Interplay of homophily and communication in online social networks: Wikipedia-based semantic metric application on Twitter

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People are observed to assortatively connect on a set of traits. Uncovering the reasons for people exhibiting this strong assortative mixing in social networks is of great interest to researchers and in practice. A popular case application exploiting the insights about social correlation in social networks is in marketing and product promotion. Suggested tendencies to induce observed social correlation are homophily and social influence. However, clearly identifying the causal relationship between these tendencies has proven to be a hard task. In this study we present the interplay between communication happening on Twitter (represented by user mentions) and different semantical aspects of user communication content (tweets). As a semantic relatedness metric we employ a database built from the English Wikipedia corpus according to the Explicit Semantic Analysis method. Our work, to the best of our knowledge, is the first to offer an in-depth analysis on semantic homophily on communication in social networks. Moreover, we quantify diverse levels of homophily and/or social influence, identify the semantic traits as the foci of such homophily, show insights in the temporal evolution of the homophily and influence and finally, we present their intricate interplay with the communication in Twitter.

I. INTRODUCTION

Homophily (assortative mixing) [McPherson et al., 2001] represents a tendency of individuals who are similar on some traits to connect to each other (become friends) in a social network. Social influence (contagion) is in a way an inverse tendency for people to become similar on some traits or to adopt certain behavior from their social contacts. Both, homophily and social influence result in a higher correlation on certain traits between friends (connections) than between random users in the network. This social correlation property is repeatedly confirmed in social network analysis [Anagnostopoulos et al., 2008; Aral and Walker, 2012; Bollen et al., 2011; De Choudhury et al., 2010; Tang et al., 2013]. A question remains, to what extent is the observed social correlation a result of an underlying homophily that shapes the formation of the network or of the social influence taking place in an already formed network. A third factor that could be the cause of social correlation is a common external influence. Moreover, a combination of these factors is often at play. For instance, an external factor might have non-homogeneous adoption in the network because friends could have a higher common latent propensity for it and adopt it to a larger extent than non-friends.

Homophily among individuals and groups in society has been extensively investigated in sociology, as presented in the seminal review by McPherson et al. [McPherson et al., 2001] Starting from the paper published in the middle of the last century [Lazarsfeld and Merton, 1954], two basic levels of homophily are defined: status and value homophily. Status homophily relates to any formal or perceived status among individuals and it includes some of the most important social dimensions, such as race, ethnicity, sex, age, education, occupation and religion. Value homophily relates to our internal states that might shape the future behavior; for example: abilities (intelligence), aspirations, and attitudes (political orientation), regardless of differences in status.

In order to explain the origin of homophily in our society, sociologist have proposed different foci of formation as the causes of homophily, as well as the process of tie dissolution that happens more often among non-similar individuals over time. Geographical proximity is considered one of the most important causes of homophily, simply put, because we are more likely to have contacts with the people who are geographically closer to us. The ties induced by proximity in space are often weak ties; however, they leave more potential for stronger friendship links formation. It is worth noting that the advent of new technologies over time did not remove this pattern of geographical homophily and recent empirical research on online social networks finds that people online still tend to connect more often to geographically close people (in Twitter network [De Choudhury, 2011]; in Facebook social graph [Ugander et al., 2011]; in mobile phone communication [Blondel et al., 2010]). Another important foci that causes homophily are family ties. Family ties are an interesting foci which causes people who are similar in some aspects and as well who are not similar on certain other aspects to connect. For this reason, when it comes to family ties, we find the largest geographic, age, sex and educational heterophily; but at the same time, the largest race, religious and ethnic homophily (as there still exists a large tendency for marriage within a group). Organizational foci turns to be the most important cause of ties that are not relatives
and not family-bound. This foci includes schoolmates, colleagues from work and voluntary organizations. A more implicit cause of homophily shows to be network position. Research finding exist that holding a same position inside an organization will induce larger homophily between individuals than it would be the case if the ties were random (Lincoln and Miller 1979). Another, more internal, foci for homophily lies inside perceived similarity and shared knowledge, and it is termed cognitive processes. It is particularly notable among teenagers who tend to connect to those who are perceived to be more similar on some of the internal traits. Looking back at the described homophily traits and foci, it is not easy to make a clear distinction between the consequences of homophily and the causes or origins of it. Whether cognitive processes foci among teenagers causes them to become friends with similar ones; or whether the friend teenagers influence each other and thus become similar on a value homophily level?

Distinguishing between main factors as causes of social correlation has been a challenge, and proven not even possible from observational data (Shalizi and Thomas 2011). Hence, in this work, we do not aim to distinguish between these tendencies in the social network, but we offer a deeper understanding on their mechanisms and how they are shaping the structure and the properties of the underlying social communication network.

Our study is different from the existing studies in several aspects.

- Firstly, we focus especially on semantic homophily, and to our knowledge this is the first study to offer an in-depth and comprehensive understanding of its mechanisms: from quantification, temporal evolution, qualitative assessment of semantic foci and their functional roles concerning the interplay with the communication network structure. To measure semantic homophily, we apply semantic relatedness (SR). SR is a more general metric compared to semantic similarity, and includes antonyms (Lehrer and Lehrer 1982; Murphy 2003) and meronyms (Murphy 2003). For instance, the term airplane is similar to the term spacecraft. The same term is related to car, train or wing, but not similar to them.

- Secondly, homophily has been identified in a diverse set of social networks, however, most of the obtained results are on a friendship and/or followers type of ties, while our analysis is on the weighted mention communication ties. The ties in our social network are not only formed once (such as in friendship and followers networks), but they require an active engagement over time from the users. In this sense, the nature of the follower/friendship network is fundamentally different. When a user A follows a user B it simply states some type of potential interest in what B has to say. Depending on the different time zones and the number of other users that A is already following s/he might not even get to see any of B’s tweets. This is why we believe that the information flow networks (like the mention or retweet networks) are much more relevant for our purpose. In this case we can clearly point to interactions and information diffusion between users, instead of simply speculating about it by using the friendship/follower network.

