Structure of Ego-Alter Relationships of Politicians in Twitter

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We analyze the ego-alter Twitter networks of 300 Italian MPs and 18 European leaders, and of about 14,000 generic users. We find structural properties typical of social environments, meaning that Twitter activity is controlled by constraints that are similar to those shaping conventional social relationships. However, the evolution of ego-alter ties is very dynamic, which suggests that they are not entirely used for social interaction, but for public signaling and self-promotion. From this standpoint, the behavior of EU leaders is much more evident, while Italian MPs are in between them and generic users. We find that politicians – more than generic users – create relationships as a side effect of tweeting on discussion topics, rather than by contacting specific alters.

Keywords: Political Social Networks, Ego-centric Networks, Ego-alter Network Structure, Twitter, Network Dynamics.

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Many politicians, especially in the US and in Europe, are adopting Online Social Networks (OSN), Twitter in particular, as official channels to communicate with their constituency and the wider public in general, and to maintain strategic relationships with other politicians (Jackson & Lilleker, 2011), to the point of impacting major political events such as the last three U.S. presidential elections1 (e.g., Stirland, 2008; Greengard, 2009; Conway, Kenski, & Wang, 2013).

Although previous studies identified differences in the use of Twitter by politicians compared to generic users, none of them, to the best of our knowledge, considered, in detail, the analysis of “ego-alter
ties,” i.e., the set of social relationships that a given user (the ego) maintains with other social peers (alters) – as defined in the “Static Properties of Twitter ego Networks of Politicians” section below. Dunbar et al. (2015) found that OSN ego-alter ties have the same structural properties as “offline” ego-alter ties (those maintained through face-to-face interactions). This indicates that the use of OSNs, including Twitter, may not substantially change the size and pattern of our social relationships, which are instead limited by the “social cognitive capacity” of the human brain (Dunbar, 1993).

In this paper, we analyze specifically the ego-alter networks of a representative set of politicians (a large fraction of Italian MPs and the most important European leaders on Twitter). The Twitter relationships characteristic of politicians are already known to be qualitatively different than those of generic users, as the former are primarily meant for self-promotion and public signaling, not for establishing social support (Murthy, 2012; Enli & Simonsen, 2017). However, politicians still invest time and cognitive resources to maintain such relationships. Thus, we hypothesize that they could be constrained by the same limits that shape relationships established for social support. Therefore, a goal of this paper is to quantitatively analyze whether politicians’ ego-alter networks show similar features to generic users’ networks, despite the different purpose of relationships for the two classes. Specifically, we analyzed the ego-alter networks of about 300 Italian MPs and 18 EU leaders, and compared them with those of about 14,000 generic users, who are neither politicians nor public figures of any kind. Note that, our analysis is data-driven, in the sense that it is not based on detailed models and parameters about politicians’ ego-alter networks. Thus, the structural model we derive is entirely driven by data analysis. While this approach might have drawbacks, we think it minimizes the risks of results being biased by specific modelling assumptions.

We found that, when observed over long time intervals, the ego-alter networks of politicians in Twitter show a structure similar to those found in other social environments, both online and offline. On the other hand, when observed over shorter time intervals, these ego networks are not stable over time: The online relationships of politicians in Twitter come and go with a very high turnover, particularly for high-frequency relationships. This feature appears also for generic users, and was previously observed in other studies on Twitter (Arnaboldi, Conti, Passarella, & Dunbar, 2013a). In offline social networks, high-frequency relationships usually correspond to stable and intimate relationships (Hill & Dunbar, 2003). Therefore, this confirms that Twitter relationships are of a somewhat different nature when observed one by one. However, our results also show, to the best of our knowledge for the first time, that when considering the entire set of ego-alter relationships of any given ego (politician or not), it exhibits constraints very similar to those observed, in general, in offline social networks. Moreover, we hypothesize that, for politicians in particular, online relationships are more related to the content that is exchanged between users and exposed to the public than by the need to exchange social support. We find that, for the analyzed politicians, a very significant percentage of relationships is created as a by-product of discussions on topics (coded in tweets with hashtags), and much more so than is the case for generic users. Finally, a regression analysis shows that the intensity and diversity of use of hashtags explains quite well the frequency of interaction over the relationships, particularly for politicians.

**Data and Methods**

**Direct Tweets and Dataset description**

Ego-alter ties are usually characterized by their strength (i.e., the intensity or importance of relationships). In this study, we use the frequency of direct tweets between users to measure this. Direct tweets can be performed through mentions (user names can be included in a tweet, with the effect that the related users will receive the tweet in their home pages), replies (a mechanism that allows users to reply
Table 1  Social Tweets Usage by European Leaders and Italian MPs

