to reach q_j at time $t_j > t_i$. This is due to the fact that a random walk might eventually get trapped in an absorbing state. If an absorbing state (i.e., any q_i with $i \leq k$) is reachable from any state q_j with $j > k$ then we are guaranteed that every random walk instantiated at any position in the chain will eventually terminate at an absorbing state. Consequently, if we simulate every possible random walk starting from some state q_j to any absorbing state q_i ($i \leq k$) we can infer the probability $P(Y = i | j)$ of ending up in any of the k initially labeled users. The classification c_i for user i is then given by $c_i = \arg \max_c P(Y = c | i)$.

We determine the values of parameters α using a uniform grid search over the space $[0, 1]^p \subset \mathbb{R}^p$ and maximize class-based agreement over a validation set. There are many weight configurations that lead to similar models as the relative relation between different weights plays an important part (e.g., multiplying a weight vector by a scalar results gives the same linear weight relations). In addition we constrain the weights to be non-negative as our model expects positive edges only (if $W_{ij} = 0$ then there is simply no directed edge from user i to user j). If t_i and c_i denote the target class and the output class for user i respectively in some validation set for a model with configuration α , then

$$\frac{1}{k} \sum_{c=1}^k \frac{\sum_i [y_i = c \wedge t_i = c]}{\sum_i [t_i = c]} \quad (1)$$

denotes the quantity we wish to maximize where we use Iverson brackets for notational convenience.

Experiments

We consider a node classification problem over eight political parties active in the Flemish region of Belgium. While some

¹The implementation of the label propagation algorithm applied in this paper can be found on-line at <https://github.com/cvangysel/social-graph-influence> for use on Hadoop or Spark clusters.

of these parties share common views, they are relatively spread out over the political spectrum. We refer to the analysis of Deschouwer (2010) for a comprehensive overview. These parties collectively published lists of 780 Twitter users with whom they associate themselves. We consider these lists as ground truth data and use these to measure classification performance and to determine the weights α_i .

We targeted 12 254 Twitter users who followed at least two of these eight parties and consequently retrieved their information as described in the previous section. We gathered 1 249 091 tweets (of which 273 213 were retweets) and 14 849 213 follower connections. These connections and tweets referred to at least 10 million users in total, which corresponds to the total number of nodes $|V|$.

We then built a graph structure from the gathered data. More precisely we introduce a directed edge from user i to user j if user i follows user j or when user i retweets a message from user j . In an initial experiment (experiment **A**) we assign both these interactions a unit weight. Later we also considered weights for the inversed edges, such that if user i follows user j a directed edge is added from user j to user i and similarly for retweets. We also considered a weight that is added when both user i and user j follow each other, which indicates reciprocal following. These additional interactions are interesting as they give insight in how actions of other users influences one’s position in the social graph.

As mentioned earlier, we assign unit weights to the interaction where someone follows or retweets in a first experiment (experiment **A**). In a second experiment (experiment **B**) we determine values for the various weights through maximum likelihood estimation. For this we sampled a separate graph from Twitter of all users which follow all eight parties and picked the value of α that maximized class-based agreement (see (1)) of the weights over half of the ground truth data. We then separately considered the classifications of the remaining half in order to avoid overfitting. Performance over both sets was similar.

Our setting is different from a regular classification problem as we are unable to provide a classification for just any unseen user. Instead, we require that we have knowledge about the user’s position in the social graph (and recursively regarding its neighbours) prior to having the ability to label them. Therefore, the amount of relevant ground truth data differs with each graph sample we consider. Writing V_{truth} for the set of users for whom we have a target label, we now evaluate the performance of our classification for the intersection of V_{truth} with $V_{targeted}$ (340 users) and V_{truth} with $V_{observed}$ (766 users). We compute precision and recall for each class individually and afterwards aggregate these measures by micro- (μ) and macro-averaging (M). These results are shown in Tables 1 and 2 for experiment **A** and **B**, respectively. Note that micro-averaged precision and recall are identical as the number of false positives and false negatives are equal in the global contingency table.

We asked Twitter users to evaluate their individual classification a week before the Flemish elections of 2014. Users were shown a distribution over the eight political parties and could voluntarily provide feedback between 0 and 100, where a higher score indicates a better classification. Some users

		Recall	Precision	F ₁
$V_{targeted}$	M (macro)	74.29%	91.59%	0.8204
	μ (micro)	84.41%	84.41%	0.8441
$V_{observed}$	M (macro)	75.35%	93.72%	0.8354
	μ (micro)	87.08%	87.08%	0.8708

Table 1: Relevance measures for $V_{targeted}$ and $V_{observed}$ in experiment **A**.