The rest of the paper is organized as follows. Section II presents the related research literature. In Section III we describe two large Web datasets (from Twitter and Wikipedia) used in our experiments. Section IV presents the framework, consisting of a communication (IV.A) and semantic (IV.B) layer, in which we analyze semantics homophily. The results on the interplay between semantic homophily and communication are reported in Section V. The article ends with a discussion and final remarks on future works in Section VI.

II. RELATED WORK

A number of studies are conducted toward distinguishing between influence and homophily (Anagnostopoulos et al. 2008; Aral et al. 2009; La Fond and Neville 2010) reporting different levels and proportions of the two traits in online social networks. However, later it is shown that in empirical settings these tendencies are indistinguishable due to confounding effects (Shalizi and Thomas 2011). A couple of more recent papers tackled this research challenge in controlled experiments. In the experiment on a representative random sample from a set of 1.3 million Facebook users (Aral and Walker 2012), the authors sent messages about user adoption of a certain product to random people (not to the friends, as is usually the case on Facebook). In this way, the authors have eliminated homophily effects in order to study influence solely. In another experiment also on Facebook (Bakshy et al. 2012) it is found that the probability for a user to share a link increases with the number of friends who shared the same link even without the user being exposed to their link shares. Hence this controlled experiment confirmed homophily or some unobserved common external influence taking place in the network.

Other studies have focused on analyzing the interplay of homophily and influence. For example, in (De Choudhury et al. 2010), the impact of various types of homophily on influence is quantified in Twitter. Users were given homophilous traits based on a couple of attributes: location, information roles they take (generators, mediators and receptors), content creation (meformer, informer) and activity behavior (number of tweets per period of time). Diffusion is analyzed in the context of a different topic and characterized by the volume, participation, dissemination,
reach, spread, cascade instances, connection size and rate. The results are that employing homophily to predict diffusion characteristics improves the prediction 15%-25% and that the impact of attribute homophily on diffusion depends on the topic and metric used to quantify the diffusion. However, none of the homophilous attributes used in the study was able to help in predicting the diffusion rate.

Most relevant to our work are the studies focusing on the interplay between homophily and social ties. A range of investigations about homophily and influence interplay, as well as their capability to predict users’ future behavior is presented in (Crandall et al. 2008). This study finds that the homophily between two users sharply rises some time before the tie formation and after that continues to slowly grow (the authors chose the term selection in that work for the definition of homophily as we provide it here). This shows that the interplay between homophily and influence is such that, at first, homophily plays a role in the tie formation, but after that, the tie formation plays a role in the continuous increase of homophily. A recent study (Zeng and Wei 2013) confirms this result on Flickr, finding more subtle results: the users who have similar popularity (defined as the average number of favorites for their pictures) are more likely to diverge in similarity after the tie formation; while the similarity continues to grow for the users who have large popularity difference. This is explained by tendency of users to stay unique and diverse in their uploaded content from equally popular users. The analysis performed on 3 online datasets: Last.fm, Flickr and aNobii (Aiello et al. 2012), presents how the homophily information can be used for link prediction. The authors present detailed empirical research related to homophily, positive correlation between user features: in-degree, activity, number of distinct tags and books in a library; mixing patterns (average number of distinct tags of nearest neighbors of users follow linear pattern with the number of tags of the user itself); assortativity of users in terms of topics etc. The topic similarity between the users (defined through their tagging behavior feature vector) is shown to increase as the distance between them decrease. In the process of testing link prediction, the authors try different similarity features of the users (tagging, group, library features, etc.). The results are the best when combining multiple features; reaching prediction accuracy of 92% in case of aNobii. The authors conclude that this particular dataset is suitable for link prediction using homophily since there are distinct language groups present in the dataset, and they are quite homogeneous and non-mixing. In the case of Last.fm, the user linguistic features are more homogeneous and thus the prediction works a bit worse. Thus, the suggestions is that, in real cases, this method might be useful depending on the clustering of the network based on linguistic clusters of the network. In the analysis on a smaller dataset of 32 students enrolled in a distance learning class from 4 universities (Yuan and Gay 2006), homophilous traits considered are: location, group assignment (if the students belong to the same assignment group), race and gender. The analysis distinguished between instrumental (group-work related) ties and expressive (friendship) ties. The results show that homophily in gender and race had no significant impact on the development of either instrumental or expressive ties. For the development of instrumental ties, the authors find important influence of both geographic location and group assignment homophily; while for the expressive ties, only the location homophily showed to be important. On the other hand, the authors in (Bisgin et al. 2012) confirmed that influence of interest-based homophily is not a very strong leading factor for constructing new ties. They done the analysis on three social media sites, BlogCatalog, Last.fm, and LiveJournal.

A sociophysics model for interplay of homophily and influence is proposed in (Holme and Newman 2006). The authors define a simple opinion dynamics model to capture both processes that define network formation – social influence (a user can pick an opinion from any of his neighbors and change his own) and homophily (a user decides to rewire one of his ties and connect to a node with the same opinion as his own). However, such model does not capture well the subtle behavior observed around the tie formation on Wikipedia (Crandall et al. 2008) and hence the authors in (Crandall et al. 2008) propose a more complex model. In their model, for the influence part, a user can pick an action from his neighbors, but also from his/her own history, from world wide history, or even be creative and start a new action. For the homophilous interaction, the user can decide to connect to a homophilous neighbor as in Holme-Newman’s model (Holme and Newman 2006), but s/he can also, with some probability, decide to connect to a random user. Such model is found to reproduce very accurately the observed behavior around the tie formation on Wikipedia.