| Name                  | % of social tweets | % of Replies | % of Mentions | % of Retweets | F-S ratio | Tweet Frequency |
|-----------------------|--------------------|--------------|---------------|---------------|-----------|----------------|
| Matteo Renzi          | 57.35              | 46.34        | 24.83         | 28.83         | 1.60      | 2.42           |
| David Cameron         | 34.04              | 1.98         | 87.43         | 10.59         | 8.26      | 1.89           |
| Enda Kenny            | 58.74              | .00          | 67.70         | 32.30         | 2.10      | .74            |
| Erna Solberg          | 89.68              | 79.66        | 9.74          | 10.60         | 7.52      | 2.16           |
| Miro Cerar            | 53.05              | 12.13        | 31.59         | 56.28         | 1.78      | 3.06           |
| Jean-Claude Juncker   | 62.29              | 3.33         | 41.60         | 55.07         | 1.32      | 1.88           |
| Donald Tusk           | 31.03              | 5.31         | 84.45         | 10.24         | 8.25      | 1.94           |
| Andrzej Duda          | 81.67              | 46.59        | 4.26          | 49.15         | 1.05      | 4.15           |
| Alexis Tsipras        | 61.76              | 2.17         | 77.96         | 19.87         | 3.92      | 2.81           |
| Taavi Rõivas          | 79.09              | 7.57         | 5.99          | 86.44         | 11.42     | 5.85           |
| Nicos Anastasiades    | 35.20              | .24          | 37.75         | 62.01         | 1.64      | 1.56           |
| Toomas Hendrik Ilves  | 82.73              | 6.83         | 52.92         | 40.25         | 1.31      | 6.85           |
| Laimdota Straujuma    | 64.94              | 17.21        | 20.71         | 62.08         | 3.00      | .95            |
| Borut Pahor           | 32.66              | 13.26        | 59.77         | 26.97         | 2.22      | 4.04           |
| Atifete Jahjaga       | 51.96              | 1.29         | 35.40         | 63.31         | 1.79      | .95            |
| Charles Michel        | 74.44              | 17.63        | 24.29         | 58.08         | 2.39      | 1.69           |
| Pablo Iglesias        | 65.41              | 7.48         | 42.50         | 50.02         | 1.18      | 7.60           |
| Pedro Sánchez         | 68.68              | 1.02         | 45.09         | 53.89         | 1.20      | 6.67           |
| Mean for EU Leaders   | 60.26              | 12.07        | 46.12         | 41.81         | 3.48      | 3.18           |
| Mean for Italian MPs (sample 1)* | 64.67 | 21.05       | 36.22         | 42.73         | 3.08      | 2.64           |

Note. Values representing the highest percentages for each user are in boldface. F-S ratio is the ratio between the first and the second highest percentages for the user. Tweet frequency is measured in number of tweets (both plain and social) created per day.

*For comparison with the rest of the politicians in the dataset.

to tweets by others and engage in conversations with them) and retweets (share of tweets created by others).

We collected the tweets created by a set of politicians’ Twitter accounts with a sufficient level of direct communication activity. Users whose engagement in the platform is too sporadic are not relevant for understanding how ego networks are created and maintained over time. We considered accounts for which we can access at least 6 months of Twitter communication. Previous research (Arnaboldi et al., 2013a; Wilson et al., 2012) demonstrated that Twitter relationships can be considered stable only after 6 months of activity, because only after that does the rate of new relationships created over time remain constant. In addition, we discarded accounts with a sporadic use of the platform, i.e., with periods of short duration of very high activity and long periods of inactivity. To do so, we used the following heuristic. We looked at the distribution of the number of direct tweets generated by each account every month of its activity, and we selected only the users who sent at least one direct tweet every 3 days (as an average frequency within each month) for at least 50% of the total number of months of their activity.

We collected two samples from Twitter, and filtered them as described above. The first (hereinafter “sample 1: Italian MPs”) includes 304 members of the Italian Government Cabinet and members of the Italian Parliament. The second sample (“sample 2: EU Leaders”) contains 18 European Leaders.
We accessed the data from Twitter between June and December 2015, using the Twitter REST API and obtaining the complete history of the tweets generated by users, up to the limit of 3,200 tweets per user imposed by the API. The list of European leaders contains, among others, the accounts of David Cameron and Matteo Renzi, two of the most followed EU leaders on Twitter as of 2014. Table 1 reports the complete list of European leaders in sample 2, together with their overall tweet frequency.

We also collected the accounts of 100,000 randomly selected Twitter users, filtered as explained above. In addition, from these accounts we automatically removed those that are not managed by human agents, which are not used for socializing with other people (e.g., bots, spammers, companies), and accounts of public figures (e.g., famous actors or political leaders). To this end, we used an account classifier built on a support vector machine (SVM) – a standard machine learning method that, after being trained on a set of manually classified accounts (the training set), is able to automatically classify unknown accounts. The same classifier has been used also by Arnaboldi et al. (2013a), and has an accuracy greater than 80%. After this filtering phase, we obtained 13,728 accounts of generic Twitter users. We refer to this hereafter as “sample 3: generic users sample.”

**Methods for Ego Network Analysis**

**Ego Network model**
The literature has proposed several definitions of ego network, depending on the focus of the study. In sociology, an ego network generally consists of a single actor (ego) together with the actors to whom the ego is connected (alters) and all the links among those alters (Everett & Borgatti, 2005). Another possible model considers only alter-alter ties, discards ego-alter ties, and is used to analyze the topological features of the social context in which the ego is immersed – e.g., (Burt, 2001; McCarty, 2002). In this paper, we focus instead only on ego-alter ties, and use the Dunbar ego network model (Hill & Dunbar, 2003; Sutcliffe, Wang, & Dunbar, 2012). This model (hereinafter the ‘ego network model’) allows us to characterize human cognitive constraints and how they impact key social processes such as cooperation and willingness to share resources (Sutcliffe et al., 2012).

Figure 1 depicts the typical representation of a Dunbar ego network (Sutcliffe et al., 2012). Two key aspects of human sociality are analyzed through these type of ego networks. The first is the social capacity of individuals, measured as the number of alters with whom an ego can actively maintain a network over time. Active relationships are defined as those that involve at least one interaction per year, which is interpreted as a signal of a minimal level of cognitive investment (Hill & Dunbar, 2003). The number of active relationships is known as the Dunbar’s Number and is around 150 both in offline and online social networks (Dunbar, 1993; Dunbar et al., 2015). The second aspect is the hierarchical organization of alters into concentric social circles around the ego (Zhou et al., 2005; Hill & Dunbar, 2003). These circles are hierarchically inclusive: Each circle includes all the alters of its inner circles, whereas rings refer to the portions of circles that exclude inner circles. Inner circles include stronger relationships (typically alters from whom the ego seeks strong social support) while outer circles include acquaintances. The typical average sizes of circles (Roberts et al., 2009; Dunbar et al., 2015) are 1.5, 5, 15, 50, and 150. The ratio between adjacent circles is around 3, and this is considered a key aspect of human ego networks (Zhou et al., 2005). It is also known that these structures do not change much over time (Saramäki et al., 2014), and in particular can also be found in popular online social networks, i.e., Facebook and Twitter (Dunbar et al., 2015).