		Recall	Precision	F ₁
$V_{targeted}$	M (macro)	85.53%	91.10%	0.8823
	μ (micro)	95.00%	95.00%	0.9500
$V_{observed}$	M (macro)	81.16%	90.15%	0.8542
	μ (micro)	94.13%	94.13%	0.9413

Table 2: Relevance measures for $V_{targeted}$ and $V_{observed}$ in experiment **B**.

expressed concern as they observed a non-zero probability for right- or left-winged extremist parties. We believe that some feedback scores were purposely negative so as to deny association with these parties, even though these associations were negligible in a statistical setting. We received feedback from 2 258 users. The distribution of the feedback scores is shown in Figure 1, along with its population mean (51.57), standard deviation (35.97) and median (62.0).

Related work

In this paper we apply graph classification through random walks on a sample of the Twitter social graph in order to determine the political climate of social circles. We do not attempt to predict the outcome of the Flemish 2014 elections from Twitter. The distribution of votes we predict diverges from intermediate polls and the final election outcome.

On the topic of political analyses of social media, Adamic and Glance (2005) study the linking patterns and discussion topics of political bloggers in the United States; they observe a divided blogosphere. Tumasjan et al. (2010) find the number of tweets referencing a political party to be a useful feature. Conover et al. (2011a) achieve 95% accuracy using a classifier based on the segregated community structure of political diffusion networks on a data set of 1 000 manually-annotated politically active individuals. Conover et al. (2011b) find that this is not the case for the user-to-user mention network. Gayo-Avello (2012) describes the problem as interesting, very difficult and possibly infeasible.

When considering semi-supervised learning methods, Szummer and Jaakkola (2002) were among the first to induce a graph structure from real-valued vectors without an underlying graph structure in order to perform random walks. Zhu, Ghahramani, and Lafferty (2003) do so similarly, but apply exponential weighting to the edges. Azran (2007) induces an exponentially weighted graph and only consider the nearest neighbors of every node. Their labeled nodes represent absorbing states in the Markov chain; they did not exploit the

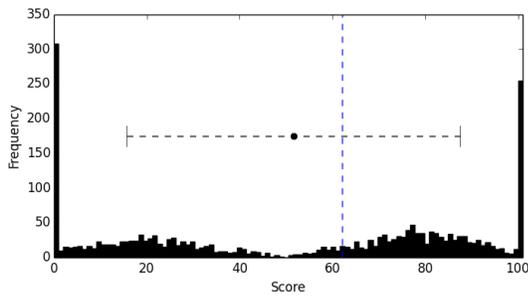


Figure 1: Histogram of feedback score distribution. The black circle indicates the mean of the distribution, while the horizontal dotted line shows the standard deviation. The vertical line denotes the median of the distribution.

inherent connections in their data but relied on a metric to provide edge weights.

Baluja et al. (2008) propose an algorithm to recommend YouTube videos based on randomly walking over the co-view graph. Bhagat, Cormode, and Muthukrishnan (2011) provide a survey on node classification methods in social networks. They introduce the idea of applying these methods on large-scale social networks for the use of electoral prediction, but do not handle practical problems such as data harvesting and graph instantiation. An iterative graph classification framework is proposed by Neville and Jensen (2000).

Conclusion and Discussion

We postulate that the presence of a political party in social circles might have good predictive power of individual political affiliation. We consider an eight-class problem where some classes are very similar to others and might overlap. Previous work (Conover et al. 2011a) focuses on the U.S. elections, which constitutes a well-divided binary problem. We achieve comparable performance as Conover et al. (2011a) on a set of politically active individuals. We go beyond existing work by testing our hypothesis with the Twitter community. We notice that more than half of the feedback group gave a feedback score of 60 or higher.

Prior work (Birmingham and Smeaton 2010; Kouloumpis, Wilson, and Moore 2011; Conover et al. 2011a) describes the challenges associated with using the contents of tweets. Because of this we ignored the contents of tweets. However, we do believe that features extracted from content may be valuable in the context of predicting political affiliation. One interesting property of our method is that it considers influence through third parties as well as direct interactions with political parties. E.g., if a user interacts with a strong advocate for a political party but not necessarily with the party itself, this will be contained within our results. Preliminary experiments in which mentions of political parties lead to a stronger connections to these parties have shown performance increases.

While our results are promising, the performance can be increased through ensembles of link- and content-based models. Further work should focus on gathering larger amounts of data from social networks. One possible approach would

be to construct a mixture of label propagation models, where each model handles a specific network feature; this should give insights in the dynamics of interactions.

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