III. DATASETS AND EXPERIMENTAL SETUP

A. Twitter mentions dataset

The target dataset on which we perform the analysis is a mention network, represented by \( G = (V, E, W) \), based on a snapshot from Twitter for the period May 2011 until Nov 2011. The nodes \( u_i \in V \) represent Twitter users, and they are connected with a directed edge \( e_{ij} = (u_i, u_j) \in E \) when a user \( u_i \) mentions \( u_j \), while the edge is assigned the weight \( w_{ij} = (u_i, u_j) \in W \) that is equal to the total number of such mentions.

We start from a dataset that contains 12,441,636 mentions between 547,368 users over the course of 6 months.
TABLE I: Twitter dataset statistics

| Dataset               | tweets | users  |
|-----------------------|--------|--------|
| Original download     | 12 441 636 | 547 368 |
| English language      | 2 527 990 | 284 100 |
| Users > 20 tweets     | 1 344 692 | 29 616  |
| Internal replies      | 744 821 | 26 717 |

The dataset contains only the internal mentions between those users, meaning, each time when a user $u_i$ from our dataset replies to a user $u_j$ from outside, we did not keep such tweets. Additionally, we clean and filter the dataset in several steps described below, resulting in a considerably smaller final network for analysis.

The original dataset consists of tweets in several different languages, and so our first filtering step is to select only English tweets from users who mostly tweet in English using NLTK Python library (Bird et al., 2009). In this step our dataset is reduced by 20% of its original size in terms of tweets, while the number of distinct users halved. For the intended semantic relatedness (SR) analysis, individual tweets are often too small and noisy, and so our next step involves filtering the remaining users based on their total number of tweets. After some research and pre-test with the semantic knowledge database that we built (described in the following subsection), we select a cut-off threshold of 20 tweets. This dataset consists of 744,821 tweets and 29,616 distinct users. Finally, again keeping only the internal replies withing this group of users, we end up with 26,717 users in our final dataset for analysis (see Table I).

B. Wikipedia Semantic Relatedness database

We build an SR database according to the Explicit Semantic Relatedness (ESA) algorithm (Gabrilovich and Markovitch, 2007, 2009) using a Wikipedia XML dump from April 2015 (English pages only, 52GB in size uncompressed).

The first step is to take the article texts as the algorithm builds on the large amount of knowledge they provide. We then apply an open-source script wikieextractor (Giuseppe Attardi, 2015) to pre-process and clean the texts. The ESA algorithm is based on the TF-IDF (term frequency - inverse document frequency) (Baeza-Yates et al., 1999) scores of words in different articles in the Wikipedia corpus. As a result a word $w_1$ is mapped to the concept vector

\[ CV(w_1) = \{ (C_1^1, V_1^1), (C_2^1, V_2^1), (C_3^1, V_3^1), ..., (C_{M_1}^1, V_{M_1}^1) \} \]

$C_j^1$ represent Wikipedia concepts and $V_j^1$ are TF-IDF scores for the word $w_1$ in those articles and are calculated as follows:

\[ V_j^1 = TF \cdot IDF = (1 + \log(f_{1,j})) \cdot \log\left(\frac{N}{n_1}\right), \]

where $TF$ is the log-normalized raw frequency ($f_{1,j}$) of the word $w_1$ in article $j$, and $IDF$ is the inverse document frequency, $N$ is the number of articles, and $n_1$ is the number of articles in which the word $w_1$ is present.

The algorithm was implemented in Python with application of the scikit-learn machine learning library (Pedregosa et al., 2011) and the resulting database was stored in a MongoDB collection. Since some of the concept vectors might have tens of thousands of terms; prior to storing, we apply the pruning process (Gabrilovich and Markovitch, 2009) that for each word keeps only important CV elements. The algorithm implementation needs tuning several parameters, and in this process we also consult some of the existing implementations of the ESA algorithm. Our implementation of ESA is open-source and published on Github (Scepanovic, 2016).

1. Word Semantic Relatedness

The semantic relatedness (SR) between words is not measured directly, but it is rather determined through a set of concepts highly related to them (Gabrilovich and Markovitch, 2009, Hieu et al., 2013). Let us assume that the SR between words $w_1$ and $w_2$ is requested. The word SR calculation follows the two steps below.

- Determining the corresponding CVs derived from Wikipedia for the words $w_1$ and $w_2$. The CVs are based on concepts (or articles) of Wikipedia which are related to the words. Let us assume that $w_1$ is mapped to concept (tf-idf) vector: $CV(w_1) = \{ (C_1^1, V_1^1), (C_2^1, V_2^1), (C_3^1, V_3^1), ..., (C_{M_1}^1, V_{M_1}^1) \}$ and $w_2$ is mapped to concept (tf-idf) vector: $CV(w_2) = \{ (C_1^2, V_1^2), (C_2^2, V_2^2), (C_3^2, V_3^2), ..., (C_{M_2}^2, V_{M_2}^2) \}$. These are the sets of Wikipedia concepts, $C_j^1$ and $C_j^2$, which are related to the word $w_1$ and $w_2$ and their TF-IDF scores, $V_j^1$ and $V_j^2$. 

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[1] Bird, E., Loper, E., & Elhadad, Y. (2009). NLTK: The Natural Language Toolkit.\n[2] Baeza-Yates, R., & Ribeiro-Neto, B. (1999). Modern information retrieval.\n[3] Gabrilovich, E., & Markovitch, S. (2007). Explicit semantic relatedness.\n[4] Gabrilovich, E., & Markovitch, S. (2009). The semantic web: a new dimension to data search. In Proceedings of the 13th Pacific Rim International Conference on Artificial Intelligence (pp. 433-444).\n[5] Hieu, V., Grenier, M., & Amblard, P. (2013). Deep semantic relatedness between concepts in text. In Proceedings of the 2nd International Conference on Knowledge Discovery in Cyberspace (ICDKC 2013).\n[6] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., et al. (2011). Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12, 2825-2830.\n[7] Scepanovic, M. (2016). ESA implementation. Github repository.\n[8] Giuseppe Attardi. (2015). wikieextractor. Github repository.
\( V_2 \), respectively. In the following, we will assume that \( N \) is the number of common concepts in \( CV(w_1) \) and \( CV(w_2) \).