**Twitter ego networks: indices for static and dynamic analysis**

From the three direct communication mechanisms of Twitter (i.e. replies, mentions, and retweets), we built, for each user obtained after the filtering process described in Section 2.1, three ego networks. As
Figure 1  Ego network model. The ego is the focal individual of the model. Alters are social contacts of the ego. Rings (R1-R5, from the innermost one to the outermost one) are noninclusive groups of alters with similar contact frequency. Circles (C1-C5) are inclusive groups. The typical hierarchical structure of human ego networks contains five circles with sizes averaging 1.5, 5, 15, 50, and 150.

shown in previous work (Dunbar et al., 2015), it is possible to find the layers of ego networks through cluster analysis (Bishop, 2006) on the frequencies of contact. Cluster analysis automatically divides the ego-alter relationships into groups with homogeneous values of contact frequency, each group representing a ring. One of the simplest of such techniques is $k$-means, a method that divides the data into a predefined number of clusters, $k$. The optimal $k$ for a set of data points can be found using various standard metrics, such as the Akaike Information Criterion (Bishop, 2006). The optimal $k$ found in Twitter is typically five (Dunbar et al., 2015). Thus, we used cluster analysis on our samples, and applied $k$-means with $k = 5$ on each ego network.

To analyze the dynamic properties of ego networks, we divided the time series of interactions into time windows of one year each, and computed the ego networks for each time window using the same clustering method described above, as was previously done by Arnaboldi et al. (2013a). To analyze the evolution of ego network structure over time, month by month, we considered the following 11 months of communications, obtaining a series of 1-year time windows, with an 11-month overlap between consecutive elements in the series. On the other hand, to analyze the turnover rate within the ego networks and the stability over time of the ego network rings, we considered nonoverlapping consecutive time windows. Specifically, for each ring, we analyzed its stability in each pair of adjacent time windows, and averaged over all adjacent time windows. We chose a temporal length of 1 year so as to be able to capture relationships with at least one message a year, which coincides with the definition of active network in the literature (Roberts et al., 2009). For this part of the analysis, we considered all three types of direct tweets together, as the goal was to characterize overall dynamic behavior.

Network structure stability indices. We used two indices to measure the stability of the ego network rings over time. First, we calculated the Jaccard index, which, given two sets of elements (which, in our case, are two adjacent time windows containing their respective alters), is defined as the cardinality of the set intersection divided by the cardinality of the set union, and is thus equal to 1 when the two sets are identical, and 0 when they have no elements in common. Second, we defined the Jump index, $C$, which
counts the number of movements, or jumps, between rings (averaged over all alters in a given ring), with each movement between adjacent rings counting as one jump, and a movement from ring $x$ (with values between 1 and 5, where 1 is the innermost ring and 5 the outermost one) to outside the ego network (or vice versa) as $5 - x + 1$ jumps. Note that we discarded all cases where no movement occurs, i.e., the index is the jump conditioned to moving to a different ring. We also defined a normalized version of the index by dividing each number of jumps for a given alter by the maximum possible number of jumps that alter could make from its ring in the first time window.

Indices for the use of hashtags over Twitter relationships. We also analyzed the relation between the use of hashtags and the dynamic properties of ego networks. For this reason, we separated the relationships that are “activated” by hashtags (i.e., which show a hashtag in the first contact associated with them) from the other relationships; we then analyzed (i) the proportion, (ii) the frequency of contact and (iii) the set of hashtags used for the two types of relationships, as a function of the layers of the ego networks in which they lie. Finally, we studied the relation between the contact frequency of Twitter direct relationships and a series of indices that quantify the intensity and the diversity in the use of hashtags on those relationships in all our datasets (described in detail in Section 3.5).

Results

Use of Twitter Direct Communication by Politicians

Table 1 shows the average tweet frequency of EU leaders and Italian MPs (# of tweets per day). In general, this is compatible with a human use of the platform. Specifically, leaders show a higher Twitter activity, which confirms prior studies on the lack of equalization among politicians of this OSN (Van Aelst et al., 2017). The percentages of direct tweets usage (for each type of direct tweet) for the European leaders and Italian MPs are reported in Table 1. We note that most EU Leaders show a marked preference for one type of direct communication in Twitter (though which type is preferred varies between politicians). This is shown by the ratio between the first and the second highest percentages per user ($F-S$ ratio in the table), which is typically much higher than 1, and is also high on average for all the EU Leaders ($M = 3.48$) as well as for Italian MPs ($M = 3.08$). The average percentages show that EU leaders slightly prefer mentions (46% over 42% retweets), while Italian MPs prefer retweets (43% over 36% mentions). Retweets are typically a sign of endorsement of the original tweet, and it might be expected that it is more often used by nonleaders than leaders in a social group.

Static Properties of Twitter Ego Networks of Politicians

Table 2 reports the size of the identified circles and the scaling ratio between adjacent circles. The table is divided into three sections, each of which is dedicated to one specific type of direct communication. Each section reports the properties of the Dunbar ego-network circles of All Italian MPs (sample 1), EU Leaders (sample 2), and the subset of Italian MPs and EU Leaders who share the specified preferred type of direct communication. For individual EU Leaders, we note a significant variability in the sizes of the layers. In some cases, the sizes of the layers are quite close to the values in the Dunbar ego network model (e.g., Matteo Renzi for replies, Donald Tusk for mentions, Charles Michel for retweets). In other cases, some layers, particularly the external ones, may be either much smaller or much bigger than those in the ego-network model. Such a marked variability is common in offline ego networks (Hill & Dunbar, 2003; Roberts et al. 2009, Zhou et al. 2005). Our analysis expects this for two reasons. On the one hand, sizes in the ego-network model are average values derived across a population, and all datasets analyzed in the literature show a significant variability across individuals. Moreover, Twitter is only one possible
means of interaction, which does not exhaust the total interaction capacity of individuals, and individual leaders may use them differentially. A positive correlation between the size of ego networks and the tweeting activity of politicians ($r = 0.39$, $p < .01$ for replies, $r = 0.5$, $p < .01$ for mentions, $r = 0.47$, $p < .01$ for retweets) also confirms this. On the other hand, as expected, when we average the results over all the ego networks in the samples (All Italian MPs and All EU Leaders), and over each subset of Italian MPs with a specific preferred type of direct communication, the sizes of the circles are similar to those of the ego-network model shown in Fig. 1.