- **Calculating the SR between words using cosine similarity between obtained CVs.** For measuring the degree of semantic relatedness, cosine similarity between the CVs for two words \( w_1 \) and \( w_2 \) is calculated. This measure gives the cosine of the angle between the two vectors \( CV(w_1) \) and \( CV(w_2) \). The cosine measure can be re-formulated for our purpose as follows:

\[
SR(w_1, w_2) = \cos(CV(w_1), CV(w_2)) = \frac{\sum_{i=1}^{N} V_1^i \cdot V_2^i}{\sqrt{\sum_{k=1}^{M_1} (V_1^k)^2} \cdot \sqrt{\sum_{l=1}^{M_2} (V_2^l)^2}},
\]

where \( i \) iterates over the common concepts.

The \( SR(w_1, w_2) \) values range from 0 (i.e., no semantic relatedness) to 1 (i.e., perfect semantic relatedness) as the TF-IDF weights can not be negative.

2. Document Semantic Relatedness

The semantic relatedness (SR) between documents is measured through the SR of the words found in the documents. Let us assume that the SR between documents \( d_1 \) and \( d_2 \) is requested. The document SR calculation follows the three steps below.

- **Analyzing documents using the term frequency (TF) approach which finds the frequency of words in the document.** The result of this step is a list of important words with their corresponding TF scores. Let us assume that:

  - \( d_1 \) is analyzed to term (tf) vector: \( T(d_1) = \{(t_1^1, v_1^1), (t_2^1, v_2^1), (t_3^1, v_3^1), ..., (t_m^1, v_m^1)\} \)
  - \( d_2 \) to term (tf) vector: \( T(d_2) = \{(t_1^2, v_1^2), (t_2^2, v_2^2), (t_3^2, v_3^2), ..., (t_n^2, v_n^2)\} \), and \( m < n \).

- **Determining the corresponding CVs derived from Wikipedia for the documents \( d_1 \) and \( d_2 \).** For each term in the lists \( T(d_1) \) and \( T(d_2) \) we derive their individual CVs (as described for words in Section [III.B.1](#iii.b.1)). For instance, the \( t_1^1 \) term is mapped to concept (tf-idf) vector: \( CV(t_1^1) = \{(C_1^1, (v_1^1 \times V_1^1)), (C_2^1, (v_1^1 \times V_2^1)), ..., (C_M^1, (v_1^1 \times V_M^1))\} \). The other terms in \( T(d_1) \) can be represented in a similar way. When summarizing the CVs for one document, the CV for each term is multiplied with its TF score in the document (found in the previous step). If the terms in \( T(d_1) \) have the same concepts in their CVs, we sum the weighted TF-IDF scores of those concepts. After this process we obtain \( CV(d_1) \), the list of Wikipedia concepts and TF-IDF scores which are related to all the terms in \( T(d_1) \). Similarly, for \( d_2 \) the list of relevant Wikipedia concepts and TF-IDF scores is found in \( CV(d_2) \).

- **Calculating the SR between documents using cosine similarity between obtained CVs.** Finally, we obtain the \( SR(d_1, d_2) \) between documents by calculating the cosine similarity of \( CV(d_1) \) and \( CV(d_2) \) (see Eq. [2](#2)).

3. SR database evaluation

The English version of Wikipedia used includes over 2.5 million articles. Since many of the articles are highly specialized, and due to the described pruning process, we find only around 15% of those articles (387,992) relevant for our tweets corpus. In a similar manner as in the original paper ([Gabrilovich and Markovitch](#gabrilovich2009), 2009), we evaluate the quality of the SR database that we built against available datasets with human judgment for word pairs relatedness. We use several such datasets available online, as one of the most comprehensive current resources ([Faruqui and Dyer](#faruqui2014), 2014). The results of the evaluation are presented in Table [I](#table-i). We do not provide herein a comparison with the existing implementations, since not all of them provide their evaluation on the same datasets with human judgments, and since a previous study comparing them has shown that some of these results are incompatible ([Cramer](#cramer2008), 2008). However, our evaluation scores are comparable to the original implementation ([Gabrilovich and Markovitch](#gabrilovich2009), 2009) and to the ESA implementations available online.
TABLE II: SR knowledge database evaluation

| Human judgments dataset | Spearman’s rank | Pearson’s correlation |
|-------------------------|-----------------|-----------------------|
| WordSim-353             | 0.51            | 0.45                  |
| Miller and Charles      | 0.79            | 0.82                  |
| Word pair similarity, MTurk | 0.53      | 0.45                  |
| Rubenstein and Goodenough | 0.81       | 0.74                  |
| MEN dataset of word pair sim. | 0.73     | 0.44                  |
| Average                 | 0.67            | 0.58                  |

C. Semantic enrichment using AlchemyAPI

We additionally enrich our dataset with with the semantic meta-data obtained from AlchemyAPI [An IBM Com-pany] [2016], after sending individual user tweets collections for natural language processing (NLP) and machine learning (ML) analysis. AlchemyAPI returns semantic meta-data from the content, out of which we utilize following: sentiment score, taxonomy, concepts, entities and keywords. Hence, for each user we obtain the information about the overall sentiment of his tweets (a real number score between -1 for fully negative and 1 for fully positive), the taxonomy tree elements, concepts and entities found relevant in his tweets, with their corresponding relevance scores.

IV. FRAMEWORK FOR SEMANTIC HOMOPHILY ANALYSIS

A. Communication layer: Twitter mention network

The mention network formed from the Twitter data based on who mentions who in their tweets we regard as a communication layer. We also consider the number of mentions between two users (edge weights) as their interaction (or communication) propensity. The described mention network exhibits some different properties compared to the usually analyzed followers network. For instance, the reciprocity of the followers network is found to be around 22% [Kwak et al.] [2010] which is lower compared to the other social networks. The reciprocity of our mention network is 64%, considerably higher than that of the followers network. More detailed statistics about the communication layer are given in Table III

B. Semantic layer: SR network

In addition to the communication layer, we extract another, semantic layer from the Twitter data. The semantic layer is the network based on the semantic relatedness (SR) between the user tweets collections, we refer to it as the SRnetwork. The SRnetwork is built using the above described Wikipedia-based SR database. After preprocessing (cleaning for stop-words and non-alphanumeric characters, and transforming all to lowercase) we collect the tweets per each user into separate documents. We then calculate the SR values between those documents applying the procedure described in Section III.B.2. For each user (or a group of users) we can also obtain a set of relevant Wikipedia concepts (articles) describing semantically their tweets contents (from their corresponding Wikipedia CVs). Secondary semantic enrichment for the mention dataset we obtain from the Alchemy semantic meta-data.

The two semantic enrichment procedures provide two additional layers of data on top of our Twitter mention network: Wikipedia SR enrichment provides edge weights and both AlchemyAPI and Wikipedia enrichment (through user CVs) provide several different node (user) attributes.

In a somewhat computationally demanding task, we calculate the SR scores between all the user pairs, resulting in a full SRnetwork. The distribution of the SR values of the initial full SRnetwork is shown in Fig. 1a. During the analysis, we also apply different thresholds (between 0.2 and 0.95) on the SR values (edge weights) and obtain several SR sub-networks, which we respectively refer to as SR_0.2, SR_0.4,..., SR_0.95 networks.

The results shown in Fig. 1b reveal that when thresholding the SRnetwork for SR value around 0.25, the largest connected component still has around 85% of the nodes and its density stabilizes, even it starts to grow, whereas the overall density in the network is significantly reduced.

Prior to presenting quantitative and qualitative analysis of social correlation, we comment the results for the degree assortativity in the mention and SRnetwork for different thresholds of interaction propensity and SR values, respectively. Namely, while the mention network and the SRnetwork both consist of the same set of nodes (representing Twitter users), depending on the threshold we put on their edge weights, they have different edge density and several
FIG. 1: SR metrics and SR network statistics

TABLE III: Mention network statistics

| Network parameter | value     |
|-------------------|-----------|
| Nodes             | 26,717    |
| Edges             | 99,910    |
| Avg weighted deg. | 55.75     |
| Avg clustering coeff. | 0.051 |

FIG. 2: Degree assortativity measures

(a) Mention network (directed) as a function of interaction propensity; directed networks have several degree assortativity measures

(b) SR network (undirected) as a function of SR threshold; branching factor, intermodular connectivity and transitivity as three ingredients for network assortativity
other network properties. A particularly interesting result we obtain for their degree assortativity (DA) [Newman, 2002] is presented in Fig. 2. The (positive) assortativity found in the mention network is expected (Fig. 2a), as social networks are generally found to be assortative (Newman, 2002). Perhaps less expected is the changing pattern from positive DA to negative DA in the SR network (see Fig. 2b). In order to make sure that this pattern is not an artifact of thresholding edge weights with values in the interval (0, 1) of a fully connected network, we apply several randomization strategies on the SR network and find no pattern in DA when thresholding such networks. Hence, we conclude that the DA pattern in Fig. 2b is specific to the human semantic relatedness metrics, showing that a structurally important change in the network takes place when we consider different SR threshold. Fig. 2b shows that the SR network, when thresholded with values over 0.6, has the branching factor that is bigger than the sum of the intermodular connectivity and network transitivity (i.e., clustering coefficient) (Estrada, 2011). The gray region in Fig. 2b shows for which SR threshold values the difference between the intermodular connectivity and the branching factor is the largest. In addition, in this region the SR network obeys highest transitivity. The conclusion is that for SR values between 0.15 and 0.35 the SR network has the highest assortativity. In this way we find lower and upper bounds for the threshold that can be used to remove the noise generated when building the SR knowledge database.

All of these results lead us to a conclusion that the best value to threshold the SR network would be somewhere in the interval between 0.2 and 0.3. For these values we also obtain the best community matching between the SR network and the mention network, as described in the results later. From an application point of view, our finding might be important to consider when designing other semantic relatedness and similarity metrics, in particular when choosing a suitable threshold.

V. THE INTERPLAY OF SEMANTIC HOMOPHILY AND COMMUNICATION

In this section we present the results that confirm the existence of semantics homophily and/or (external) influence in our dataset, and we quantify their levels. In order to quantify interaction propensity for semantically related users, we calculate the likelihood of edges from the mention graph being present in the SR network for different thresholds $x \in \{0.2, 0.4, ..., 0.95\}$. For instance, the SR$_{0.2}$ network has 40,765,520 links, or 9.30% out of all possible 438,538,920 links in the SR network. Hence, if mention links were randomly distributed on the SR network (i.e., if communication would be independent from SR), we would expect a similar percent of mention links in the SR network. However, we actually find their percent to be considerably higher: 27.30%. Moreover, the likelihood of mention edges increases as the SR threshold increases, and also, on another dimension, as we increase the threshold on the mention edges themselves. The overall results are presented in Fig. 3. The gradient increase indicates the existence of both tendencies in the Twitter mention network: semantic homophily (across the increasing SR thresholds) and social influence (across the increasing number of mentions between users, i.e., increased interaction propensity). Still, we underline that we do not try to distinguish between these two tendencies, and eventual common external influences that could be the causes of the presented social correlation.

A. Temporal interplay aspects

In addition to the measurements of social correlation on a static snapshot of the Twitter network, another important thread we analyze is the temporal change of social correlation. First, operating on all 99,910 edges in the mention network, we calculate the monthly average SR values on them from June until November 2011 (because we do not have the data for whole May and November, we present only the results for the other five months). Average monthly SR in the whole network increases steadily, as presented in the top plot in Fig. 4. In this manner, we show and quantify a gradual temporal increase in semantic social correlation in the network. The increase can be caused by homophily taking place (users are forming new communication with similar users during time), or by social influence (the users who are already communicating become more similar and hence their SR increases in time), or there could be an external influence taking place at the time causing the users to talk more on a similar (external) topic.