Analyses of the scaling ratio provide even more insights. The scaling ratio between adjacent circles averages, for Italian MPs, 2.6 for replies, 2.5 for mentions, and 3.0 for retweets; for EU Leaders, 2.2 for replies, 2.3 for mentions, and 2.7 for retweets. Aside from the impressive consistency of these ratios (and there is no empirical reason why this should be so), these values are close to the value of 3 for the Dunbar ego-network model. To compare the variability of sizes and scaling ratios with each other, we defined index C, which is the ratio between the width of the confidence interval of the mean and the mean itself. The average value of $C$ for the sizes of the circles is 0.16 for replies, 0.10 for mentions, and 0.13 for retweets for Italian MPs; and 1.42 for replies, 0.55 for mentions, and 0.55 for retweets for EU Leaders. The value of $C$ for the scaling ratios is 0.08 for replies, 0.07 for mentions, and 0.07 for retweets for Italian MPs, and 0.39 for replies, 0.25 for mentions, and 0.33 for retweets for EU Leaders. This shows that, even though the sizes of layers can vary considerably across politicians, the scaling ratios vary much less. This suggests that the structural properties of the ego networks are remarkably constant across users, resulting in scaling ratios that are quite stable.

**Dynamic Ego Network Properties**

Overall, we found a marked dynamism over time in the use of Twitter, particularly for EU Leaders. As an example, Figure 2 shows the number of nondondirect and direct tweets per month for Matteo Renzi, David Cameron, Jean-Claude Juncker, and Andrzej Duda. Vertical lines show the most important political events in the countries of the specific leader. Tweeting activity varies significantly over time, and is particularly high before key political events. This result agrees with findings in the literature on legislative ambition: Politicians who seek higher offices usually try to enlarge the size of their electorate community, changing their public behavior to appeal to as many people as possible (Black, 1972).

Figure 3 depicts the values of the Jaccard index and the Jump index (raw and normalized), averaged for all the ego networks for politicians and for generic users. The results indicate a very high variability in the inner layers of the ego networks for both politicians and generic users, whereas the outer rings are progressively more stable. This tells us that Twitter ego networks are substantially different from the ego networks analyzed in environments such as phone call networks, where inner layers are found to be more stable than outer ones (Saramäki et al., 2014). In addition, the high values of the Jump index for the inner layers indicate that alters tend to enter these layers from external parts of the ego network directly (the mean number of jumps both considering jumps starting from R1 and arriving at R1 is around 3 over a maximum number of 5 jumps), and they return to these external regions when they quit the inner rings. On the other hand, alters in R5 tend to jump to the adjacent rings (the mean number of jumps is close to 1) when they move. This means that looking at ego-networks over 1-year time windows (dynamic ego networks), inner layers are much less stable than the outer ones.

It is interesting to understand the relationship between layers in the static and dynamic ego networks. Specifically, Figure 4 shows a separate plot for each layer in the static network. For ego-alter ties in a given static layer, it shows the average frequency of appearance in the layers of the dynamic ego networks. Note that the “OUT” layer groups all ties outside the active network. For generic users, the figures show that, ego-alter ties of a given layer in the static network appear with the highest frequency in the same layer of
| Measure | C1       | C2       | C3       | C4       | C5       |
|---------|----------|----------|----------|----------|----------|
| **User** | **Reply Networks** | **Ratio (M±SD)** | **Ratio (M±SD)** | **Ratio (M±SD)** | **Ratio (M±SD)** |
| All Italian MPs | Size (M±SD) | 1.58±.21 | 4.89±.70 | 12.3±1.9 | 29.50±4.97 | 70.26±13.0 |
|          | Ratio (M±SD) | 3.27±.32 | 2.57±.20 | 2.41±18  | 2.25±.18  | 47.43±31   |
| All EU Leaders | Size (M±SD) | 1.87±.9  | 4.51±4.1 | 11.86±10 | 26.52±20  | 47.43±31   |
|          | Ratio (M±SD) | 2.61±.89 | 2.06±.96 | 2.19±1.01| 1.86±.08  | 141±46.19 |
| Matteo Renzi | Size | 1        | 6        | 15       | 48        | 107       |
|          | Sc. ratio | 3.2      | 2.5      | 3.2      | 2.2       | 302       |
| Erna Solberg | Size | 13       | 41       | 92       | 180       | 302       |
| Italian MPs who mostly use replies | Size | 2.07±.89 | 7.5±3.1  | 20.1±7.7 | 52±18.41  | 141±46.19 |
|          | Sc. ratio | 3.92±.95 | 2.87±0.5 | 2.84±.49 | 2.85±.48  |           |