To understand better the drivers of the presented temporal SR change, we focus on interaction activation and/or decommission. At this point we remind the reader of our definition of the communication network, where the users are actively participating through time. With regard to such a definition, in this step we consider only reciprocal edges. Operating on the 62,757 reciprocal edges in the dataset, we define interaction activation time to be the month when for the first time both users have mentioned each other in our dataset. Interaction decommission time is given by the last month in our dataset that the users have both mentioned each other, after which one or both sides ceased the communication. Additionally, in order to have enough data to calculate the users similarity prior/after to the interaction activation/decommission time, we require the month of activation/decommission to be between July and September. With this approach, in our dataset we find in total 20,548 interaction activations and 11,813 interaction
FIG. 3: Mention edges likelihood in the SR network: the darker color represents how much more likely are the mention edges in the SR network with the respective thresholds than would be the case in an uniformly random setting; the colormap is log scale; minimum value is 2.94 and maximum 42.89 (the darkest square).

decommission. As a first insight, we can notice that more interactions are activated than decommissioned, which could be one of the causes of the observed temporal SR increase.

Going further, the average temporal SR change on the interaction prior to and after the activation/decommission is shown in the second from the top plots in Fig. 4 left/right, respectively. We first notice that the user similarity significantly increases at the month of interaction activation. Similar result has been found in other networks, for instance among Wikipedia admins (Crandall et al. 2008) and for Flickr users (Zeng and Wei 2013) for their edge formation. The observation of a drop in average SR in the months after the interaction activation (edge formation) is also reported in earlier studies (Zeng and Wei 2013). To investigate the drop in our case, as a first step we look for an evidence that some interactions might not be preserved for long. This is one aspect where our approach is advantageous compared to the previous approaches, that consider a formal edge formation (adding someone as a friend or following) that often do not require an active user engagement afterwards. Indeed, we find in total 8,166 interactions that are activated and then also decommissioned during our dataset period. Their temporal SR change is shown in the third from the top plot. This result clearly shows that communication interaction need to be considered together with their temporal dynamics. Finally, observing only the persisting interactions that were already active and not decommissioned during the whole time period of our dataset (which is 6 months), we obtain the results in the bottom plot. One can notice that such persisting interactions have a stable average SR through time (about 0.07) even when the average SR in the whole network has changed considerably from June until October. This stability of the SR on an already established user interaction suggests a lack of influence in our network. However, we are careful with such an interpretation, since this result might also indicate a saturation effect taking place: at first, the users
FIG. 4: Temporal SR change: on the all mention edges (top), during interaction activation (second from the top, left), decommission (second from the top, right), on short period interaction (third from the top), and on persisting interaction (bottom); error bars show the standard deviation values.

might influence each other for some time, and then their similarity stabilizes at this specific value. Another reason not to exclude the presence of influence is when we look at interaction decommissions: the user pairs between whom the interactions ceases still preserve some similarity effect after that.

In summary, the presented types of interaction show the importance of considering both homophily and influence as dynamic interdependent tendencies [Yavaş and Yücel, 2014] in the temporal network, instead of a static. We also analyze interaction decommission and find similar results as the authors in [Noel and Nyhan, 2011] who showed how not accounting for homophily effect on tie dissolution (“unfriending”) may importantly affect social influence estimation. Precisely, we suggest that on a same communication link (interaction) at different points of time with reference to its activation/decommission time, one or the other of the tendencies might be playing a stronger role.

Our dataset time-frame does not allow for that, but as a future work, we aim to look at the period in which edge formations and deletions might be happening, and whether there are some natural cycles in the human communication networks.

B. Foci of semantic homophily in communication

Another way to quantify homophily in a network is to measure the level of assortative mixing on semantic traits. In addition to the degree assortativity, social networks are shown to exhibit assortativity on diverse attributes of nodes [Aiello et al., 2012; Bollen et al., 2011; Eom and Jo, 2014]. In line with such findings, our Twitter mention network
exhibits high levels of assortativity on the user sentiment, several topics and, interestingly, also on the diversity of user concept vectors (CVs), entities and taxonomies present in their tweets, as shown in Table IV. The last set of node attributes represents semantic diversity and it is referred as semantic capital (Roth and Cointet [2010]). The node degree or number of friends with whom s/he communicates, and the number of replies or interaction propensity can be referred as social capital.

The results suggest presence of both, value (topics of tweeting, sentiment) and status (social capital) homophily in the mention network. Moreover, using several attributes for the semantic capital foci we prove that, as for the bloggers (Roth and Cointet [2010]), the Twitter users who are network-central also tend to have a large semantic capital (since these traits correlate with the degree).

After confirming and quantifying social correlation of the Twitter communication network for several semantics traits, next we qualitatively asses observed social correlation levels, and work towards discovering their foci of formation.

1. External influences foci

The enrichment of the Twitter dataset with taxonomies from AlchemyAPI enables to gain insights into the concrete topics and sentiment of the communication. For this reason we visualize the output from AlchemyAPI, as a taxonomy tree for the whole Twitter dataset, see Fig. 5. The higher the distance from the center, and a larger bubble, represent a more specific taxonomy label that is more discussed in the dataset. This taxonomy output from AlchemyAPI defines contextual content categories for up to five different levels, such that the first level (level0) is a broad category, second level subcategories nested under level1 are more specific, and so on.

As a first insight, we display the overall most popular categories among the users in our dataset in Fig. 5 (left side of the figure). The central nodes in the bubble tree represent level1 categories, with their nested subcategories to the periphery. The size of the bubble corresponds to the overall score for a topic, hence we can see that arts and entertainment taxonomy including movies, tv shows, music and humor is the dominant topic of conversation.

Second set of most popular taxonomies includes sex (under society), sports and technology and computing.

After this insight into general topics, we turn to the Wikipedia-based semantic enrichment layer of our dataset. The results are consistent with those from AlchemyAPI. In Table V we present some of overall top hundred concepts, per subcategories identified using AlchemyAPI. Out of the top ten concepts, the two seasons of the TV series This Is England (that has been aired at the time corresponding to the dataset) are ranked 2nd and 3rd. Next, we also find several musicians and bands. The concepts LOL and Smiley Face are in part a result of how the ESA algorithm (Gabrilovich and Markovitch, 2007, 2009), that the Wikipedia SR database is built with, works. They are also in agreement with humor being prevalent subcategory among users in our dataset. The total number of over 300K Wikipedia concepts found to describe our dataset communication results in a fine SR metrics. At the same time, from Table V we see that already the top hundred concepts provide insights into the concrete topics of the conversation in the dataset.

In addition to the series This is England being aired at the time of our dataset, the death of Osama bin Laden also happened at the time. After these insights, we conclude that there is some external influence taking place in our dataset and we continue to analyze the semantics on a more granular level.

2. Internal semantics foci

Here we analyze whether there are some categories of topics that are discussed often together, i.e., if a user tweets on one category, then s/he is more likely to tweet on another, too. It is natural to compare the categories on a same taxonomy level, hence we created five taxonomy graphs for each level from the AlchemyAPI output. Sometimes a user tweet corpus is classified up to the fifth levels of taxonomies, but more often only to the third or second. Hence, the richest information is present for the first taxonomy level (level0); however, this level also turns out to be too general (most of the users talk about the same general categories). On the deeper levels, on the other hand, the data becomes too sparse, and so we identify the taxonomy level1 categories to offer the best information to answer our question.

In Fig. 5 (right side of the figure), we present identified communities in the taxonomy level1 network. This result is likely very specific to our dataset, i.e., user sample, who tweet a lot about music, and mobile technologies. However, the presented analysis is useful as it reveals what semantic foci (topic categories) go together in our context. In the next section, we investigate what semantics foci shape the network structure of communication.
C. Semantic homophily and community network structure

In order to see what are the semantics traits that shape community structures between Twitter users we first run the modularity-based community detection algorithm (Newman, 2006) on the weighted mention network.

In a similar way to the existing studies (Yang and Leskovec, 2015; Yang et al., 2014), we distinguish between the structural and functional definitions of network communities. The connectivity pattern between users defines structural communities, whereas a common function or a role of the members in the network defines functional communities. In this part, we allow different semantic traits of user communication to define semantic structural communities (i.e., communities on the semantic layer), while the connectivity of their communication network (communication layer) defines structural communities of communication. The goal of network community detection is to extract semantic
TABLE VI: Largest communities in the mention network and their semantic foci

| Num of users | 2222  | 686  | 636  | 435  | 381  | 343  | 343 |
|--------------|-------|------|------|------|------|------|------|
| Main geo-entities | Nigeria Indonesia South, Philippines, Jamaica, U.K. NY, LA, Africa, Malaysia, Miami |
| Sentiment     | 0.38  | 0.87 | 0.67 | 0.72 | 0.5  | 0.59 | 0.71 |

FIG. 6: Mention modular communities; left: radial axis visualization with identified user geo-location entities (based on the output from AlchemyAPI) in each community; right: SR communities produced by Infomap on top of the mention community representation; we can see how the largest modular communities from the communication layer overlap with those produced from the semantic layer.

Communities to some extent based on the connections in the communication layer, i.e., the mentioning between Twitter users and based on semantical analysis of their tweets to find the common function and then to show that to some extent there is similarity between the functional communities on the communication layer and the semantic structural communities obtained from the SRnetwork. The procedure for this is as follows.

After the users are divided into (disjoint) sets of structural communities, we apply semantic analysis on each set separately, finding most popular concepts, keywords, entities and categories on different levels of taxonomy tree and overall sentiment. After careful analysis, we conclude that only the entities of conversation can be used to explain...
this type of communities. The results for several top size communities are presented in Table VI and visualized in Fig. 6 (left side of the figure) using radial axis layout in Gephi (Bastian et al., 2009).

While the concepts (see Fig. 9), keywords (results are not shown) and taxonomy categories (see Fig. 8) offer insights into the topics of conversation, entities (see Table VI and Fig. 7) seem to be the only able to explain the mention communities because they capture geographical locations. Namely, the geographic loci (De Choudhury, 2011; Leskovec and Horvitz, 2008) and language (Aiello et al., 2012) are good predictors of cohesive communication groups, and these is the type of communities that the modularity-based community-detection algorithm finds (Blondel et al., 2010). As a remark, the mention communities in our communication layer may be also formed due to the ethnicity of the Twitter users or their geolocation, while in any of the cases, their tweet contents contain relevant geo-location entities. As an example, we present the results on the taxonomy Fig. 8, top concepts in Fig. 9, and top entities in Fig. 7 in the two largest communities: Nigeria and Indonesia. We performed a careful analysis for each community and similarly to these two communities, we do not find important differences in main concepts or taxonomies. For instance,
we can see that both in the Indonesian and Nigerian community the strongest categories in the taxonomy tree are *art and entertainment*, *society* and *technology and computing*, those same that are prevalent in the whole dataset. The two slight notable differences are that in Indonesia, *Islam* is a more strong subcategory under *religion*, and, on the other hand, *Africa* is present under *tourist destinations* in the Nigerian taxonomy. As for the concepts, we again notice a lot of general concepts, such as music singles and *English-language films*. A large difference in the sentiment between these two communities (see Table VI), however can be inferred by more prevalent swear words concepts in Nigeria (having negative sentiment), and, on the other hand, *Gratitude* and *Luck* being dominant in positive Indonesia. Previous studies found that Indonesian users have higher than average tweets per user ratio, which is related to higher reciprocity, and in turn a higher-reciprocity communities display a happier language ([Poblete et al., 2011]). Our findings both on a high positive sentiment of the Indonesian community and the fact that we detect this community as a cohesive, modular group of users are in agreement with such findings.