| **Mention Networks** | **Size (M±SD)** | **Ratio (M±SD)** | **Ratio (M±SD)** | **Ratio (M±SD)** | **Ratio (M±SD)** |
|----------------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| All Italian MPs      | Size (M±SD)     | 1.27±.1         | 3.18±.28       | 6.86±.69       | 15.83±1.71     | 41.74±5.3     |
|          | Ratio (M±SD)    | 2.62±.20        | 2.21±.15       | 2.35±1.15      | 2.65±.22       | 38.89±31      |
| All EU Leaders       | Size (M±SD)     | 1.47±1.03       | 3.79±2.54      | 8.26±5.65      | 17.6±12        | 38.89±31      |
|          | Ratio (M±SD)    | 2.71±0.97       | 2.24±0.8       | 2.14±0.75      | 1.97±0.77      |               |
| David Cameron        | Size             | 2               | 5               | 15             | 38             | 85            |
|          | Sc. ratio       | 2.5             | 3               | 2.5            | 2.2            | 39            |
| Enda Kenny           | Size             | 1               | 5               | 15             | 28             | 141±46.19     |
|          | Sc. ratio       | 2.5             | 3               | 2.5            | 2.2            | 39            |
| Donald Tusk          | Size             | 2               | 5               | 15             | 28             | 141±46.19     |
|          | Sc. ratio       | 2.5             | 3               | 2.5            | 2.2            | 39            |
| Alexis Tsipras       | Size             | 1               | 2               | 6              | 12             | 57            |
|          | Sc. ratio       | 2.5             | 3               | 2.5            | 2.2            | 39            |
| Toomas Hendrik Ilves | Size             | 1               | 3               | 10             | 45             | 159           |
|          | Sc. ratio       | 2.5             | 3               | 2.5            | 2.2            | 39            |
| Borut Pahor          | Size             | 3               | 9               | 18             | 33             | 78            |
|          | Sc. ratio       | 2.5             | 3               | 2.5            | 2.2            | 39            |
| Italian MPs who mostly use mentions | Size | 1.32±.18 | 3.41±.54 | 7.7±1.39 | 19.53±3.4 | 58.9±10 |
|          | Sc. ratio       | 2.7±.37         | 2.32±.26        | 2.63±.27       | 3.17±.36       |               |

| **Retweet Networks** | **Size (M±SD)** | **Ratio (M±SD)** | **Ratio (M±SD)** | **Ratio (M±SD)** | **Ratio (M±SD)** |
|----------------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| All Italian MPs      | Size (M±SD)     | 1.59±.20        | 4.82±.60        | 12.84±1.6       | 35.25±4.55      | 118.2±17.1    |
|          | Ratio (M±SD)    | 3.25±3.3        | 2.74±2.16       | 2.86±2.0        | 3.3±2.6         | 72.02±70      |
| All EU Leaders       | Size (M±SD)     | 1.14±.35        | 3.08±1.66       | 7.51±6.16       | 19.59±20        | 72.02±70      |
|          | Ratio (M±SD)    | 2.72±1.18       | 2.32±0.89       | 2.46±0.94       | 3.18±2.39       |               |
| Miro Cerar           | Size             | 1               | 3               | 1.7            | 3              | 3.9           |
|          | Sc. ratio       | 2               | 5               | 3              | 3.9            | 39            |
| Jean-Claude Juncker  | Size             | 1               | 2               | 5              | 3              | 3.9           |
|          | Sc. ratio       | 2               | 5               | 3              | 3.9            | 39            |
| Andrzej Duda         | Size             | 1               | 6               | 2.5            | 2.6            | 3.5           |
|          | Sc. ratio       | 2               | 5               | 3              | 3.9            | 39            |
| Taavi Rõivas         | Size             | 1               | 2               | 3              | 3.8            | 11.7          |
|          | Sc. ratio       | 2               | 3              | 3              | 3.9            | 39            |
| Nicos Anastasrades   | Size             | 1               | 3               | 1.7            | 3              | 3.9           |
|          | Sc. ratio       | 2               | 5               | 3              | 3.9            | 39            |
Table 2  Continued

| User | Measure | C1 | C2 | C3 | C4 | C5 |
|------|---------|----|----|----|----|----|
|      |         |    |    |    |    |    |
| User Retweet Networks | C1 | C2 | C3 | C4 | C5 |
| Laimdota Straujuma | Size | 2  | 4  | 7  | 16 | 39 |
| Atifete Jahjaga | Sc. ratio | 2 | 2 | 8 | 2.3 | 14 | 2.4 |
| Charles Michel | Size | 2 | 2 | 8 | 4.25 | 41 | 119 |
| Italian MPs who mostly use retweets | Sc. ratio | 2 | 8 | 23 | 1.8 | 2.9 |

the dynamic ego networks. However, for inner static layers (R1-R4), the distribution of average frequencies inside dynamic layers is more dispersed than for outer static layers (R5-OUT). In addition, for any static layer, even for the most internal ones, there is a significant frequency of appearance in the OUT dynamic layer, i.e., outside the ego network. It is also interesting to note that Italian MPs show a behavior similar to the generic users, while for EU Leaders there is a less marked correspondence between the static and the dynamic views. This agrees with the high burstiness found in Twitter communications for EU Leaders, also shown in Figure 2, which results in ephemeral high-frequency relationships.

The Use of Hashtags Over Twitter Relationships

We conjecture that, especially for politicians, the findings we reported in the preceding section may reflect the use of Twitter as a tool to discuss and make the public aware of a range of different topics through intense interactions with alters. This is based on the observation that, for politicians in particular, Twitter is not only used to broadcast political messages but also to engage conversation on political opinions (Tumasjan et al., 2010). To explore this further, we first analyzed whether ego-alter ties are created as a “by-product” of exchange of information on specific topics, and whether this is more evident for the politicians than for generic users. We also analyzed whether there is a significant difference in the two classes of users in the number of hashtags exchanged over ego-alter ties. Finally, we analyzed whether intensity and diversity of use of hashtags can explain the frequency of contact over ego-alter ties, again for both classes of users.

We measured the number of new alters and new hashtags added in the ego network every month, considering “time 0” for each ego network as the point in time when the ego activated its first relationship. Their average values are 9.78 and 14.13 for Italian MPs, and 11.24 and 0.67 for generic users, respectively. The number of new alters contacted by politicians and generic users have the same order of magnitude, whereas for the new hashtags the value is much higher for Italian MPs.

We then analyzed whether there is any evidence of ego-alter ties being created because of the use of hashtags, and, if so, the pattern of interactions over these relationships. We separated relationships “activated” by hashtags (i.e., containing a hashtag in the first direct tweet over that relationship) from all the other relationships. The analysis shows a significant difference between politicians and generic users. The relationships activated by hashtags are 15% of the total number of relationships for EU Leaders, 17% for Italian MPs, and 5.9% for generic users. Figure 5 shows more detailed statistics. The graphs in the first column indicate that, for Italian MPs and EU Leaders, the percentage of relationships activated by hashtags is higher than for generic users in all ego network layers. Graphs in the
Figure 2 Number of plain and social tweets created per month by Matteo Renzi, David Cameron, Jean-Claude Juncker, and Andrzej Duda. Vertical lines in red represent the most important political events for these users between 2012 and 2015.

The second columns show that, in contrast to generic users, the mean frequency of contact of relationships activated by hashtags for Italian MPs and EU Leaders is similar to that of other relationships. Finally, graphs in the third and fourth columns show that the number of hashtags exchanged (both in total and for distinct hashtags) is higher for politicians (both Italian MPs and EU Leaders). In addition, relationships activated by hashtags show higher values than relationships not activated by hashtags in all layers for Italian MPs and EU Leaders, whereas there is no such clear trend in the ego networks of generic users.

All in all, these results indicate that politicians (i) tend to activate ego-alter ties because of the topic discussed and do so more than generic users do; (ii) maintain a higher frequency of interactions, compared to generic users, over those ties, with respect to the frequency over the rest of the ties; (iii) in general use many more hashtags than generic users; and (iv) do so preferentially over ties activated by hashtags, much more than generic users do. All this is consistent with the use, particularly by politicians, of Twitter ego-alter links as a means to expose to the public positions about specific topics, through an interaction with a specific alter.

Relation between contact frequency and use of hashtags
Finally, we analyzed the relationship between the indices defined to capture the intensity and diversity in the use of hashtags and contact frequency, through regression analysis on a ring-by-ring basis. As a first measure of intensity of hashtag use over a relationship $r$, we calculated, for relationships activated by a
Stability (and instability) indices of ego network rings for EU Leaders, Italian MPs, and generic Twitter users. Jaccard index indicates the stability over time of each ring, whereas the Jump index indicates the variability of the rings.

Relationship between the position within the ego network rings for relationships considering static and dynamic view of the ego networks.

hashtag $h_{act}$, the number of direct tweets containing that hashtag $N(r, h_{act})$. We also calculated this measure cumulatively for the ego $e$, as the number of times $h$ has been used by the ego in all its relationships, $N(e, h_{act})$. These measures embody the importance for the users of the hashtags that activated their relationships. The indexes are clearly null for relationships not activated by any hashtags. Indices $N(r, h_{max})$ and $N(e, h_{max})$ are analogous to the previous measures, but are related to the hashtag ($h_{max}$) that appears with the highest frequency in relationship $r$, instead of the activating hashtag. Finally, to measure the
Statistics for social relationships activated by hashtags (#tags) and other relationships for EU Leaders, Italian MPs, and generic Twitter users, divided into the different ego network rings.

To quantify the diversity of the hashtags in direct tweets, we calculated $D_{rel}(r)$ (the number of hashtags appearing in a relationship $r$) and $U_{rel}(r)$ (the number of distinct hashtags appearing in $r$).

The results of the regression analysis are reported in Table 3. We report the values of $R^2$ for all the different models created. $R^2$ is the coefficient of determination of the models, and measures the degree to which the model is able to approximate contact frequency (values range from 0 – worst fit – to 1 – best fit). We built different linear regression models for EU Leaders, Italian MPs, and generic users, considering only relationships activated by hashtags or other relationships separately, and considering all the relationships in the ego networks together or dividing them into the different circles. All the estimates for the regression coefficients show positive signs and are consistent among the models. It is worth noting that, in general, the $R^2$ values are medium/high for most models – $R^2$ higher than 0.3 is usually considered a sufficiently high value. Moreover, values are higher for politicians than for generic users, and are higher for relationships activated by hashtags than for the other relationships. This confirms the hypothesis that direct contact frequency in Twitter is largely correlated with the intensity and diversity of use of hashtags, i.e. that the strength of ego-alter ties is explained by the need to expose communication on a topic or person to the public, and that this is even more marked for politicians.

Discussions and Conclusion

For EU Leaders and Italian MPs, the structural patterns of ego networks are very close to those found in the literature for offline social networks. It is worth noting that the scaling ratio between adjacent layers is always close to 3, which is the typical value found in Dunbar ego networks. This indicates that, when controlling for Twitter activity, online ego networks may be shaped by the same cognitive and time constraints at the basis of the structure of offline social networks. This tells us that, although
Table 3  Coefficient of determination ($R^2$) of different regression models created using measures of the use rate of hashtags by Twitter users to explain the contact frequency of their social ties

|                      | Links with an activating hashtag | Links w/o an activating hashtag |
|----------------------|----------------------------------|---------------------------------|
|                      | Linear Regression                 |                                 |
| Rings                | ALL   | R1   | R2   | R3   | R4   | R5   | ALL | R1 | R2 | R3 | R4 | R5 | ALL | R1 | R2 | R3 | R4 | R5 |
| Italian MPs          | .68   | .56  | .46  | .52  | .36  | .31  | .39 | .22 | .32 | .23 | .21 | .16 |
| EU Leaders           | .61   | .48  | .60  | .54  | .42  | .23  | .33 | .35 | .08 | .19 | .17 | .11 |
| Generic Users        | .57   | .47  | .25  | .24  | .22  | .16  | .30 | .20 | .10 | .09 | .08 | .06 |

Note. (1) The signs for all the regression coefficients were positive. (2) Links with an “activating” hashtag have a hashtag in the first social tweet exchanged between the involved users.

eyo-alter ties of politicians in Twitter are largely a means of self-promotion (Enli and Simonsen, 2017), the way politicians organize their contacts obeys the same principles that underpin the formation and management of human social relationships in general, which are related to cognitive constraints imposed by the human brain.