1. Semantic Layer Community Structure

Furthermore, in order to see the semantic communities in our dataset, we apply community detection on the semantic layer (i.e., on the SR,x networks). While we tried running several community detection algorithms (such as modularity-based, InfoMap [Rosvall and Bergstrom, 2008] and BigClam [Yang and Leskovec, 2013]), on different threshold x ∈ (0.2, ..., 0.95) SR,x networks.

In order to evaluate the matching between the communication and semantic communities we compare a set of communication layer communities P to a set of semantic layer communities L by adopting an evaluation procedure used in [Yang and Leskovec, 2012, 2015, Yang et al., 2014], i.e., $S = \max_{P, L} F_1(L_i, P_j)$, where $F_1$ uses $F_1$ as a score for similarity between the two sets and $S \in [0, 1]$ (where 1 indicates perfect matching). The best results in terms of similarity with the communication layer communities we obtain running InfoMap algorithm on the SR,0.2 network. The rationale why modularity-based community detection algorithm does perform well on the semantic layer is that the SR,x networks are so dense, that the modularity-based algorithm does not perform well on them. This is

(a) Nigerian concepts
(b) Indonesian concepts

**FIG. 9: Top concepts in the tweets of the two largest communities**

**TABLE VII: Community similarity between communication and semantic layer**

| P communities | L communities | S |
|---------------|---------------|---|
| $P_0$ - Philippines | $L_{326}$ | 0.41 |
| $P_8$ - Nigeria | $L_2$ | 0.45 |
| $P_{10}$ - Indonesia | $L_{159}$ | 0.18 |
| $P_{11}$ - Nigeria | $L_2$ | 0.18 |
| $P_{102}$ - UK | $L_{211}$ | 0.13 |
FIG. 10: **Homophily and network structure**: average SR in communities

a consequence of the modularity measure which is optimized by the algorithm, where high modularity means dense connections between the nodes within communities but **sparse** connections between nodes in different communities.

In Table VII we show the community similarity value between some of the biggest communication layer communities (with more than 50 users) obtained using modularity and semantics layer communities obtained using InfoMap (again with more than 50 users). The results show high level of mapping between the Philippines, Nigerian and Indonesian community, and are visualized in Fig. 6 confirming that the **semantic relatedness** between users is one of the foci of large cohesive communities in communication networks. In order to have firm confirmation of this result, we compare the average SR values for these communities on the existing mention edges (green crosses in Fig. 10) to the average SR values in the network (the dotted red line in Fig. 10) and average SR values in these communities without taking into consideration the communication layer (the blue dots in Fig. 10). With this we conclude that with very high probability (especially for communities with more than 200 users) the average SR value on the communication layer within a community is bigger than the overall average SR value or the average SR value within the community neglecting the communication layer. For the smaller communities (see the in-plot in Fig. 10), it does not hold for all the communities, even though the difference is noticeable.

2. Pluralistic homophily

Pluralistic homophily results from a several different foci. It is often the case that users form a community around at least one foci (and we have seen it in this dataset for modular communities and geolocation foci). Yang et al. (Yang and Leskovec, 2014) suggest that the nodes that share more communities have more homophilous foci in common, and hence a higher probability of having a connection between them, forming the network core (Yang and Leskovec, 2014) of nodes that have a large social capital.
Thereby, we investigate the evidence of pluralistic homophily (see Fig. 11a) in our dataset. The interaction likelihood that the users sharing two communities have an edge greatly increases compared to those who share only one community, whereas the interaction likelihood for the users that share more than two communities has a slower linear growth. On the other hand, the results shown in the in-plot in Fig. 11a reveal that the interaction propensity is the highest if the users belong to only one common community. We explain this with the specificity of our social network under analysis: when requiring an active participation for communication and network edges, it seems that the users are not able to handle too many such active ties and at the same time belong to more communities.

Furthermore, we investigate what type of interaction propensity is important to be in the core of the communication network, i.e., mentioning or being mentioned (see Fig. 11b). Our results point to the existence of diva users in the core, since they are being mentioned more, but their propensity of mentioning others falls down as they belong to more communities.

VI. DISCUSSION AND CONCLUSION

Despite the vast and growing literature and research on what interweaves people in social networks, the importance of homophily, influence and external influence as three main factors for social correlation is still not fully explored and understood. Our findings quantify to what extent semantic homophily and social influence affect the communication and its propensity in online social networks, though we are not trying to distinguish between the two tendencies. Moreover, using temporal social network we show that both tendencies are dynamic and change their role and magnitude in time. Besides the temporal dimension, we show that several types of homophily are present in the social communication network, such as value (topics, sentiment) and status (social capital) homophily. One question, connected to the social correlation levels, that we also tackle is to discover the external influences foci and internal semantics foci. In this way we present a way to qualitatively analyze the possible semantic foci of homophily in social networks.

Further analyses of the community structure of the communication and semantic layer show that semantics foci heavily influence the communication network structure or vice versa. For existing structural communities in the communication network, we discover corresponding semantical structural communities and explain their foci. Using the community structure of the communication network we also prove the interplay of pluralistic homophily with interaction propensity and with users social capital.

A limitation of our work posed by the restricted dataset is that we are not considering the entire Twitter channel for information flow, as there are also considerable amount of information flowing along the retweet network, which is not taken into consideration in this work. Besides this, the mention mechanism in Twitter can be sometimes biased towards specific target audiences for specific information (Tang et al., 2015).

Further investigation is needed on the influence of the threshold for semantic relatedness on the semantic homophily, as we show in this work that the semantic layer became disassortative after threshold equal to 0.6. Additional and
improved sentiment analysis is needed to understand how the social reinforcement influences communication between users and if there exists happiness paradox while people communicate in social network.

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