The analysis of the dynamic evolution of ego networks over time revealed that the structural properties of the ego networks in our samples are rather unstable over time, especially in their inner layers (on a year-by-year basis, 80% turnover in the inner layers vs. 40% turnover in the outer layers), which was unexpected. If Twitter is used to maintain social relationships exactly as any other communication means, one would expect more stable relationships in inner than in outer layers, since in social environments contact frequency is a proxy of tie strength and emotional closeness. This suggests that the nature of ego-alter ties in Twitter is significantly different than in offline social environments, in particular for Italian MPs and EU Leaders. The high turnover also matches a bursty use of Twitter that we observed for many politicians and the EU leaders in particular: Sudden increments in the use of direct tweets coincide with important political events where the leader seeks higher office or higher popular support.

A notable difference between politicians and generic users is in the way politicians use ego-alter ties to contribute to public discussions, to advertise positions on certain topics, or for self-promotion. Politicians have a much higher percentage of relationships “activated” by hashtags (i.e., showing a hashtag in their first direct tweet) than generic users in all ego network layers. Their activity (frequency of contact) on these relationships is comparable with respect to their activity on other relationships, while generic users are much less active on relationships activated by hashtags. Moreover, the number of hashtags exchanged over relationships by politicians is much higher than for generic users, and it is markedly biased towards links activated by hashtags. This confirms that the use of Twitter relationships by politicians is a way to expose the public to particular information, rather than to keep social contacts with alters. Evidence about the higher use of hashtags by politicians has been found before (Enli and Simonsen, 2017). However, we found that this does not apply just to general tweeting activity, but also to “social” tweets containing explicit mentions to other users. This is a sign of the mix between a social-centric and information-centric use of Twitter by politicians.

A regression analysis between the intensity and diversity of use of hashtags in direct tweets and the contact frequency of direct relationships provides further insights into the use of Twitter as an information-oriented platform, for both classes of analyzed users. Specifically, the intensity and diversity
of hashtag use is positively correlated with the frequency of contact. This suggests that, as with generic Twitter users, politicians use Twitter as a means to discuss and exchange information publicly through direct relationships, rather than to maintain social relationships. For politicians, this behavior is even more evident than for generic users. Moreover, when analyzed on a ring-by-ring basis, models have better fit for inner layers than for outer layers, showing that intensity and diversity of use of hashtags are associated with high-frequency interactions.

Considering both (i) the high turnover of inner layers and (ii) the relationships between direct contact frequency and use of hashtags, we arrive at a view of Twitter use as a mix of social- and self-promotion platforms for generic users, but especially so for the politicians. For the latter, high contact frequency relationships involve a large number of topics (high diversity) with high frequency per topic (high intensity), but do not mean stable relationships with specific individuals (high turnover).

By and large, our results confirm general prior findings about the use of Twitter in the political sphere. Specifically, there is increasing evidence in the literature about Twitter being an important tool that politicians use in their public activities (Jungherr, 2016). Starting from a relatively low use a few years ago (Larsson & Moe, 2011; Effing et al., 2011), politicians are increasingly using Twitter during electoral campaigns, with a noticeable effect on the electoral outcomes (Effing et al., 2011; Stirland, 2008; Green-gard, 2009; Conway, Kenski, & Wang, 2013). Also, politicians’ use of Twitter is changing. In addition to being a means for self-promotion and broadcasting (Enli & Simonsen, 2017), it is increasingly, though not primarily (Jungherr, 2016), becoming a means for bidirectional interactions with voters, for mobilizing supporters, for consulting (Tumasjan et al., 2010; Graham et al., 2013). Despite clear evidence about these facts, the literature highlights the need for a more detailed understanding of how politicians use Twitter (Jungherr, 2016), in particular through longitudinal studies on the use of Twitter by politicians (Graham et al., 2013). We believe that our results help begin to fill this gap. First, they confirm previous findings about the increasing importance of Twitter for politicians. Second, through the detailed analysis of the ego-alter structures provided in the paper, they could suggest ways to optimise political communication over Twitter. Our results show that, despite Twitter not being used as a tool for establishing social relationships, the same constraints observed in other social networks (both online and offline) control the behavior of the entire set of ego-alter ties for any given Twitter user, and this is true even for politicians (EU Leaders and Italian MPs). As the cognitive and time resources politicians can allocate to Twitter activities is limited, our results could suggest ways politicians should distribute their “Twitter time” over their ego-alter networks so as to achieve an optimally efficient allocation of their limited resources when engaging in this social platform. As it is known that social ties at the different levels of the Dunbar’s ego network model results in different willingness of social peers to share resources and collaborate with the ego (Roberts et al., 2009), politicians may monitor the various levels of their ego networks to understand which alters are more likely to contribute spreading their messages, and tune their communication campaigns accordingly. For example, trusted information flows preferentially through strong ties due to their associated level of trust (Arnaboldi et al., 2016). Politicians might want to engage Twitter influencers in their inner layers, to maximize the impact of their communication. Based on our results, an effective means to increase tie strength could be the use of hashtag relationships both to consolidate interactions and foster information diffusion at the same time, as witnessed by the higher values for communication frequency on relationships activated by hashtags.

Notes

1 https://www.wired.com/2016/11/facebook-won-trump-election-not-just-fake-news/
2 obtained from the Italian Government official website: http://www.governo.it/Governo/Ministeri/ministri_gov.html
3 obtained from a website collecting open data about the Italian Parliament: http://parlamento17.openpolis.it/
4 obtained after filtering, as described above, a public Twitter list of European leaders’ accounts, excluding the accounts not associated with individuals: https://twitter.com/twiplomacy/lists/european-leaders/members
5 https://marcorecorder.com/2014/03/07/personal-twitter-accounts-of-european-prime-ministers-whos-scoring-best/
6 We omit the results for EU Leaders since the confidence intervals for their means are too large to be significant.

References

Arnaboldi, V., Conti, M., Passarella, A., & Dunbar, R. I. M. (2013a). Dynamics of personal social relationships in online social networks: A study on Twitter. ACM Conference on Online Social Networks: 15-26.

Arnaboldi, V., Conti, M., La Gala, M., Passarella, A., & Pezzoni, F. (2016). Ego network structure in online social networks and its impact on information diffusion. Computer Communications, 76, 26-41. https://doi.org/10.1016/j.comcom.2015.09.028.

Bishop, C. M. (2006). Pattern recognition and machine learning. Information Science and Statistics Series. Springer. ISBN: 978-0387-31073-2.

Black, G. (1972). A theory of political ambition: Career choices and the role of structural incentives. American Political Science Review, 66(1), 144-159. https://doi.org/10.2307/1959283.

Burt, R. (2001). Structural holes versus network closure as social capital. Social Capital: Theory and Research, 31-56. Aldine Transaction. ISBN: 978-0202306445.

Conway, B.A., Kenski, k., & Wang, D. (2013). Twitter use by presidential primary candidates during the 2012 campaign. American Behavioral Scientist, 57(11), 1596–1610. https://doi.org/10.1177/0002764213489014.

Dunbar, R. I. M. (1993). Co-evolution of neocortex size, group size and language in humans. Behavioral and Brain Science, 16(4), 681-734, https://doi.org/10.1017/S0140525X00032325.

Dunbar, R. I. M., Arnaboldi, V., Conti, M., & Passarella, A. (2015). The structure of online social networks mirrors those in the offline world. Social Networks, 43, 39–47. https://doi.org/10.1016/j.socnet.2015.04.005.

Everett, M., & Borgatti, S. P. (2005). Ego network betweenness. Social Networks, 27(1): 31-38.

Graham, T., Broersma, M., Hazelhoff, K., & Van’t Haar, G. (2013). Between broadcasting political messages and interacting with voters. Information, Communication & Society, 16(5), 692-716. https://doi.org/10.1080/1369118X.2013.785581.

Greengard, S. (2009). The first Internet president. Communications of the ACM, 52(2), 16–18. https://doi.org/10.1145/1461928.1461935.

Enli, G., & Simonsen, C.A., (2017): ‘Social media logic’ meets professional norms: Twitter hashtags usage by journalists and politicians. Information, Communication & Society. https://doi.org/10.1080/1369118X.2017.1301515

Hill, R.A., & Dunbar, R. I. M. (2003). Social network size in humans. Human Nature, 14(1), 53–72, https://doi.org/10.1007/s12110-003-1016-y.

Jackson, N., & Lilleker, D. (2011). Microblogging, constituency service and impression management: UK MPs and the use of Twitter. The Journal of Legislative Studies, 17(1), 86-105, https://doi.org/10.1080/13572334.2011.545181.
Jungherr, A. (2016). Twitter use in election campaigns: A systematic literature review. *Journal of Information Technology & Politics*, 13(1), 72-91. https://doi.org/10.1080/19331681.2015.1132401.

Larsson, A. O., & Moe, H. (2011). Studying political microblogging: Twitter users in the 2010 Swedish election campaign. *New Media & Society*, 14(5), 729-747. https://doi.org/10.1177/1461444811422894.

McCarty, C. (2002). Measuring structures in personal networks. *Journal of Social Structure*, 3(1). https://doi.org/10.1.1.90.8899.

Murthy, D. (2012). Towards a sociological understanding of social media: Theorizing Twitter. *Sociology*, 46(6), 1059-1073, https://doi.org/10.1177/0038038511422553.

Roberts, S. B. G., Dunbar, R. I. M., Pollet, T., & Kuppens, T. (2009). Exploring variations in active network size: Constraints and ego characteristics. *Social Networks*, 31, 138-146. https://doi.org/10.1016/j.socnet.2008.12.002.

Saramäki, J., Leicht, E. A., López, E., Roberts, S. G. B., Reed-Tsochas F., & Dunbar, R. I. M. (2014). Persistence of social signature in human communication. *PNAS*, 111(3), 942–947. https://doi.org/10.1073/pnas.1308540110.

Stirland, S. (2008, 4 November). *Propelled by Internet*, Barack Obama wins presidency. *Wired Magazine*. Available from: http://www.wired.com/threatlevel/2008/11/propelled-by-in.

Sutcliffe, A., Wang, D., & Dunbar, R. I. M. (2012). Relationships and the social brain: Integrating psychological and evolutionary perspectives. *British Journal of Psychology*, 103(2), 149–168. https://doi.org/10.1111/j.2044-8295.2011.02061.x.

Tumasjan, A., Sprenger, T. O., Sandner, P. G., & Welpe, I. M. (2010). Predicting elections with Twitter: What 140 characters reveal about political sentiment. *ICWSM*, 178-185.

Van Aelst, P., van Erkel, P., D’heer, E., & Harder, R.-A., (2017). Who is leading the campaign charts? Comparing individual popularity on old and new media. *Information, Communication & Society*, 20:5, 715-732. https://doi.org/10.1080/1369118X.2016.1203973.

Wilson, C., Sala, A., Puttaswamy, K. P. N., & Zhao, B. Y. (2012). Beyond social graphs: User interactions in online social networks and their implications. *ACM Transactions on the Web*, 6(4), 1 –31. https://doi.org/10.1145/2382616.2382620.

Zhou, W-X., Sornette, D., Hill, R. A., & Dunbar, R. I. M. (2005). Discrete hierarchical organization of social group sizes. *Proceedings of the Royal Society, London*, 272B, 439-444. https://doi.org/10.1098/rspb.2004.2970.

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